Intangible Investment, Displacement Risk, and the Value Discount*

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Abstract

Composition matters. The composition of assets in place and growth opportunities affect risk premia. Firms with growth opportunities in the form of intangible investments exposed to displacement risk have larger expected returns than firms with growth opportunities in the form of tangible investments. I develop a production-based asset pricing model showing that a firm's exposures to priced productivity and displacement risk depend on multiple firm characteristics. None of these characteristics alone can capture the firm's total exposure. Empirically, intangible investment positively predicts returns, and firms undertaking more intangible investment are more exposed to proxies for displacement risk. I develop six proxies to measure displacement risk shocks: three based on sorting firms into portfolios and three based on aggregate variables. A portfolio double-sorted on two key firm characteristics, the book-to-market ratio (including intangible capital) and the difference between the intangible and tangible investment rates, produces large excess returns that existing models cannot explain. This double-sort can explain the decline of the Value Premium.

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1 Introduction

Not all forms of capital or investment have similar implications for a firm's equity risk premium. A firm whose capital stock primarily consists of tangible capital (i.e., real assets) is exposed to different risks than a firm whose capital stock consists of intangible assets (e.g., patents, software, and branding). Firms' market values reflect current, installed capital and future capital stocks, which are captured in the investment rates of the firms.[1] In this paper, I study how the composition of assets in place and growth opportunities affect risk premia and our understanding of the link between firm characteristics and asset prices.

Empirically, as I discuss and show below, the intangible and tangible investment predict stock returns with opposite signs. Firms with similar levels of this investment difference comove, suggesting that intangible and tangible investment are related to a common factor but with opposite signs. I refer to this risk factor as *displacement risk*.[2] Intangible capital is at greater risk of "creative destruction."[3] Firms undertaking intangible investment are at risk of having their future, "fragile" intangible capital displaced. On the other hand, firms undertaking tangible investment can benefit from technologies embodied in new physical capital, which are brought about by the same creative destruction that displaces intangible capital.

As intangible capital has increased in importance in the economy, understanding differences in the composition of assets and investment opportunities has also become more important. Belo et al. (2021) estimate that the contribution of knowledge capital, a type of intangible capital, to firm value has nearly doubled since the 1970s. Evidence like this suggests that ignoring composition effects, or assuming a tangible capital-only model of the firm, may no longer be appropriate.

The paper's organizing framework is a partial-equilibrium production-based asset pricing model that features tangible and intangible capital and investment. The firm is exposed to tangible capital productivity shocks[4] and displacement risk shocks.[5] These shocks appear

[1]Market values can differ from accounting, or book, values for other reasons such as behavioral biases and market frictions, e.g., as in Bolton et al. (2011). I focus on the value embodied in investment.

[2]Kogan et al. (2020)

[3]Schumpeter (1942), Govindarajan and Srivastava (2016)

[4]I refer to this as "productivity" for short.

[5]Displacement risk in my model works similarly to the displacement risk in Kogan et al. (2020) and the

in the model's stochastic discount factor, affecting the risk premium of firms exposed to them. Like other production-based models, productivity shocks increase the output from tangible capital. In this paper, displacement risk serves two functions. First, following a positive displacement risk shock, output from intangible capital decreases. For example, new technology could render a firm's patent(s) obsolete.[6] Second, a positive displacement risk shock increases the quality of new tangible capital goods. For example, the same technology can make new tangible investment more productive. That is, new technology resulting from intangible investments could have adverse effects on existing intangible assets while having beneficial effects on new tangible investments.

The model developed here shows that a firm's value can be expressed as the sum of four terms. Each term is a function of capital stocks and/or productivity and displacement levels[7], and each term can be mapped to a firm characteristic: the book value of tangible capital, the book value of intangible capital, the tangible investment rate, and the intangible investment rate. A key insight is that a firm's betas on the two priced shocks can be written as functions of the four characteristics, but that no individual characteristic can serve as a sufficient statistic for exposure to a given shock. For example, a firm's tangible investment is "long" (positively exposed to) displacement risk, but a firm's intangible investment is "short" (negatively exposed to) displacement risk. Failing to account for all firm characteristics would distort inference about a firm's exposure to priced risk factors.[8]

Using techniques from Peters and Taylor (2017) for measuring intangible capital and investment, I map the firm characteristics from the model to the data and test the model's main asset pricing implications.[9] According to the existing asset pricing literature, productivity shocks should carry positive prices of risk,[10] and displacement risk shocks should carry negative prices.[11] It follows that the firm characteristics highlighted by the model

"frontier technology risk" in Eisfeldt and Papanikolaou (2013).

[6]In the model of Aghion and Howitt (1992) the flow output from a firm's existing patent(s) goes to zero following an innovative technological advance.

[7]The model also features idiosyncratic investment productivities which appear in these terms as well.

[8]In fact, the book value of intangible capital is also short displacement risk, so in this case, the beta depends on three different characteristics.

[9]See Van Criekingen et al. (2021) for a survey on measurement of intangibles.

[10]Jermann (1998)

[11]Papanikolaou (2011), Eisfeldt and Papanikolaou (2013), Kogan and Papanikolaou (2014), Kogan et al. (2020)

should have opposite effects on a firm's expected return. I confirm the asset pricing implications of the model in firm-level panel regressions with several controls and fixed-effects. Intangible investment and the book-to-market ratio (where book equity includes intangible capital) positively predict returns, while tangible investment and the fraction of assets in place attributable to intangible capital negatively predict returns. This latter effect reflects the impact of the firm's capital composition, indicating that productivity shocks are riskier than displacement risk shocks.

I further examine the relationship between displacement risk and intangible investment and capital. I develop and employ six proxies for displacement shocks: (a) a mimicking portfolio based on sorting firms by their intangible minus tangible investment rates, which should track the shocks according to the model, (b) a mimicking portfolio based on sorting firms by their intangible capital stocks to market values, (c) a mimicking portfolio based on sorting firms by their tangible investment rates, (d) the aggregate mean difference between intangible and tangible investment, (e) a measure of the marginal product of intangible capital in a year, and (f) a measure from the existing literature based on the economic value of patents (Kogan et al. (2017)). The tangible investment sorted portfolio and the patent measure are proxies for positive displacement risk shocks. The other measures are proxies for negative shocks. Firms undertaking more intangible investment relative to tangible are more adversely exposed to displacement risk shocks: A positive shock reduces their cash flows.

This paper finds that firms with larger exposure to displacement risk through their intangible investment have lower returns following displacement risk shocks. When I sort firms into portfolios based on their intangible investment minus tangible investment rates, I find betas on displacement risk measures decrease as the difference in investment rates increases. The model also implies that earnings of firms that are short displacement risk should fall more following displacement risk shocks. Using empirical proxies, I confirm this prediction in the data.

Though my model signifies the importance of tracking four different firm characteristics to account for all risk exposures, I rely on trends in the data and transformations of these characteristics to form a parsimonious double-sort to maximize expected returns. Since firms undertaking more intangible investment tend to have larger intangible capital stocks as a fraction of their total capital, it is empirically difficult to sort on these characteristics separately. Also, since intangible and tangible investment predict returns in opposite directions, I use the difference in investment rates (intangible minus tangible) as a sorting variable. In the end, I double-sort on the book-to-market ratio (where book equity includes intangible capital) and the difference in investment rates. I find that leading factor models cannot explain the expected returns on these double-sorted portfolios. The reason is that none of them are designed to simultaneously explain risk exposure through all four firm characteristics considered here. The estimated annualized mispricing of these models ranges from 7 to 10%.

The success of this double-sort leads me to consider its implications for the "value premium".[12] Over the last two decades, the value premium has disappeared, and new research has sought to resuscitate it by including intangible capital in the book equity of the firm.[13] The classic value premium captured by the "high minus low" (HML) factor of Fama and French (1996) has had a negative mean return since 2005. The new "iHML"[14] factor, which uses the same sorting procedure but includes intangible capital in book equity, has had a negative mean return since 2010.[15]

The firm model presented here, and the empirical findings discussed above suggest that the underperformance of the value factors could be due to incomplete, or mismeasured, exposures to underlying risk factors. Indeed, theoretical models rationalizing the existence of the value premium (e.g., Kogan and Papanikolaou (2014)) rely on the book-to-market ratio being a sufficient statistic for relative exposure to the two risk factors considered in this paper. In those models, the book-to-market ratio is a sufficient statistic because firms with lower values of this ratio have more growth opportunities that are long displacement risk, i.e., they are exposed to negative price of risk shocks. My results show that this need not be the case.

The above double-sort results allow me to create a new value factor that closely tracks

[12]This is the idea that high book-to-market firms have higher expected returns than low book-to-market firms Fama and French (1993), Fama and French (1996).

[13]Eisfeldt et al. (2020), Arnott et al. (2021), Park (2019).

[14]Arnott et al. (2021)

[15]Bongaerts et al. (2021) split out intangible capital into its own factor along with HML.

the two existing value factors during "normal times." The key feature of this factor is that, unlike the existing factors, it does not decline around the Dot-Com bust and since 2010. Its cumulative return is 2-3 times that of the existing factors. Beyond its empirical performance, this new value factor also does an excellent job of removing firms from the long and short portfolios of the old factors that do not conform to our anecdotal notions of value and growth.

Table 1: Changes to Value Factor Composition

	High Int. - Tan. Inv.		Low Int. - Tan. Inv.	
Growth	Amazon	Netflix	Tesla	Haliburton
	J&J	Cisco	Starbucks	Darden Restaurants
	Pfizer			
Value	Xerox	Kodak	GM	Hyatt
	Barnes & Noble	Zillow	US Steel	Hertz
	Bed, Bath, and Beyond		AMC	

This table displays examples of firms in book-to-market portfolios and intangible minus tangible investment portfolios. The book-to-market portfolio is based on the book-to-market ratio corrected for intangible capital. The investment difference portfolio is based on investment differences divided by total assets. All classifications are based on either 2017-2019.

Table 1 shows examples of firms defined as either growth or value under the iHML framework that may not necessarily fall into those two categories under my framework. The top right column shows firms classified as growth under both frameworks. They are physically expanding firms (by undertaking tangible investment) and have market values far above their book values (low book-to-market ratios). In the bottom left panel, we see established firms with large book-to-market ratios undertaking more intangible investment than tangible. Popular examples of displaced firms, like Xerox and Kodak, appear here. Others, like Barnes & Noble, are frequently discussed in the media as on the verge of displacement. These firms are retained as value firms in this new framework. The bottom right panel shows firms with large book-to-market values that undertake much more tangible investment than intangible. Firms placed here are traditional "blue chips" like GM and US Steel. They are no longer classified as value firms under my framework. The top left panel displays firms classified as growth by the iHML framework that are excluded in my framework. In this panel, the role of intangible investment is most evident. Firms like Amazon, which are frequently accused of being monopolies, do not conform to our notions of a growth firm. Yet, their market values far exceed their book values. They have a great deal of intangible capital (like agglomeration effects) and are expending money in the form of intangible investment to retain their dominant position.

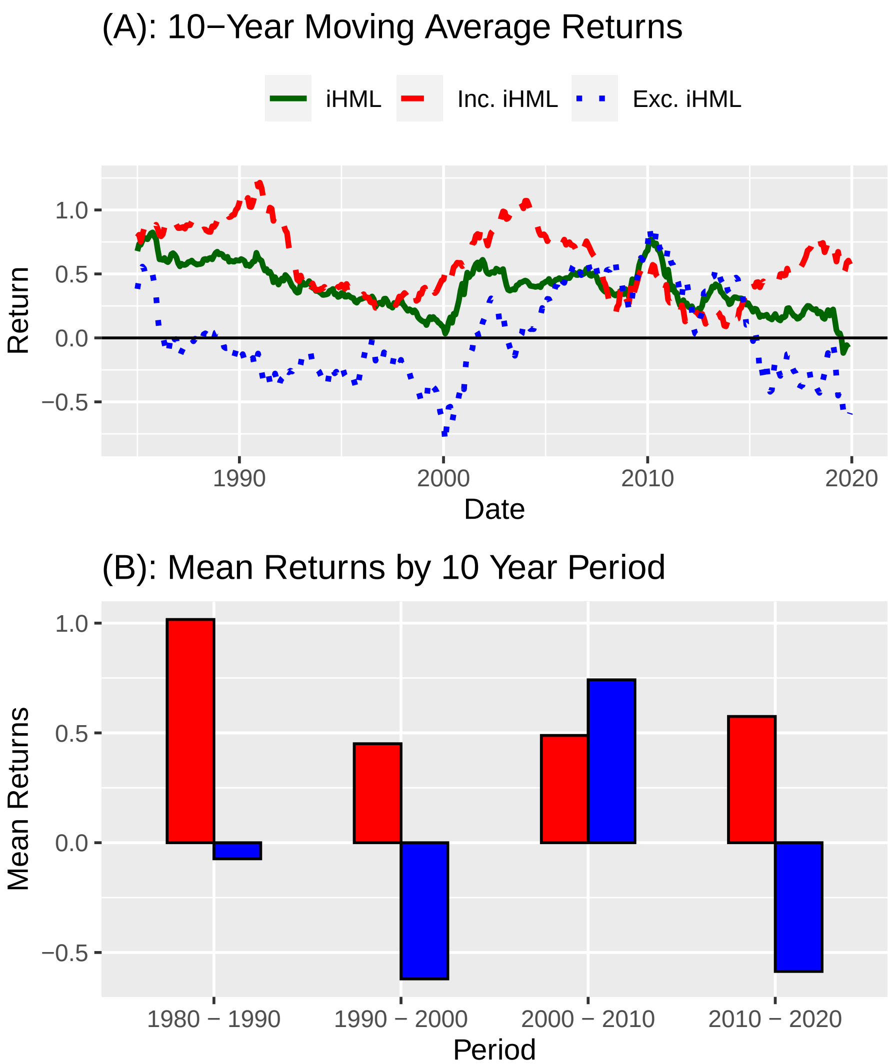
One might worry that the success of this sort is driven by an unusually successful decade for tech firms and other high intangible investment firms. This is not the case. Figure 1 compares the performance of the excluded and included firms from Table 1. I create two "value factors" based on that table. The first is the new value factor discussed above. It is long the included value firms and short the included growth firms (bottom left column of Table 1 minus top right). The second is constructed analogously from the excluded firms (bottom right minus top left). For brevity, I will call them the included and excluded iHML, respectively. Figure 1 also includes the iHML portfolio return. Panel (A) shows the 10-year moving average return of each factor. Aside from 2005-2015, the included iHML has a positive return, while the excluded iHML has a negative return. These results date back to before 1996, the publication date of Fama and French (1996). Panel (B) displays the mean return of the included and excluded iHML over 10 year periods.[16] The included iHML has a larger mean return than the excluded, and the latter has had a negative mean return since 1990. The only exception to this pattern is the period around the Financial Crisis. Finally, in the Appendix I show that the included iHML has a positive and significant CAPM alpha, while the excluded does not.

In some sense, my new factor is not a true value factor since it depends on sorting on more than just the book-to-market ratio. It does exclude some firms we might traditionally think of as value firms (the bottom right panel of Table 1). Yet, this new factor is in fact a strict subset of the iHML value factor. Regardless, a better name could be a fragile versus unfragile factor. The first aspect of the long end of the sort, by book-to-market, retains firms that do not have many growth opportunities, either tangible or intangible. The second aspect of the long end of the sort, intangible minus tangible investment, ensures that these firms' growth opportunities are the fragile, intangible kind. The opposite is true for the short end of the factor.

This study contributes to the literature in several ways. It shows that exposure to displacement risk depends on multiple firm characteristics (namely, intangible investment

[16]Results are similar for different period splits.

Figure 1: Included Versus Excluded iHML Portfolios



This figure displays rolling average monthly returns (panel A) and monthly mean returns by subperiod (panel B) of different value factors. The factor "Inc. iHML" is long high book-to-market and intangible minus tangible investment firms. It is short the firms with low values of these variables. These are the firms included in my new value factor. The factor "Exc. iHML" is long high book-to-market and low intangible minus tangible investment firms. It is short low book-to-market and high intangible minus tangible investment firms. The factor iHML is the value factor prosed by Eisfeldt et al. (2020), Arnott et al. (2021), and others. Panel A displays the rolling 10-year average return of each factor. Panel B displays the mean return over 10 year periods for Inc. iHML and Exc. iHML.

and capital and tangible investment), explicitly linking displacement risk and intangible investment.[17] This link between the tangible and intangible sides of the firm is novel. This is also the first paper to propose combining information on the book-to-market ratio and investment rates to explain the decline of the value premium.

My paper is related to the literature that has emphasized the growing importance of intangible capital in the macroeconomy and financial markets (Peters and Taylor (2017), Falato et al. (2020), Lustig et al. (2011), Tronconi and Marzetti (2011), Corrado and Hulten (2010), Corrado et al. (2009), De and Dutta (2007), Black et al. (2005), Lev and Radhakrishnan (2005), Prescott and Visscher (1980)). In particular, I rely heavily on the data construction and cleaning procedures put forth in Peters and Taylor (2017) when building my measures of intangible capital and investment.

A subset of that literature looks at the implications of intangible capital for firm risk (Linnainmaa and Roberts (2018), Eisfeldt and Papanikolaou (2014), Vitorino (2014), Li et al. (2014), Hansen et al. (2005)). These papers do not focus on intangible investment.

My firm model is a production-based asset pricing model (Kuehn et al. (2017), Belo et al. (2017). Belo et al. (2014), Kogan and Papanikolaou (2012), Cooper et al. (2008), Carlson et al. (2004),Titman et al. (2004), Gomes et al. (2003), Cochrane (1996), Cochrane (1991), Hou et al. (2021), Bai et al. (2019)), and in particular, is closely related to the subset of the literature that has studied production models to explain the value premium. [18] Fama and French (2008) survey the literature linking firm characteristics to stock returns.

One of the roles displacement risk plays in my model is similar to that of investment-specific technology (IST). IST shocks have been studied in the macro literature (Solow (1960), Greenwood et al. (1997)) and the asset pricing literature (Papanikolaou (2011)). These papers have not made the connection to intangibles. Kogan et al. (2020) also connect displacement risk and IST shocks, though they also exclude intangibles.

Displacement risk is similar to frontier technology as in Lin et al. (2020). They do not consider intangibles, and their asset pricing results are consistent with mine.

[17] The focus of Eisfeldt and Papanikolaou (2013) is on intangible capital, but they do briefly consider intangible investment as well. The link to tangible investment is not made. Kogan et al. (2020) only focuses on tangible investment and capital.

[18] Zhang (2017), Kogan and Papanikolaou (2013), Ai and Kiku (2013), Kogan et al. (2020), Papanikolaou (2011), Xing (2008), Zhang (2005), Liu et al. (2009).

The decline of the value premium has recently entered the academic literature.[19] Goncalves and Leonard (2021) argue that traditional book equity is no longer a good proxy for expected future cash flows. This argument is consistent with mine, but is not based in an explicit model of the firm. Other papers have noted that the classic HML factor has been weak for longer than expected (Blitz and Hanauer (2020)). The idea of capitalizing intangibles to form iHML has been proposed by a number of papers (Arnott et al. (2021)). None of these discuss investments (tangible or intangible) or the relative risk of growth options.

The rest of this paper is organized as follows. Section 2 develops a partial equilibrium model of the firm and derives implications for the data. Section 3 describes our data construction. Section 4 displays summary statistics and asset pricing results based on the firm model. Section 5 links displacement risk and firm characteristics. Section 6 constructs my double sort and discusses the new value factor. Section 7 concludes.

2 The Model

In this section, I develop a partial-equilibrium production-based asset pricing model of the firm that features tangible investment and capital as well as intangible investment and capital. I start by describing the production function and the capital accumulation equations of the firm. I then define the firm's value and describe it in terms of the value of assets in place and the present value of growth opportunities, which allows me to define a model version of the book-to-market ratio. I express expected returns as a function of four firm characteristics, which can be mapped to the data. The section concludes with a comparison between the model in this paper and models from the existing literature, in particular the model of Kogan and Papanikolaou (2014).

2.1 Output

The flow output, Y_{ft}, of firm f during instant t is:

$$Y_{ft} = X_t K_{ft} + \frac{O_{ft}}{Z_t}, \tag{1}$$

[19]Some papers argue that the decline may not be statistically significant (Fama and French (2021)).

where X_t is productivity, K_{ft} is the firm's tangible capital stock, Z_t is the displacement risk level, and O_{ft} is the firm's intangible capital stock.

The production function is separable in tangible and intangible capital for tractability.[20] This form can also be motivated by defining the variable $O_{ft}/(Z_t K_{ft})$ as the difference between the average product of tangible capital and the marginal product of tangible capital. That is:

$$\frac{O_{ft}}{K_{ft}Z_t} \equiv \frac{Y_{ft}}{K_{ft}} - \frac{\mathrm{d}Y_{ft}}{\mathrm{d}K_{ft}}. \tag{2}$$

Equation (1) is a solution to equation (2). The left-hand side of equation (2) is the value of the firm's intangible capital stock relative to its size as measured by its tangible capital stock.[21] This variable defines the flow of output that cannot be explained by tangible capital. For example, Amazon can generate more sales for each server than a less well-known rival can because of agglomeration effects, brand value, and other intangible capital.

Increases in productivity, X_t, increase the output generated from the firm's tangible capital stock. If the firm had no intangible capital, then its production function would collapse to the well known "AK" production technology. Increases in the level of displacement risk, Z_t, decrease output from intangible capital. My definition of intangible capital includes non-technological capital like brand value. However, intangible capital also includes many assets we associate with the technological frontier, such as patents, software, and non-patented firm-specific technology. Therefore, the ratio O_{ft}/Z_t can be thought of as the firm's "distance" to the technological frontier. If the value of this ratio is small, then the firm cannot generate much output from its intangible capital (e.g., its patents are outdated, its internal software is inefficient, etc.).

Productivity and the displacement risk level follow Geometric Brownian Motions:

$$\frac{\mathrm{d}X_t}{X_t} = \mu_X \mathrm{d}t + \sigma_X \mathrm{d}B_{Xt} \tag{3}$$
$$\frac{\mathrm{d}Z_t}{Z_t} = \mu_Z \mathrm{d}t + \sigma_Z \mathrm{d}B_{Zt}. \tag{4}$$

The two Brownian Motions, B_{Xt} and B_{Zt}, are uncorrelated with each other and all other

[20] Van Rens (2004) and Eisfeldt and Papanikolaou (2013) make the same assumption.
[21] Crouzet and Eberly (2021) call the difference between average and marginal product "rents."

Brownian motions introduced later. The parameters, $\mu_X > 0$ and $\mu_Z > 0$ govern the mean growth rates of X_t and Z_t, respectively. The parameters $\sigma_X > 0$ and $\sigma_Z > 0$ govern the volatility of the two variables.

2.2 Investment

The firm optimally chooses its tangible investment rate, I_{ft}, and its intangible investment rate, S_{ft}.

For tangible investment, the firm pays a cost of I_{ft} today and accumulates tangible capital according to:

$$\mathrm{d}K_{ft} = \left[\frac{\left(H^I_{ft} Z_t I_{ft}\right)^{\gamma_1}}{X_t} - \delta_K K_{ft}\right] \mathrm{d}t. \tag{5}$$

Here H^I_{ft} is idiosyncratic tangible investment productivity. It also follows a Geometric Brownian Motion:

$$\frac{\mathrm{d}H^I_{ft}}{H^I_{ft}} = \mu^I_f \mathrm{d}t + \sigma^I_f \mathrm{d}B^I_{ft} \tag{6}$$

where the Brownian Motion B^I_{ft} is orthogonal to all other Brownian Motions in the model. The purpose of this idiosyncratic productivity is to generate cross-sectional dispersion in tangible investment rates and, hence, cross-sectional dispersion in tangible capital stocks. This idiosyncratic productivity can represent investment opportunities due to geography, executives with a keen eye for investment, or firm-specific efficiencies.

The displacement risk level, Z_t, improves the efficiency of tangible investment.[22] Periods of high displacement lead to creative destruction replacing old technologies with new ones. These new technologies can only be integrated into the tangible capital stock through newly formed capital, i.e., through tangible investment. Having the efficiency of tangible investment decreasing in the productivity level, X_t, is a reduced form way of capturing two effects. First, when the marginal product of tangible capital is high, the cost of purchasing new investment goods is higher.[23] Second, when the marginal product of tangible capital is high, it is more costly to interrupt production to undertake more investment. Thus, having X_t in the

[22] In this regard, it plays the same role as the investment-specific technology (IST) in, e.g., Papanikolaou (2011).

[23] The cost of investment is increasing in the productivity level in Kogan and Papanikolaou (2014) and Papanikolaou (2011).

denominator represents a form of adjustment cost.

The parameter $0 < \gamma_1 < 1$ governs the returns to scale of tangible investment. This represents adjustment costs in the style of, e.g., Hayashi (1982). The parameter $0 < \delta_K < 1$ is the tangible capital depreciation rate.

For intangible investment, the firm spends S_{ft} and accumulates new intangible capital as:

$$\mathrm{d}O_{ft} = \left[\left(H^S_{ft} S_{ft}\right)^{\gamma_2} - \delta_O O_{ft}\right] \mathrm{d}t. \tag{7}$$

Once again, H^S_{ft} is idiosyncratic investment productivity, this time affecting intangible investment. It too follows a Geometric Brownian Motion:

$$\frac{\mathrm{d}H^S_{ft}}{H^S_{ft}} = \mu^S_f \mathrm{d}t + \sigma^S_f \mathrm{d}B^S_{ft} \tag{8}$$

where B^S_{ft} is orthogonal to all other shocks. The purpose of H^S_{ft} is similar to that of H^I_{ft}: to generate cross-sectional dispersion in intangible investment rates and intangible capital. Since intangible investment is idea and human capital intensive, H^S_{ft} could simply be called "luck." Scientists at a research firm have good ideas, a branding executive concocts a catchy advertising campaign, etc.

I do not assume that displacement risk affects intangible capital accumulation directly. It would be consistent with my framework to allow displacement risk to decrease the efficiency of intangible investment.[24] Including displacement risk in this way would not qualitatively affect my results. As before, $0 < \gamma_2 < 1$ represents adjustment costs, and $0 < \delta_O < 1$ is the depreciation rate.

2.3 Valuation

Since the model is partial-equilibrium, the stochastic discount factor (SDF) is exogenous:

$$\frac{\mathrm{d}M_t}{M_t} = -r_F \mathrm{d}t - \gamma_X M_t \mathrm{d}B_{Xt} - \gamma_Z M_t \mathrm{d}B_{Zt} \tag{9}$$

[24] For example, losing a patent race causes each dollar of intangible investment to produce less intangible capital: Some of the technologies invested in are now obsolete.

where r_F is the fixed risk-free rate. The parameters γ_X and γ_Z are the prices of risk of the productivity shock and displacement risk shock, respectively. I will discuss their signs when computing the expected return on the firm. Notice that only the two aggregate shocks appear in the SDF. The idiosyncratic shocks do not, and hence the SDF is uncorrelated with them.

The objective function of the firm is:

$$V_{ft} = \sup_{S_{fs}, I_{fs}} \mathbb{E}_t \int_t^\infty \frac{M_s}{M_t} \left(Y_{fs} - I_{fs} - S_{fs}\right) \mathrm{d}s \tag{10}$$

subject to the capital accumulation equations and the laws of motion for the productivities and displacement risk. The separability of the production function in tangible and intangible capital provides tractability: The firm's two investment decisions can be split up into two separate "value functions" and then added back together. That is, I can solve:

$$V_{ft}^P = \sup_{I_{fs}} \mathbb{E}_t \int_t^\infty \frac{M_s}{M_t} \left(X_s K_{fs} - I_{fs}\right) \mathrm{d}s \tag{11}$$

and

$$V_{ft}^I = \sup_{S_{fs}} \mathbb{E}_t \int_t^\infty \frac{M_s}{M_t} \left(\frac{O_{fs}}{Z_s} - S_{fs}\right) \mathrm{d}s \tag{12}$$

with the result that:

$$V_{ft} = V_{ft}^P + V_{ft}^I. \tag{13}$$

Proposition 2.1 *Let:*

$$A_1 = \frac{1}{r_F + \delta_K - \mu_X + \gamma_X \sigma_X} \tag{14}$$

$$A_2 = \frac{1}{r_F + \delta_O + \mu_Z - \sigma_Z^2 - \sigma_Z \gamma_Z} \tag{15}$$

$$B_1 = \frac{A_1^{\frac{1}{1-\gamma_1}} \left[\gamma_1^{\frac{\gamma_1}{1-\gamma_1}} - \gamma_1^{\frac{1}{1-\gamma_1}}\right]}{r_F - \frac{\gamma_1}{1-\gamma_1}\left(\mu_Z + \mu_f^I - \sigma_Z\gamma_Z\right) - \frac{1}{2}\frac{\gamma_1}{1-\gamma_1}\frac{2\gamma_1 - 1}{1-\gamma_1}\left(\sigma_Z^2 + \left(\sigma_f^I\right)^2\right)} \tag{16}$$

$$B_2 = \frac{A_2^{\frac{1}{1-\gamma_2}} \left[\gamma_2^{\frac{\gamma_2}{1-\gamma_2}} - \gamma_2^{\frac{1}{1-\gamma_2}}\right]}{r_F + \frac{1}{1-\gamma_2}\left(\mu_Z - \sigma_Z\gamma_Z\right) - \frac{\gamma_2}{1-\gamma_2}\mu_f^S - \frac{1}{2}\frac{\gamma_2}{1-\gamma_2}\frac{2\gamma_2-1}{1-\gamma_2}\left(\sigma_f^S\right)^2 + \frac{1}{2}\frac{1}{1-\gamma_2}\frac{\gamma_2-2}{1-\gamma_2}\sigma_Z^2} \tag{17}$$

The value of the firm is:

$$V_{ft} = A_1 X_t K_{ft} + A_2 \frac{O_{ft}}{Z_2} + B_1 \left(Z_t H^I_{ft}\right)^{\frac{\gamma_1}{1-\gamma_1}} + B_2 \left(H^S_{ft}\right)^{\frac{\gamma_2}{1-\gamma_2}} Z_t^{-\frac{1}{1-\gamma_2}}. \tag{18}$$

The optimal investment rates are:

$$I_{ft} = (\gamma_1 A_1)^{\frac{1}{1-\gamma_1}} \left(Z_t H^I_{ft}\right)^{\frac{\gamma_1}{1-\gamma_1}} \tag{19}$$

$$S_{ft} = (\gamma_2 A_2)^{\frac{1}{1-\gamma_2}} \left(H^S_{ft}\right)^{\frac{\gamma_2}{1-\gamma_2}} Z_t^{-\frac{1}{1-\gamma_2}} \tag{20}$$

The firm's value, equation (18), depends on four terms. The first two terms are Gordon Growth formulas. Recall that the Gordon Growth formula, under certain assumptions, defines the value of an asset as $D/(r-g)$ where D is the dividend, r is the discount rate, and g is the growth rate of the dividend. The first term in equation (18) is the value of the dividend $X_t K_{ft}$ where the growth rate of this dividend is $\mu_X - \delta_K$. The dividend grows because the productivity X_t grows, and it shrinks because the tangible capital stock is depreciating. The discount rate on this dividend is $r_F + \sigma_X \gamma_X$. The first component is the risk-free rate, and the second component is adjustment for risk. If $\gamma_X > 0$, the discount rate is larger than the risk-free rate: Investors require higher rates of return for holding an asset that pays $X_t K_{ft}$ because this asset's dividends covary positively with the SDF. In "bad times," this asset pays out less.

The second term in equation (18) is analogous to the first, except now the dividend is generated by the intangible capital stock, O_{ft}/Z_t. However, there are a few differences. First, because increases in Z_t decrease the dividends, the mean growth rate of Z_t, μ_Z, appears positively in A_2. The term σ_Z^2 appears as a Jensen's inequality term. Because $1/Z_t$ is hyperbolic, decreases in Z_t increase the flow dividend more than increases. Thus the dividend's value is increasing in Z_t's volatility. Finally, there is the usual covariance with the SDF plus the risk-free rate. Once again, the sign of γ_Z will determine whether $r_F - \sigma_Z \gamma_Z > r_F$ or not.

The next two terms correspond to the value of growth opportunities attributable to tangible and intangible investment, respectively. The constants in front of the terms, B_1 and B_2, are also Gordon Growth constants. First, consider B_1. The numerator is proportional to the marginal value of tangible capital, $\partial V_{ft}/\partial K_{ft} = X_t A_1$. However, since the cost of investment is increasing in the productivity level, X_t cancels, leaving us with A_1 only. The denominator is another version of "$r - g$". The first term, $\frac{\gamma_1}{1-\gamma_1}\left(\mu_Z + \mu_f^I - \sigma_Z \gamma_Z\right)$, accounts for the growth of both Z_t and idiosyncratic productivity. However, only Z_t covaries with the SDF. Because Z_t and H_{ft}^I enter growth opportunities non-linearly, the growth rate is multiplied by a constant not necessarily equal to one. The second term in the denominator is the Jensen's inequality term. Whether or not this enters positively depends on whether the growth opportunities are convex or concave functions of Z_t and H_{ft}^I, that is, whether $\gamma_1 > 0.5$. Putting the pieces together, the constant B_1 is the Gordon Growth formula for the marginal value of tangible capital, $X_t A_1$. The constant B_1 is multiplied by an increasing function of Z_t and H_{ft}^I because the efficiency of tangible investment is increasing in both variables. For example, when Z_t is high, the firm can add B_1 units of "value" at lower cost. This changing cost is reflected in the value of tangible growth opportunities.

The final term in equation (18) is analogous to the third term. However, it is related to the growth opportunities of intangible investment. The main difference is that the marginal value of intangible capital is decreasing in Z_t. This is reflected in the denominator of B_2, where the mean growth rate of Z_t, μ_Z, increases the Gordon Growth denominator, and because Z_t enters hyperbolically in the flow dividend of intangible capital, the variance of Z_t, σ_Z^2, unambiguously decreases the discount rate. The effect of idiosyncratic productivity, H_{ft}^S, is analogous to the effect of H_{ft}^I discussed above. Finally, the function multiplying B_2 is increasing in idiosyncratic productivity, as it is for tangible investment opportunities, but decreasing in Z_t because the marginal value of intangible capital is decreasing in Z_t.

Next, consider the investment rates in equations (19) and (20). The main takeaway is that these investment rates are proportional to the growth opportunities described above. That is:

$$\text{Tangible Investment}_{ft} \propto B_1 \left(Z_t H_{ft}^I\right)^{\frac{\gamma_1}{1-\gamma_1}} \tag{21}$$

$$\text{Intangible Investment}_{ft} \propto B_2 \left(H_{ft}^S\right)^{\frac{\gamma_2}{1-\gamma_2}} Z_t^{-\frac{1}{1-\gamma_2}}. \tag{22}$$

When deriving the expected return on the firm, these functions will appear in the loadings on aggregate risk factors. Thus, I can map loadings to investment rates.[25] Most importantly, tangible and intangible investment respond with opposite signs to changes in Z_t.

2.4 Value of Assets in Place and the Value of Growth Opportunities

Before deriving the expected return, it is helpful to define the value of assets in place (VAP) and the present value of growth opportunities (PVGO). I write the firm's value as $V_{ft} = VAP_{ft} + PVGO_{ft}$.[26] I will define VAP to be a certain quantity, in particular, the value of the firm assuming 0 future investment. Then, PVGO will simply be the difference $V_{ft} - VAP_{ft}$.

Following Berk et al. (1999) and Kogan and Papanikolaou (2014), I define the VAP of the firm to be its "accounting value." This is the value of the current capital stocks without considering future investments. That is:

$$VAP_{ft} = \mathbb{E}_t \left[\int_t^\infty \frac{M_s}{M_t} \left(X_s K_{fs} + \frac{O_{fs}}{Z_s} \right) \mathrm{d}s \right] \tag{23}$$

subject to:

$$\begin{aligned} \mathrm{d}K_{ft} &= -\delta_K K_{ft} \mathrm{d}t \\ \mathrm{d}O_{ft} &= -\delta_O O_{ft} \mathrm{d}t \end{aligned} \tag{24}$$

and the two laws of motion for X_t and Z_t. The difference between VAP and V_{ft} is that the investment decisions are excluded: They do not appear in either the flow costs or in the capital accumulation equations. In empirical terms, the VAP of the firm is akin to the book equity of the firm.[27]

I assume that the researcher properly accounts for the intangible capital stock when calculating the firm's accounting value. Recent papers[28] have pointed to missing intangible assets in book equity to explain the value premium's decline. While it is indeed true that

[25] The loadings will depend on capital stocks as well.

[26] See Berk et al. (1999) for the canonical example of a model using this firm decomposition.

[27] The existence of debt makes book value and book equity different. This model has no debt, so the two quantities are the same.

[28] Park (2019), Eisfeldt et al. (2020), Arnott et al. (2021)

excluding intangible capital from book equity would lead to measurement problems, I show that even when one does make this correction, the book-to-market ratio is still not a sufficient statistic for risk exposure. Following Park (2019), I call this "new" book-to-market ratio, both in the data and the model, as the iB/M ratio. I reserve B/M ratio for the book-to-market ratio when book equity excludes intangible capital.

The VAP of the firm is:

$$VAP_{ft} = A_1 X_t K_{ft} + A_2 \frac{O_{ft}}{Z_2} \tag{25}$$

where A_1 and A_2 are the same as before. Looking at equation (18), using $PVGO_{ft} = V_{ft} - VAP_{ft}$, one sees that:

$$PVGO_{ft} = B_1 \left(Z_t H^I_{ft}\right)^{\frac{\gamma_1}{1-\gamma_1}} + B_2 \left(H^S_{ft}\right)^{\frac{\gamma_2}{1-\gamma_2}} Z_t^{-\frac{1}{1-\gamma_2}}. \tag{26}$$

, what I have been calling the growth opportunities due to investment map directly to this definition of PVGO.

It is useful to further break up the VAP into two parts. The first is the book value of tangible assets, and the second is the book value of intangible assets:

$$\text{Book Value of Tangible Assets}_{ft} = A_1 X_t K_{ft} \tag{27}$$

$$\text{Book Value of Intangible Assets}_{ft} = A_2 \frac{O_{ft}}{Z_t} \tag{28}$$

For example, a firm with no intangible assets would have a VAP equal to the book value of tangible assets. These two terms will appear in the firm's betas on the two priced shocks.

Finally, define the model-implied book-to-market ratio:

$$iBM_{ft} = \frac{VAP_{ft}}{V_{ft}}. \tag{29}$$

2.5 Expected Returns

There are two aggregate shocks in this model, $\mathrm{d}B_t^X$ and $\mathrm{d}B_t^Z$, and expected returns depend on exposures, or betas, on these shocks. I use the no-arbitrage condition:

$$\mathbb{E}_t\left[\frac{\mathrm{d}M_t}{M_t}\frac{\mathrm{d}V_{ft}}{V_{ft}}\right] = 0 \tag{30}$$

to compute the expected return on the firm in excess of the risk-free rate. The expression for the expected return will also reveal the betas on the shocks.

Proposition 2.2 *The expected return on the firm is:*

$$\begin{aligned}
&\mathbb{E}_t\left[\frac{dV_{ft}}{V_{ft}}\right]/dt - r_F = \\
&\sigma_X\gamma_X \underbrace{[A_1X_tK_{ft}]\Big/V_{ft}}_{\textit{Productivity shock beta}} \\
&+\sigma_Z\gamma_Z \underbrace{\left[-A_2\frac{O_{ft}}{Z_2}+\frac{\gamma_1}{1-\gamma_1}B_1\left(Z_tH^I_{ft}\right)^{\frac{\gamma_1}{1-\gamma_1}}-\frac{1}{1-\gamma_2}B_2\left(H^S_{ft}\right)^{\frac{\gamma_2}{1-\gamma_2}}Z_t^{-\frac{1}{1-\gamma_2}}\right]\Big/V_{ft}}_{\textit{Displacement risk shock beta}}
\end{aligned} \tag{31}$$

The two terms in square brackets (divided by V_{ft}) in equation (31) are the betas with respect to the two shocks. These can all be mapped to firm characteristics:

$$\begin{aligned}
&\mathbb{E}_t\left[\frac{\mathrm{d}V_{ft}}{V_{ft}}\right]/\mathrm{d}t - r_F = \\
&\left[\text{Book Value of Tangible Assets}_{ft}\right]\sigma_X\gamma_X\Big/V_{ft} + \\
&\left\{\left[-\text{Book Value of Intangible Assets}_{ft} - C_1\times\text{Intangible Investment}_{ft} + C_2\times\text{Tangible Investment}_{ft}\right]\right\} \\
&\times\sigma_Z\gamma_Z\Big/V_{ft}
\end{aligned} \tag{32}$$

where C_1 and C_2 are constants.

Here we see the critical role played by the four characteristics discussed in the Introduction: (a) the book value of tangible assets, (b) the book value of intangible assets, (c) tangible investment, and (d) intangible investment. Note also that both of the betas depend on more than one firm characteristic.

To see that the iB/M ratio is not a sufficient statistic, I rewrite equation (32) using the iB/M ratio. First, it is useful to define the fraction of VAP coming from intangible capital:

$$\omega_{ft} \equiv \frac{A_2 Z_t^{-1} O_{ft}}{VAP_{ft}} = \frac{\text{Book Value of Intangible Capital}_{ft}}{\text{Book Equity}_{ft}}. \tag{33}$$

I also refer to this ratio, in both the model and the data, as the firm's "intangible capital intensity', since the larger ω_{ft} is, the larger is the fraction of output attributable to intangible capital.

Rewriting equation (32) using ω_{ft} and the iB/M_{ft} ratio reveals:

$$\begin{aligned} &\mathbb{E}_t\left[\frac{\mathrm{d}V_{ft}}{V_{ft}}\right]\Big/\mathrm{d}t - r_F = \\ &iB/M_{ft}\Bigg[\sigma_X\gamma_X - \omega_{ft}\left(\sigma_Z\gamma_Z + \sigma_X\gamma_X\right) \\ &+ C_2 \times \frac{\text{Tangible Investment}_{ft}}{VAP_{ft}}\frac{\gamma_1}{1-\gamma_1}\sigma_Z\gamma_Z \\ &- C_1 \times \frac{\text{Intangible Investment}_{ft}}{VAP_{ft}}\frac{1}{1-\gamma_2}\sigma_Z\gamma_Z\Bigg]. \end{aligned} \tag{34}$$

Notice that we still need to track four characteristics: the iB/M ratio, the intangible capital intensity, ω_{ft}, and the two investment rates. The effects of these firm characteristics depend on the signs of γ_X and γ_Z which I now discuss.

The productivity shock, $\mathrm{d}B_{Xt}$, is expected to carry a positive price of risk, γ_X. Following increases in X_t, the output from tangible capital increases. In general equilibrium, this increases consumption, so increases in X_t are associated with "good times," and therefore $\gamma_X > 0$.[29] The displacement risk shock, $\mathrm{d}B_{Zt}$, is expected to carry a negative price of risk, $\gamma_Z < 0$. There are two justifications for this. First, as the name suggests, periods of increased displacement risk are associated with the reallocation of factors of production across firms.[30] This is costly, reducing output and consumption. Second, along with this reallocation across

[29] See Jermann (1998).
[30] Eisfeldt and Papanikolaou (2013)

firms, there is reallocation across agents in the economy. For example, the benefits of displacing technologies often accrue to a small set of people (e.g., the inventors), increasing wealth and income inequality. Under certain preference assumptions, these increases in Z_t lead to increases in marginal utility, i.e., they are associated with "bad times," so $\gamma_Z < 0$.[31]

Note that, even with these signs in hand, not all the coefficients on the firm characteristics can be unambiguously signed. The existing production-based asset pricing literature has generally found that tangible investment is associated with lower expected returns.[32] This is consistent with the model, and I confirm this in the empirical sections of the paper. The sign on the coefficient of ω_{ft}, the intangible capital intensity, is implied by the calibrated model parameters in Eisfeldt and Papanikolaou (2013).[33] Based on that paper, this coefficient is expected to be negative. This finding is also confirmed in the empirical section of this paper. Finally, the sign on the intangible investment coefficient is unambiguously positive.

I can "shut off" certain channels to recover more familiar production-based frameworks like the one in Kogan and Papanikolaou (2014). This case corresponds to a "classic" firm that only has tangible assets and tangible investment opportunities. If I set intangible investment and ω_{ft} to 0, the expected return on the firm is:

$$\mathbb{E}_t\left[\frac{\mathrm{d}V_{ft}}{V_{ft}}\right]\Big/\mathrm{d}t - r_F = \frac{\gamma_1}{1-\gamma_1}\sigma_Z\gamma_Z + BM_{ft}\left[\sigma_X\gamma_X - \frac{\gamma_1}{1-\gamma_1}\sigma_Z\gamma_Z\right]. \tag{35}$$

Since $0 < \gamma_1 < 1$ and $\gamma_Z < 0, \gamma_X > 0$, firms with larger B/M ratios have larger expected returns.[34] Also, the B/M ratio is a sufficient statistic for understanding cross-sectional differences in expected returns. As far as growth opportunities go, this model can be used to compare firms in the bottom right and top left panels of Table 1.[35] For example, both Tesla and GM are automobile manufacturers and likely have similar *types* of growth opportunities (e.g., product markets for future car models, etc.). However, Tesla has many more of these growth opportunities, according to the model. This feature of the model is consistent with

[31] Kogan et al. (2020)

[32] Papanikolaou (2011), Hou et al. (2015)

[33] They find that firms with more organization capital, a type of intangible capital, compared to their tangible capital, have higher expected returns. That is also true in my model. The sign on ω_{ft} is conditional on a fixed iB/M ratio.

[34] I the B/M ratio because there is no intangible capital in the ratio.

[35] I used the iB/M ratio instead of the B/M ratio in constructing Table 1, so the mapping is not exact.

anecdotal and media impressions.

On the other hand, consider a firm with only intangible capital and investment opportunities. The expected return on this firm is:

$$\mathbb{E}_t\left[\frac{\mathrm{d}V_{ft}}{V_{ft}}\right]\Big/\mathrm{d}t - r_F = \frac{2-\gamma_2}{1-\gamma_2}\sigma_Z\gamma_Z + \frac{1}{1-\gamma_2}iBM_{ft}\sigma_Z\gamma_Z. \tag{36}$$

Since $0 < \gamma_2 < 1$ and $\gamma_Z < 0$, firms with larger iB/M ratios have lower expected returns. Once again, the iB/M ratio is a sufficient statistic for describing cross-sectional differences in expected returns. This model roughly describes firms in the top right and bottom left panels of Table 1. Barnes and Noble is a "fallen angel," essentially displaced by Amazon. Amazon has many more opportunities to invest in intangible assets to help secure its dominant position. This fact manifests as a large market value and a low iB/M ratio. However, all those future intangible investments put Amazon at risk of following in Barnes and Noble's footsteps and falling from grace itself. For example, a rival firm could develop a more efficient algorithm matching sellers and buyers on the marketplace, causing an exodus from Amazon.

Of course, most firms fall somewhere between these two models, which is what equation (31) shows. Also, it is important to note that, empirically, many of these firm characteristics are correlated. For example, the data sections will show that high iB/M (and B/M) firms have very different investment rates than growth firms. In the classic version of the model without intangibles, this is by construction. The B/M ratio is:

$$BM_{ft} = \frac{A_1X_tK_t}{A_1X_tK_{ft} + B_1\left(Z_tH^I_{ft}\right)^{\frac{\gamma_1}{1-\gamma_1}}} \tag{37}$$

The displacement risk level, Z_t, unambiguously decreases the B/M ratio. Also, as equation (19) shows, tangible investment and Z_t are positively correlated. It follows that high B/M firms are low tangible investment firms.

In the full version of the model, the iB/M ratio could be either increasing or decreasing in the displacement risk level:

$$iBM_{ft} = \frac{A_1X_tK_{ft} + A_2\frac{O_{ft}}{Z_t}}{A_1X_tK_{ft} + A_2\frac{O_{ft}}{Z_t} + B_1\left(Z_tH^I_{ft}\right)^{\frac{\gamma_1}{1-\gamma_1}} + B_2\left(H^S_{ft}\right)^{\frac{\gamma_2}{1-\gamma_2}}Z_t^{-\frac{1}{1-\gamma_2}}} \tag{38}$$

Z_t unambiguously decreases the book equity of the firm, but its effect on the denominator, the total value of the firm, is unclear.

This completes my presentation of the model. I will refer back to the results here often, as this framework will guide the empirical studies in this paper. In the next section, I describe the data I will use.

3 Data

This section describes how I construct the firm-level variables. Most of these are based on the Center for Research in Security Prices (CRSP) and Compustat data. These are described in the first subsection. In the second subsection, I describe proxies for displacement risk, Z_t.[36]

3.1 CRSP and Compustat

The CRSP data is monthly and has information on stock prices and returns. The Compustat data is annual and has information on all other balance sheet and income statement items. The sample runs from January 1950 through December 2019. However, to remove the effects of initial normalizations, I use data from 1975 onward.[37]

I keep only common shares (share codes 10 and 11 in CRSP) and firms listed on either the NYSE, AMEX, or NASDAQ stock exchanges. Compustat provides several checks, which I also use. First, I make sure the industry and data formats are "standard."[38] Second, I use only valid links (from CRSP to Compustat).[39] Finally, I make sure the link is still active.[40]

I construct two variables from CRSP: Market capitalization (market cap.) and stock returns. For market cap. I simply compute shares outstanding times the stock price.[41]

[36] The proxies are actually more akin to $\mathrm{d}B_{Zt}$. Regardless, I refer to them as displacement risk proxies instead of displacement risk shock proxies.

[37] This is the same "normalization period" used in Peters and Taylor (2017).

[38] indfmt = INDL and datafmt = STD.

[39] linktype either equal to LU or LC.

[40] The linkdate must either be missing or less than or equal to the data date.

[41] I use the "alternative price" in CRSP. This has fewer missing values than the standard price measure. If the market cap value is 0, I set it to missing.

Returns are collected from CRSP and corrected for delisting bias using the method from Shumway (1997).

I follow Peters and Taylor (2017) and Belo et al. (2017) for much of the data construction. First, if any of the following are missing, I set them to 0: R&D (xrd), Selling, General, and Administrative (xsga), R&D in progress (rdip), and Costs of Goods Sold (cogs). Next, following Peters and Taylor (2017)), I create a cleaned version of Selling, General, and Administrative, which I will call SGA. First, if xrd is larger than xsga and if xrd is less than cogs, I simply set SGA equal to xsga. Otherwise, I set it equal to xsga - cogs - rdip.

With these measures in hand, I can create the Knowledge Capital stock and the Organization Capital stock as defined by Peters and Taylor (2017). Knowledge Capital is simply the accumulated R&D investments net of the undepreciated value from the previous period. I use a depreciation rate of 0.15 following Peters and Taylor (2017). That is, knowledge capital evolves according to:

$$K^K_{ft} = 0.85 \times K^K_{f,t-1} + R\&D_{ft}. \tag{39}$$

Organization capital is defined similarly, except instead of accumulating R&D expenses, I accumulate $0.3 \times SGA$.[42] The depreciation rate here, again from Peters and Taylor (2017), is 0.2. Thus:

$$K^O_{ft} = 0.8 \times K^O_{f,t-1} + 0.3SGA_{ft} \tag{40}$$

Then, the intangible capital stock is simply the sum of these two capital stocks:[43]

$$O_{ft} = K^K_{ft} + K^O_{ft}. \tag{41}$$

My measure of intangible investment follows directly from the construction of the intan-

[42]See Appendix of Peters and Taylor (2017) for explanation of the 0.3. Basically, even after the cleaning I did above, some SGA still goes to administrative expenses that have little to do with organization capital.

[43]A word on software, which is a common form of intangible asset. Purchased software is included in book equity (capitalized on the balance sheet in "Goodwill + Other Intangibles"). Developed software is not included until it reaches "technological feasibility." (Financial Accounting Standard Board, Peters and Taylor (2017).)

gible capital stock above. I add R&D expenditures to $0.3\times$SGA:

$$\text{Intangible Investment}_{ft} = R\&D_{ft} + 0.3 \times SGA_{ft}. \tag{42}$$

The analogous definition for tangible investment is:

$$\text{Tangible Investment}_{ft} = CAPX_{ft} \tag{43}$$

where $CAPX_t$ is capital expenditures (Compustat code: CAPX).

The last three important variables I construct are the B/M ratio, the iB/M ratio and, intangible capital over book equity plus intangible capital (intangible capital intensity, ω_{ft}). The B/M ratio is computed in the standard way (see the textbook by Bali et al. (2016)). That is:

$$BM_{ft} = \frac{BE_{ft}}{V_{ft}} \tag{44}$$

where BE_{ft} is the book equity, and V_{ft} is the market value of the firm. Similarly,

$$iBM_{ft} = \frac{\overbrace{BE_{ft} + O_{ft}}^{\text{Adjusted Book Equity}}}{V_{ft}}. \tag{45}$$

I call the book equity plus the intangible capital stock adjusted book equity. I refer the BE_{ft} (i.e., without the intangible capital stock) as book equity. It follows that the intangible capital intensity, ω_{ft}, is:

$$\omega_{ft} = \frac{O_{ft}}{BE_{ft} + O_{ft}} \tag{46}$$

Several other control variables will appear in regressions. However, it will be simpler to discuss them as they appear.

To merge the annual Compustat data with the monthly CRSP data, I follow Fama and French (1993). That is, I assume all financial information about a firm in year t is public information by the end of June of year $t+1$. So, for example, in February 2002, the relevant Compustat information for a firm would be from the calendar year 2000. The main import of this assumption comes about when forming portfolios: These are formed in July and

Table 2: Model to Data Mapping

Firm characteristic	Model	Data
iB/M ratio	$\frac{A_1 X_t K_{ft} + A_2 \frac{O_{ft}}{Z_t}}{A_1 X_t K_{ft} + A_2 \frac{O_{ft}}{Z_t} + B_1 X_t \left(Z_t H^I_{ft}\right)^{\frac{\gamma_1}{1-\gamma_1}} + B_2 \left(H^S_{ft}\right)^{\frac{\gamma_2}{1-\gamma_2}} Z_t^{-\frac{1}{1-\gamma_2}}}$	$\frac{BE_{ft} + O_{ft}}{V_{ft}}$
B/M ratio	$\frac{A_1 X_t K_{ft}}{A_1 X_t K_{ft} + A_2 \frac{O_{ft}}{Z_t} + B_1 X_t \left(Z_t H^I_{ft}\right)^{\frac{\gamma_1}{1-\gamma_1}} + B_2 \left(H^S_{ft}\right)^{\frac{\gamma_2}{1-\gamma_2}} Z_t^{-\frac{1}{1-\gamma_2}}}$	$\frac{BE_{ft}}{V_{ft}}$
Intangible Investment	$B_2 \left(H^S_{ft}\right)^{\frac{\gamma_2}{1-\gamma_2}} Z_t^{-\frac{1}{1-\gamma_2}}$	$R\&D_{ft} + 0.3 \times SGA_{ft}$
Tangible Investment	$B_1 X_t \left(Z_t H^I_{ft}\right)^{\frac{\gamma_1}{1-\gamma_1}}$	$CAPX_{ft}$
Int. Cap. Intensity (ω_{ft})	$\frac{A_2 \frac{O_{ft}}{Z_t}}{A_1 X_t K_{ft} + A_2 \frac{O_{ft}}{Z_t}}$	$\frac{O_{ft}}{BE_{ft} + O_{ft}}$

This table displays mappings from model variables to data variables. The first column gives the name of the variable, the second column gives the model definition of the variable, and the third column gives the data definition of the variable. See body of Data section for more details on the variables in the third column.

held through the following June. Thus, whenever I discuss annual returns, unless stated otherwise, I am assuming a July-to-July year.

For industry classification, I use the SIC class for all years prior to 2002 and NAICS thereafter. I exclude Transportation, Finance, and Public firms. My other filter is a size filter. Each June, I calculate the 20th percentile market cap of NYSE firms. I then drop firms below this size. This is the same cutoff used by Fama and French (2015).[44]

Table 2 shows mappings for the four key firm characteristics from the model in the previous section to the data variables defined in this section.

3.2 Displacement Risk Proxies

This subsection, described proxies for displacement risk. I use three stock-based measures and three measures based on real variables. The first five measures are directly implied by the model. The sixth measure is based on the existing literature around displacement risk and asset prices.[45]

[44]Results hold without excluding micro-caps as well.

[45]Kogan et al. (2020)

3.2.1 Measure 1: Investment Difference (IDiff) Factor

Recall the expressions for investment, tangible and intangible, from the model, equations (21) and (22). Tangible investment is long Z_t risk, and intangible investment is short this risk. Holding everything else equal, firms with a large investment difference, intangible minus tangible, should have large, negative exposure to Z_t shocks. That is, firms with large differences in investment rates should have lower returns following Z_t shocks: Their betas on Z_t shocks are smaller. I call this difference IDiff.

My first measure of displacement risk sorts firms each yearbased on their IDiff to adjusted book equity.[46] As discussed in the previous subsection, I sort firms every July of year t based on financial information from year $t-1$. So, every July, I form three breakpoints based on the IDiff to adjusted book equity ratio. The breakpoints are based on NYSE firms, and the breakpoints split the sample into three groups each July: Top 30%, middle 40%, and bottom 30%. Call these groups High, Middle, Low. Also, each July, I split the sample into large and small firms based on the NYSE breakpoints of market cap. I form value-weighted portfolios within each combination of IDiff by adjusted book equity group and size group (e.g., Low/Small, High/Small, etc.). Then, within each IDiff to adjusted book equity group I take an equal weighted average of the two sub portfolios based on size (i.e., the High portfolio is the simple average return of the High/Small and High/Big portfolios). Finally, I create an excess return portfolio by taking the difference between the High portfolio and Low portfolio returns. The portfolios are rebalanced after 12 months. This is the standard procedure used by, e.g., Fama and French (1996) in forming their HML portfolio, where IDiff to adjusted book equity is replaced by the B/M ratio.

This procedure delivers a return R_t^I which mimics movements in the Z_t shock. In fact, it is a mimicking portfolio for $-\mathrm{d}B_{Zt}$. Because it is a portfolio return, it is available at monthly frequency. Call this the IDiff Factor.

[46] Recall that adjusted book equity is traditional book equity plus intangibles.

3.2.2 Measure 2: Intangible Capital to Market Value Factor

My second proxy is based on the firm's ratio of intangible capital to market value. Looking at equation (31), one sees that the betas on Z_t shocks are decreasing in this ratio. Thus, I follow the same procedure, sorting on the intangible capital to market value ratio of firms. Call this proxy R_t^O.

3.2.3 Measure 3: Tangible Investment to Adjusted Book Equity Factor

The other two terms in the firm's Z_t beta in equation (31) are the intangible investment to market value ratio and the tangible investment to market value ratio. My IDiff factor is a rough proxy for these ratios as well.[47] The previous two proxies were variables that should decrease a firm's Z_t beta. I use the tangible investment to adjusted book equity ratio as a variable which *increases* the exposure to Z_t shocks. Call this proxy R_t^T.

3.2.4 Measure 4: Marginal Product of Intangible Capital

According to equation (1), the marginal product of intangible capital is decreasing in Z_t. Therefore, each year, I estimate the following cross-sectional regression:

$$Sales_{ft} = \alpha_t + \beta_{1t} IntCap + \beta_{2t} TanCap + \varepsilon_{ft} \tag{47}$$

where $Sales_{ft}$ is firm sales (SALE in Compustat), and $TanCap_{ft}$ is the firm's tangible capital (property, plant, and equipment, PPEGT, in Compustat). Then, $\beta_{1t} \propto Z_t^{-1}$. Therefore, my first proxy for Z_t shocks based on real variables is innovations in β_{1t}. Again, $\Delta\beta_{1t} \propto -\mathrm{d}B_{Zt}$. I will call this ΔM_t, since I wish to reserve β notation for stock exposures.

3.2.5 Measure 5: Mean IDiff

My second real proxy for Z_t shocks is changes in mean IDiff. That is:

$$TotIDiff_t = \frac{1}{N_t} \sum_{f=1}^{N_t} \left[IntInv_{ft} - TanInv_{ft} \right] \tag{48}$$

[47]It is not an exact proxy because the difference between investment rates does not appear in the betas. IDiff is a first-order linear approximation to the difference which does appear.

where N_t is the number of firms in the sample in year t. I call innovations to this variable $\Delta TIDiff_t$.

3.2.6 Measure 6: Aggregate Patent Values

This final measure is external to the model. That is, it is a direct proxy for Z_t based on the existing literature.[48] I use the dataset from the Kogan et al. (2017) (KPSS). It contains estimated economic values of patents filed by firms. These values are derived from stock market reactions to patent filings.[49] Since there is a patent value per patent, there are multiple observations per firm-year. Therefore, I sum up the total value of patents filed within a year for each firm. My proxy for Z_t shocks uses the aggregate patent value to aggregate market value in a given year:

$$AggPat_t = \frac{\sum_{f=1}^{N_t} PatentValue_{ft}}{\sum_{f=1}^{N_t} ME_{ft}}. \tag{49}$$

Once again, I use innovations, ΔP_t.

Kogan et al. (2020) use a similar measure built on aggregate patent values as a proxy for displacement risk. Therefore, in my framework, this assumption implies $\Delta P_t \propto \mathrm{d}B_{Zt}$.

3.2.7 Summary Statistics for Proxies

Table 3 displays summary statistics for the mimicking portfolios. For the final three measures, which are based on real variables, I construct the mimicking portfolio as follows. First, using annual returns, I compute annual betas with respect to innovations in the real variables using 10 year rolling windows. Second, I treat the annual betas the same ways as firm characteristics. That is, each July, I sort firms into portfolios based on their annual betas with respect to the real factor. Third, I calculate the portfolio returns analogously to the firm characteristics portfolios. The benefit of forming portfolios like this is that I can directly compare the real variable factors to the firm-characteristics based ones

As the top row of Panel A shows, the mean return on the factors is lower than the mean

[48] Kogan et al. (2020).

[49] I refer the reader to the original paper for more details.

Table 3: Summary Statistics: Factor Mimicking Portfolios

	R^I	R^O	R^T	R^{TIDiff}	R^M	R^P	R^{MKT}
Panel A: Means and Standard Deviations							
Mean	0.26	0.47	-0.15	0.16	-0.01	-0.01	0.70
SD	2.68	2.23	2.16	2.37	1.93	2.34	4.40
Panel B: Correlations							
R^O	0.44						
R^T	-0.88	-0.31					
$R^{TIDifff}$	0.53	0.41	-0.46				
R^M	-0.08	0.06	0.09	0.09			
R^P	-0.37	-0.09	0.28	-0.55	-0.11		
R^{MKT}	0.26	0.14	-0.20	0.37	0.23	-0.43	

This table displays summary statistics for the factor mimicking portfolios. Going left to right along the top of the table the factors are the IDiff sorted portfolio, the intangible capital to market value sorted portfolio, the tangible investment sorted portfolio, the aggregate IDiff portfolio, the marginal product portfolio, the aggregate patent value portfolio, and the value-weighted market portfolio. The first row of Panel A shows monthly mean returns in percentage. The second row of Panel A shows the monthly standard deviation. Panel B shows correlations among the portfolios. The data is monthly from 1975-2020.

return on the market portfolio (last column). Similarly, their standard deviations are lower as well. The three factors with negative mean returns are the tangible investment sorted portfolio, R^T, the marginal product of intangible capital portfolio, R^M, and the aggregate patent value portfolio, R^P. The first and last ones make sense, as they are supposed to mimic innovations in Z_t, which carries a negative price of risk. The mean of the marginal product factor is surprising, since it is expected to mimic the Z_t shock, which carries a positive price of risk. However, equation (47) is an approximation to the true expression relating output to capital stocks. Thus, R^M and the associated ΔM likely have more measurement error than the other factors.

Panel B displays the correlations amongst the factors. Similar to the means in Panel A, one sees that the factors meant to track *negative* innovations to Z_t comove positively with each other. The tangible investment and aggregate patent value factors comove negatively with R^I, R^O, R^{TIDiff}, and R^{MKT}. The marginal product factor's correlations are more complicated. That factor covaries negatively with the aggregate patent value factor, as expected, but it covaries positively with the tangible investment factor.

4 Empirical Results

This section explores the model's main empirical implications. First, I show that firms with more exposure to displacement risk undertake more intangible investment relative to tangible and have larger intangible capital to market value ratios. Second, I show that firms with more exposure to displacement risk decrease their intangible investment relative to tangible following displacement risk shocks. Third, and similarly, I show that these firms have lower cash flows going forward. In the final subsection, I look at stock returns. I use panel regressions to demonstrate that firm characteristics predict returns with the signs implied by the model. Further, I go beyond displacement risk and consider firm exposure to the productivity risk as well. In particular, the model says that firms that have large betas on X_t shocks and small betas on Z_t shocks should have large expected returns. I propose a parsimonious double-sort which should deliver large expected returns. I find that leading factor models cannot explain the return spread generated by this sort.

4.1 Portfolio Sorts: Co-movement and Characteristics

This subsection shows that sorting firms based on measures of displacement risk exposure leads to spreads in different measures of exposure and firm characteristics as predicted by the model. Table 4 sorts firms into 10 decile portfolios based on their IDiff to total assets ratios.[50] Each July, firms are assigned to one of 10 portfolios, and the portfolios are rebalanced after 12 months. The top panel displays firm characteristics of the portfolios, and the bottom panel shows average betas on the displacement risk measures I consider. The data in the table are generated by taking cross-sectional medians each year within each portfolio and then taking time-series averages of these medians.

The difference between intangible and tangible investment, IDiff, is increasing as the portfolio increases. The results indicate that firms undertaking more intangible investment in year t continue to do so in year $t+1$, on average. The next two rows split this difference into its positive and negative components. Firms with large IDiffs in year t undertake more intangible investment in year $t+1$. Conversely, they undertake less tangible investment.

[50] The cutoffs are based on NYSE listed firms.

Note that this is not by construction. A firm could be undertaking a lot of tangible and intangible investment and still have a large IDiff. Thus, this large spread in both types of investment rates, is evidence of intangible and tangible investment reacting with opposite signs to a common signal or factor. Firms with large IDiff tend to have larger intangible capital to market value ratios.[51] High IDiff firms are smaller than low IDiff firms. The next two rows show the B/M ratio (excluding intangibles) and the iB/M ratio (including intangibles). The former is decreasing in the IDiff portfolio, but the latter is increasing. This is related to the trend in intangible capital we saw above. Finally, high IDiff firms are less profitable. This finding is interesting, since it means the asset pricing results related to intangible investment are not driven by profitability (Asness et al. (2019)).

[51] This is not obvious, since Q-theory tells us that if there are decreasing returns to capital, the capital stock and investment rate should be negatively related.

Table 4: Summary Statistics: Portfolios Sorted on IDiff to Total Assets

Portfolio	1	2	3	4	5	6	7	8	9	10
					Characteristics					
(Int. Inv. - Phy. Inv.) / TA	-0.12	-0.04	-0.02	-0.00	0.01	0.03	0.04	0.05	0.06	0.10
(Int. Inv.) / TA	0.02	0.03	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.12
(Phy. Inv.) / TA	0.14	0.07	0.05	0.04	0.03	0.03	0.03	0.03	0.02	0.02
Int. Cap. / ME	0.08	0.15	0.21	0.27	0.34	0.40	0.44	0.50	0.57	0.64
size	551.16	624.10	586.61	566.06	609.81	674.04	656.67	563.87	412.90	244.85
B/M	0.67	0.72	0.74	0.74	0.72	0.68	0.65	0.64	0.61	0.51
iB/M	0.78	0.91	1.00	1.06	1.10	1.12	1.13	1.17	1.22	1.19
Profits	93.04	102.65	101.67	88.98	88.90	90.32	84.07	65.63	44.72	9.35
Int. Inv. - Phy. Inv. Beta	-0.23	0.36	0.46	0.50	0.60	0.66	0.70	0.77	0.85	1.18
Int. Cap. Beta	0.07	0.60	0.71	0.76	0.78	0.81	0.82	0.87	0.91	1.03
Phy. Inv. Beta	0.00	-0.58	-0.75	-0.84	-0.95	-0.97	-0.99	-1.07	-1.11	-1.41
TIDiff Beta	-0.52	0.23	0.36	0.42	0.52	0.51	0.57	0.60	0.66	0.80
Marg. Prod. Beta	0.74	0.83	0.85	0.83	0.77	0.78	0.81	0.80	0.81	0.96
Pat. Val. Beta	-0.89	-0.86	-0.91	-0.92	-0.93	-0.96	-0.98	-1.01	-1.08	-1.26

This table displays average characteristics of firms sorted by their intangible minus tangible investment rates divided by total firm assets. Each July, firms are split into 10 decile portfolios based on that ratio. The values in the table are calculated by taking cross-sectional medians each year and then taking time-series means of those medians. The variables are the IDiff to adjusted book equity ratio, the intangible investment to adjusted book equity ratio, the tangible investment to adjusted book equity ratio, the intangible capital to market value ratio, log market capitalization, the book-to-market ratio, the adjusted book equity to market ratio, profits, the beta on R^I, the beta on R^O, the beta on R^T, the beta on R^{TIDiff}, the beta on R^M, and the beta on R^P. See the body of the paper for details on the different portfolio returns.

The second panel shows average betas on the displacement risk measures. Recall that there are four measures that proxy for *negative* innovations to Z_t. These are R^I, R^O, R^{TIDiff}, and R^M. Average betas on these factors are displayed in the first, second, fourth, and fifth rows of the panel. The average beta for all these factors is increasing in IDiff portfolio. The t-statistics for the difference between the 10 and 1 portfolio are, in order, 6.77, 5.53, 4.2, and 0.3. Only the marginal product beta does not have a significant spread in betas. Recall that this factor was also the one that was the roughest approximation. The two proxies for positive innovations to Z_t are R^T and R^P, the tangible investment sorted portfolio and the aggregate patent value innovations portfolio. The average betas are decreasing with IDiff portfolio. The t-statistics for the difference between the 10 and 1 portfolios are, in order, -7.13 and -1.79.

As a robustness check, I perform more portfolio sorts and display the same statistics for these sorts. First, I sort on the intangible capital to market value ratio. These results are displayed in Table 5. Second, I sort firms based on their betas with respect to R^I. To compute these betas, I first estimate monthly rolling regressions of firm returns on R^I.[52] Then within each calendar year, I compute the average beta, giving me a single beta per firm-year. I then treat these annual betas the same as other annual firm characteristics, sorting firms the following July based on their betas. The results of that sort are displayed in Table 6. Finally, I sort firms based on their tangible investment to adjusted book equity. These results are displayed in Table 7.

[52]The window size is 36 months. Results are robust to different windows.

Table 5: Summary Statistics: Portfolios Sorted on Intangible Capital to Adjusted Book Equity

Portfolio	1	2	3	4	5	6	7	8	9	10
Characteristics										
Int. Inv. - Phy. Inv.) / TBE	-0.10	-0.02	0.02	0.04	0.05	0.06	0.07	0.08	0.09	0.10
(Int. Inv.) / TBE	0.02	0.06	0.09	0.10	0.10	0.11	0.12	0.12	0.13	0.14
(Phy. Inv.) / TBE	0.13	0.08	0.07	0.06	0.06	0.05	0.05	0.04	0.04	0.03
Int. Cap. / ME	0.03	0.11	0.18	0.25	0.32	0.41	0.53	0.69	0.98	1.86
ME	872.07	833.45	666.71	716.65	645.71	555.12	459.71	348.47	227.89	143.31
B/M	0.46	0.46	0.49	0.55	0.59	0.64	0.69	0.78	0.88	1.10
iB/M	0.50	0.59	0.70	0.82	0.93	1.07	1.25	1.49	1.89	3.06
Profits	86.77	77.41	68.39	71.28	70.10	65.08	55.20	41.82	26.67	23.21
Betas										
Int. Inv. - Phy. Inv. Beta	0.29	0.59	0.67	0.70	0.71	0.73	0.76	0.75	0.78	0.78
Int. Cap. Beta	0.24	0.52	0.61	0.71	0.77	0.85	0.90	0.98	1.07	1.22
Phy. Inv. Beta	-0.33	-0.67	-0.76	-0.78	-0.80	-0.82	-0.83	-0.85	-0.89	-0.86
TIDiff Beta	0.71	0.86	0.94	0.95	0.96	0.99	1.08	1.11	1.18	1.25
Marg. Prod. Beta	0.56	0.56	0.55	0.59	0.54	0.61	0.62	0.63	0.62	0.61
Pat. Val. Beta	-0.90	-0.94	-1.00	-0.97	-0.98	-1.00	-1.02	-1.06	-1.10	-1.06

This table displays average characteristics of firms sorted by their intangible capital to adjusted book equity ratios. Each July, firms are split into 10 decile portfolios based on that ratio. The values in the table are calculated by taking cross-sectional medians each year and then taking time-series means of those medians. The variables are the IDiff to adjusted book equity ratio, the intangible investment to adjusted book equity ratio, the tangible investment to adjusted book equity ratio, the intangible capital to market value ratio, log market capitalization, the book-to-market ratio, the adjusted book equity to market ratio, profits, the beta on R^I, the beta on R^O, the beta on R^T, the beta on R^{TIDiff}, the beta on R^M, and the beta on R^P. See the body of the paper for details on the different portfolio returns.

Table 6: Summary Statistics: Portfolios Sorted on IDiff Beta

Portfolio	1	2	3	4	5	6	7	8	9	10
				Characteristics						
(Int. Inv. - Phy. Inv.) / TBE	-0.07	0.02	0.03	0.04	0.04	0.05	0.05	0.06	0.06	0.08
(Int. Inv.) / TBE	0.05	0.09	0.09	0.10	0.10	0.10	0.11	0.11	0.11	0.13
(Phy. Inv.) / TBE	0.13	0.07	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.04
Int. Cap. / ME	0.18	0.33	0.36	0.36	0.36	0.37	0.37	0.38	0.38	0.41
size	614.49	600.45	611.49	621.62	720.75	766.24	756.06	719.52	605.42	410.23
B/M	0.72	0.68	0.66	0.64	0.64	0.61	0.59	0.59	0.56	0.52
iB/M	0.97	1.07	1.06	1.06	1.04	1.03	1.01	1.00	0.99	0.96
Profits	105.99	92.37	92.92	93.87	101.04	102.49	94.18	84.04	69.47	29.17
Int. Inv. - Phy. Inv. Beta	-1.00	-0.19	0.12	0.32	0.48	0.64	0.81	0.98	1.27	2.01
Int. Cap. Beta	-0.38	0.24	0.45	0.57	0.67	0.77	0.86	0.99	1.17	1.61
Phy. Inv. Beta	1.10	0.14	-0.20	-0.40	-0.56	-0.74	-0.90	-1.09	-1.39	-2.17
TIDiff Beta	0.13	0.58	0.68	0.76	0.82	0.90	1.02	1.13	1.34	1.90
Marg. Prod. Beta	0.44	0.63	0.61	0.66	0.64	0.63	0.65	0.66	0.72	0.76
Pat. Val. Beta	-0.59	-0.68	-0.70	-0.77	-0.84	-0.90	-1.02	-1.09	-1.31	-1.78

This table displays average characteristics of firms sorted by their IDiff betas. Each July, firms are split into 10 decile portfolios based on that ratio. The values in the table are calculated by taking cross-sectional medians each year and then taking time-series means of those medians. The variables are the IDiff to adjusted book equity ratio, the intangible investment to adjusted book equity ratio, the tangible investment to adjusted book equity ratio, the intangible capital to market value ratio, log market capitalization, the book-to-market ratio, the adjusted book equity to market ratio, profits, the beta on R^I, the beta on R^O, the beta on R^T, the beta on R^{TIDiff}, the beta on R^M, and the beta on R^P. See the body of the paper for details on the different portfolio returns.

Table 7: Summary Statistics: Portfolios Sorted on Tangible Investment to Adjusted Book Equity

Portfolio	1	2	3	4	5	6	7	8	9	10
				Characteristics						
(Int. Inv. - Phy. Inv.) / TBE	0.10	0.08	0.08	0.07	0.05	0.04	0.02	-0.01	-0.06	-0.23
(Int. Inv.) / TBE	0.12	0.12	0.12	0.11	0.11	0.11	0.10	0.09	0.07	0.05
(Phy. Inv.) / TBE	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.10	0.14	0.28
Int. Cap. / ME	0.48	0.47	0.46	0.43	0.40	0.37	0.34	0.28	0.21	0.11
size	207.79	423.86	505.63	588.51	613.19	618.55	684.93	699.26	687.12	532.63
B/M	0.66	0.65	0.65	0.64	0.64	0.64	0.65	0.66	0.65	0.64
iB/M	1.21	1.17	1.17	1.12	1.09	1.06	1.04	0.99	0.93	0.80
Profits	9.98	38.22	54.38	68.36	79.39	79.06	94.16	103.80	107.02	92.75
Int. Inv. - Phy. Inv. Beta	0.99	0.85	0.75	0.73	0.70	0.65	0.63	0.55	0.46	-0.03
Int. Cap. Beta	0.96	0.87	0.83	0.84	0.82	0.77	0.77	0.73	0.67	0.25
Phy. Inv. Beta	-1.14	-0.95	-0.85	-0.81	-0.78	-0.74	-0.70	-0.63	-0.48	0.03
TIDiff Beta	1.25	1.09	1.01	0.98	0.98	0.97	0.98	0.94	0.92	0.72
Marg. Prod. Beta	0.56	0.53	0.59	0.58	0.58	0.59	0.63	0.62	0.59	0.51
Pat. Val. Beta	-1.20	-1.05	-0.99	-0.99	-0.96	-0.95	-0.92	-0.93	-0.95	-0.92

This table displays average characteristics of firms sorted by their tangible investment to adjusted book equity ratios. Each July, firms are split into 10 decile portfolios based on that ratio. The values in the table are calculated by taking cross-sectional medians each year and then taking time-series means of those medians. The variables are the IDiff to adjusted book equity ratio, the intangible investment to adjusted book equity ratio, the tangible investment to adjusted book equity ratio, the intangible capital to market value ratio, log market capitalization, the book-to-market ratio, the adjusted book equity to market ratio, profits, the beta on R^I, the beta on R^O, the beta on R^T, the beta on R^{TIDiff}, the beta on R^M, and the beta on R^P. See the body of the paper for details on the different portfolio returns.

The first two tables show very similar patterns as Table 4. Since the goal is to sort on characteristics that isolate exposure to negative Z_t shocks, this is reassuring. The first three sorts all plausibly sort on displacement risk. The final table, Table 7, shows a reversed pattern to the previous three, an expected finding. Recall that tangible investment is positively related to displacement risk, so one would expect to see increasing exposure to displacement risk shocks. The empirical findsings displayed in the table confirm this.

4.2 Investment and Cash Flows

The model's mechanism has two critical implications for firm investment and cash flows. First, tangible and intangible investment should react to displacement risk shocks with opposite signs: The latter should increase, and the former should decrease. Second, after displacement risk shocks, intangible intensive firms should have lower cash flows. To test these two implications requires proxies for both the displacement risk shocks and displacement risk exposure.

As a proxy for displacement risk exposure, I use an indicator variable that equals one if the firm's IDiff to adjusted book equity ratio was in the top tercile within a given year. Call this indicator G_{ft}. For measures of displacement risk, I use the six proxies discussed earlier. In particular, since investment and cash flow data are measured annually, I use the actual time series, ΔI, ΔM, and ΔP instead of their factor mimicking portfolios.[53]

I estimate panel regressions of the form:

$$IDiff_{f,t+1} = \alpha_f + \beta_1 G_{ft} \times F_{t+1} + \beta_2 F_{t+1} + \beta_3 G_{ft} + \boldsymbol{X}_{ft}\boldsymbol{\beta} + \varepsilon_{ft} \tag{50}$$

where α_f is a firm fixed-effect, F_t is the shock measure, and $\boldsymbol{X}_{ft}$ is a vector of firm controls, all measured in year t, which include the lagged iB/M ratio, the lagged intangible capital to market value ratio, and lagged profitability to adjusted book equity ratio. Note the timing of the specification. The exposure, G_{ft}, is measured with a lag compared to the response and the shock. This is consistent with model, whereby a firm enters a given period with some exposure, and then shock realizations determine its investment choices.

[53] The variables are standardized to have mean 0 and variance 1.

Table 8: Investment Responses to Displacement Shocks

	Dependent variable:		
	IDiff (t+1)		
	(1)	(2)	(3)
$G_t \times R^I_{t+1}$	0.023***		
	(0.004)		
$G_t \times R^O_{t+1}$		0.023***	
		(0.004)	
$G_t \times R^P_{t+1}$			−0.009**
			(0.005)
G_t	0.117***	0.117***	0.116***
	(0.021)	(0.021)	(0.021)
R^I_{t+1}	−0.012***		
	(0.004)		
R^O_{t+1}		−0.009**	
		(0.004)	
R^P_{t+1}			0.013***
			(0.003)
Lag. iB/M	0.011	0.011	0.010
	(0.011)	(0.011)	(0.011)
Lag. Int. Cap. / ME	−0.002	−0.002	−0.001
	(0.012)	(0.012)	(0.012)
Lag. Prof. / Adj. BE	0.00003	0.00004	0.00002
	(0.0003)	(0.0003)	(0.0003)
Observations	89,656	89,656	89,656
R^2	0.545	0.545	0.545
Adjusted R^2	0.494	0.494	0.494
Residual Std. Error (df = 80609)	0.757	0.757	0.757
Note:			*p<0.1; **p<0.05; ***p<0.01

This table displays results from estimating equation (50). All variables, aside from G_{ft} are standardized to have 0 means and unit standard deviation. The variable G_{ft} is a dummy equal to one if the firm's IDiff to adjusted book equity ratio is in the top tercile in year t. The variables R^I_t, R^O_t, and R^P_t are the portfolios sorted on IDiff to adjusted book equity, intangible capital to market value, and tangible investment to adjusted book equity. See body of the paper for details on their construction. All regression include firm fixed-effects and are clustered at the firm level.

Table 8 displays the results. I focus on the coefficients on F_{t+1} and $G_{ft} \times F_{t+1}$ as these give estimates of how much a firm's IDiff increases or decreases following shocks depending on if the firm is highly negatively exposed to displacement risk shocks or not. Also, recall that R_t^I and R_t^O proxy for negative displacement risk shocks, and R_t^P proxies for positive ones. First, looking at the coefficients on R_{t+1}^I, R_{t+1}^O, and R_{t+1}^P, we see that firms in the lowest IDiff to adjusted book equity groups increase their intangible investment relative to tangible following a displacement risk shock. This is inconsistent with the model, but interesting, nonetheless. However, when one compares the coefficients on $G_{ft} \times F_{t+1}$ to the ones on F_{t+1}, the model's predictions are borne out. Firms with the greatest negative, or short, exposure to displacement risk decrease their intangible investment relative to their tangible by 0.021-0.035 standard deviations more than the lower tercile firms. These relative differences are statistically significant at the 1% level. Thus, the model can explain relative intangible versus tangible investment responses, but I leave the study of the *level* of investment for future work.

Table 9 displays results from estimating equation (50) using the aggregate proxies for displacement risk, $\Delta TIDiff_t$, ΔM_t, and ΔP_t. The results are similar to those in Table 8. While the interaction of exposure and $\Delta TIDiff_{t+1}$ is insignificant, the effect of $\Delta TIDiff_{t+1}$ alone is large and significant, implying that firm level and aggregate IDiff are related. Comparing the coefficients on $G_{ft} \times F_{t+1}$ to those on F_{t+1}, one sees the estimated decrease in intangible versus tangible investment for firms short displacement risk decreases 0-0.028 standard deviations more than those firms in the bottom terciles of exposure following a positive displacement risk shock.

The model also makes predictions about cash flows following displacement risk shocks. Recall the expression for firm output in the model is:

$$Y_{ft} = X_t K_{ft} + \frac{O_{ft}}{Z_t}. \tag{51}$$

It follows from this expression that firms with more intangible capital out of their total capital stock should have lower cash flow, or profits, following displacement risk shocks. I

Table 9: Investment Responses to Displacement Shocks: Different Proxies

	Dependent variable:		
	IDiff (t+1)		
	(1)	(2)	(3)
$G_t \times \Delta TIDiff_{t+1}$	0.003		
	(0.006)		
$G_t \times \Delta M_{t+1}$		0.027^{***}	
		(0.006)	
$G_t \times \Delta P^P_{t+1}$			-0.012^{***}
			(0.004)
G_t	0.117^{***}	0.115^{***}	0.117^{***}
	(0.021)	(0.021)	(0.021)
$\Delta TIDiff_{t+1}$	0.021^{***}		
	(0.005)		
ΔM_{t+1}		−0.001	
		(0.005)	
ΔP^P_{t+1}			-0.004^{*}
			(0.003)
Lag. iB/M	0.008	0.010	0.009
	(0.011)	(0.011)	(0.011)
Lag. Int. Cap. / ME	−0.001	−0.002	−0.001
	(0.012)	(0.012)	(0.012)
Lag. Prof. / Adj. BE	−0.0001	0.00004	0.00005
	(0.0003)	(0.0003)	(0.0003)
Observations	89,656	89,656	89,656
R^2	0.545	0.545	0.545
Adjusted R^2	0.494	0.494	0.494
Residual Std. Error (df = 80609)	0.757	0.757	0.757
Note:	*p<0.1; **p<0.05; ***p<0.01		

This table displays results from estimating equation (50). All variables, aside from G_{ft} are standardized to have 0 means and unit standard deviation. The variable G_{ft} is a dummy equal to one if the firm's IDiff to adjusted book equity ratio is in the top tercile in year t. The variables $\Delta TIDiff_t$, ΔM_t, and ΔP_t are innovations to aggregate IDiff, innovations to the marginal product of intangible capital, and innovations to the aggregate value of filed patents to the aggregate market value. See body of the paper for details on their construction. All regression include firm fixed-effects and are clustered at the firm level.

test this prediction by estimating regressions of the form:

$$\frac{Profits}{Assets}_{f,t+1} = \alpha_f + \beta_1 G_{ft} \times F_{t+1} + \beta_2 F_{t+1} + \beta_3 G_{ft} + \boldsymbol{X}_{ft}\boldsymbol{\beta} + \varepsilon_{ft} \tag{52}$$

where the indicator, G_{ft}, equals one if the firm is in the top tercile of firms in a given year with respect to its intangible capital to adjusted book equity ratio.[54]

Table 10 displays the results of estimating equation (52) using the return-based proxies for displacement risk, R_t^I, R_t^O, and R_t^P. The controls are the same as in equation (50). The response of profits to assets is similar to that of IDiff. A one-standard deviation displacement risk shock is associated with a decrease in profits to asset for high intangible capital firms that is 0.033-0.037 standard deviations larger than that of low intangible capital firms. Once again, the level effect is not entirely consistent with the model. I leave that to future research.

Table 11 displays results from estimating equation (52) using the aggregate proxies for displacement shocks, $\Delta TIDiff_{t+1}$, ΔM_{t+1}, and ΔP_{t+1}. Note first that the effect of displacement risk shocks is positive when not interacted with G_{ft}.[55] Once again, we see that firms with large intangible capital to adjusted book equity ratios are less profitable following displacement risk shocks. For example, after a negative one standard deviation shock to $\Delta TIDiff_{t+1}$, high intangible capital firms have profits that 0.042 standard deviations lower than low intangible capital firms. The effect ranges from 0.08-0.042 standard deviations.

4.3 Asset Returns

The model implies that firm exposure to productivity risk is governed by the iB/M ratio. Firm exposure to displacement risk is governed by the intangible capital to market value ratio, the intangible investment rate, and the tangible investment rate. In this subsection, I estimate panel regressions and undertake portfolio sorts to study if these firm characteristics indeed predict cross-sectional differences in returns. From there, I form a double-sort that attempts to maximize loadings on the two risk factors. I show that leading asset pricing model cannot price this double sort.

[54] Results are similar if I use the same indicator as in equation (50).

[55] For example, $-\Delta TIDiff_{t+1}$ is a proxy for the displacement shock. The coefficient on this variable would be -1×-0.033.

Table 10: Response of Profits to Displacement Shocks

	Dependent variable:		
	Profits / Assets (t+1)		
	(1)	(2)	(3)
$G_t \times R^I_{t+1}$	0.015***		
	(0.004)		
$G_t \times R^O_{t+1}$		0.012***	
		(0.004)	
$G_t \times R^P_{t+1}$			−0.014***
			(0.004)
G_t	−0.054***	−0.054***	−0.055***
	(0.010)	(0.010)	(0.010)
R^I_{t+1}	−0.022***		
	(0.002)		
R^O_{t+1}		−0.024***	
		(0.002)	
R^P_{t+1}			0.019***
			(0.002)
Lag. iB/M	−0.121***	−0.119***	−0.122***
	(0.028)	(0.028)	(0.028)
Lag. Int. Cap. / ME	0.062**	0.061**	0.062**
	(0.027)	(0.027)	(0.028)
Lag. Prof. / Adj. BE	0.008	0.008	0.008
	(0.007)	(0.007)	(0.007)
Observations	90,604	90,604	90,604
R^2	0.651	0.651	0.651
Adjusted R^2	0.612	0.612	0.612
Residual Std. Error (df = 81534)	0.539	0.539	0.539
Note:	*p<0.1; **p<0.05; ***p<0.01		

This table displays results from estimating equation (50). All variables, aside from G_{ft} are standardized to have 0 means and unit standard deviation. The variable G_{ft} is a dummy equal to one if the firm's IDiff to adjusted book equity ratio is in the top tercile in year t. The variables R^I_t, R^O_t, and R^P_t are the portfolios sorted on IDiff to adjusted book equity, intangible capital to market value, and tangible investment to adjusted book equity. See body of the paper for details on their construction. All regression include firm fixed-effects and are clustered at the firm level.

Table 11: Response of Profits to Displacement Shocks: Different Proxies

	Dependent variable:		
	Profits / Assets (t+1)		
	(1)	(2)	(3)
$G_t \times \Delta TIDiff_{t+1}$	0.023***		
	(0.004)		
$G_t \times \Delta M_{t+1}$		0.001	
		(0.003)	
$G_t \times \Delta P^P_{t+1}$			−0.009*
			(0.005)
G_t	−0.053***	−0.054***	−0.055***
	(0.010)	(0.010)	(0.010)
$\Delta TIDiff_{t+1}$	−0.035***		
	(0.003)		
ΔM_{t+1}		−0.009***	
		(0.002)	
ΔP^P_{t+1}			0.006**
			(0.002)
Lag. iB/M	−0.118***	−0.122***	−0.122***
	(0.027)	(0.028)	(0.028)
Lag. Int. Cap. / ME	0.060**	0.062**	0.062**
	(0.027)	(0.028)	(0.028)
Lag. Prof. / Adj. BE	0.008	0.008	0.008
	(0.007)	(0.007)	(0.007)
Observations	90,604	90,604	90,604
R^2	0.651	0.651	0.651
Adjusted R^2	0.613	0.612	0.612
Residual Std. Error (df = 81534)	0.539	0.539	0.539
Note:	*p<0.1; **p<0.05; ***p<0.01		

This table displays results from estimating equation (52). All variables, aside from G_{ft} are standardized to have 0 means and unit standard deviation. The variable G_{ft} is a dummy equal to one if the firm's IDiff to adjusted book equity ratio is in the top tercile in year t. The variables $\Delta TIDiff_t$, ΔM_t, and $\Delta P_t P$ are innovations to aggregate IDiff, innovations to the marginal product of intangible capital, and innovations to the aggregate value of filed patents to the aggregate market value. See body of the paper for details on their construction. All regression include firm fixed-effects and are clustered at the firm level.

I estimate panel regressions of the form:

$$R_{f,t+1} = \alpha_f + \alpha_t + \beta_1 \text{Intangible Investment Rate}_{ft} + \beta_2 \text{Tangible Investment Rate}_{ft} \\ + \beta_3 \text{Intangible Capital to Market Value Ratio}_{ft} + \beta_4 \text{iB/M Ratio}_{ft} + \boldsymbol{X}_{ft}\boldsymbol{\beta} + \varepsilon_{ft}. \tag{53}$$

Controls in $\boldsymbol{X}_{ft}$ include profits, lagged returns, and leave-one-out industry mean returns. When measuring the investment rates, I normalize by either the market value of the firm or the adjusted book equity.[56] I include year and firm fixed-effects (α_t and α_f). Standard errors are clustered at the firm level. Variables are unit standard deviation and 0 mean.

According to the model, the signs on the coefficients should be as follows; $\beta_1 > 0, \beta_2 < 0, \beta_4 > 0$. The sign on β_3 is not assigned by the model. Recall that, conditional on the iB/M ratio, the intangible capital to market value ratio estimates the sign of $-\sigma_X\gamma_X - \sigma_Z\gamma_Z$. This could be positive or negative depending on which shock is riskier.

Table 12 displays the results. The first two columns normalize investment rates by adjusted book equity, and the final two columns normalize by market value. The second and fourth columns include the control variables. The signs on the betas of interest are as expected. Also, the sign on β_3 is negative across all specifications suggesting that general productivity is riskier than displacement risk. The coefficient on intangible investment is positive and significant across all specifications. The sign on tangible investment is negative but not significant across all specifications, and the same is true for the intangible capital stock to market value ratio. Finally, the iB/M ratio has positive and significant coefficients across specifications. The iB/M ratio also has the largest effect on returns: A one standard deviation increase in the iB/M ratio is associated with a 0.17 standard deviation increase in returns. Note that the effect of intangible investment is smaller but comparable: The coefficient is about 1/10 the size. The effects are economically significant as well. In the final column, the association between intangible investment and stock returns is similar to that of the lagged stock return.

The model shows that one needs to track four different firm characteristics to capture

[56] The model implies the correct measure uses the market value in the denominator. However, it is less standard in empirical asset pricing to do this, so I provide both normalizations.

Table 12: Returns and Firm Characteristics

	Dependent variable:			
	$R_{f,t+1}$			
	(1)	(2)	(3)	(4)
$\frac{\text{Intangible Investment}}{\text{Adjusted Book Equity}}$	0.014^{***}	0.022^{*}		
	(0.005)	(0.012)		
$\frac{\text{Tangible Investment}}{\text{Adjusted Book Equity}}$	-0.018^{***}	-0.014^{*}		
	(0.006)	(0.008)		
$\frac{\text{Intangible Investment}}{\text{Market Value}}$			0.060^{*}	0.089^{**}
			(0.032)	(0.036)
$\frac{\text{Tangible Investment}}{\text{Market Value}}$			-0.010	-0.009
			(0.008)	(0.008)
$\frac{\text{Intangible Capital}}{\text{Market Value}}$	-0.060	-0.070	-0.110^{**}	-0.141^{***}
	(0.044)	(0.045)	(0.044)	(0.043)
iB/M Ratio	0.165^{***}	0.179^{***}	0.160^{***}	0.166^{***}
	(0.031)	(0.032)	(0.033)	(0.033)
$\frac{\text{Profits}}{\text{Adjusted Book Equity}}$		0.012		-0.003^{***}
		(0.008)		(0.0004)
$R_{f,t}$		-0.090^{***}		-0.090^{***}
		(0.005)		(0.005)
$R_{j,t,-f}$		-0.082^{***}		-0.082^{***}
		(0.003)		(0.003)
Observations	100,264	99,124	100,264	99,124
R^2	0.248	0.152	0.248	0.152
Adjusted R^2	0.160	0.054	0.160	0.055
Residual Std. Error	0.866 (df = 89795)	0.915 (df = 88894)	0.866 (df = 89795)	0.915 (df = 88894)
Note:				*p<0.1; **p<0.05; ***p<0.01

This table displays results from estimating equation (53). The main variables are defined in the text, in particular, in the Data section. The variable $R_{f,t}$ is the lagged firm stock return, and $R_{j,t,-f}$ is the leave-one-out industry mean return. The first column normalizes the investment rates using adjusted book equity. The second column adds controls. The third and fourth column normalize investment rates by market value with and without controls, respectively. All standard errors are clustered at the firm level and regressions include firm and date fixed-effects.

all the firm's risk exposure. The panel regressions above have also shown that each of these characteristics does have predictive power over returns with the expected signs. I now consider how to construct a portfolio which is long productivity risk and short the displacement risk. Given the signs of the price of risk on these shocks, this portfolio should have large expected returns.

As implied by the model, creating large exposure to productivity risk is simple. One must select high iB/M firms. This is the first variable on which I sort. Creating large negative exposure to displacement risk is more difficult. It is not efficient to simultaneously sort on all three characteristics which appear in the beta in equation (31). I instead sort on IDiff. There are two reasons for this. First, while the difference between intangible and tangible investment (IDiff) does not appear directly in equation (31), IDiff is a first order approximation to the difference that does. The important fact is that intangible and tangible investment affect exposure to displacement risk with opposite signs. The second reason is a practical one. IDiff and the intangible capital to market ratio are highly rank correlated. That is, firms which have large values of one variable tend to have large values of the other. For example, the average number of firms in the bottom tercile in terms of IDiff over adjusted book equity and simultaneously in the top tercile in terms of intangible capital to market value in a given year is only 30. On the other hand, the number of firms simultaneously in the top tercile for each variable is on average 620. Therefore, a sort on IDiff is implicitly a sort on the intangible capital to market value ratio.

In the end, I construct a double sort on iB/M and IDiff to adjusted book equity.[57] Since iB/M increases exposure to productivity risk, all else equal, firms with larger iB/M ratios should have larger expected returns. Similarly, since IDiff decreases exposure to displacement risk, firms with larger IDiff to adjusted book equity ratios should have higher expected returns.[58] Consequently, expected returns should be increasing in both IDiff portfolio and iB/M portfolio.

Table 13 displays mean returns and t-statistics by portfolio.[59] Portfolios are formed at the end of June of year t and held through June of $t+1$. Annual re-balancing reduces transaction

[57]Similar results emerge if I normalize IDiff by market value or total assets.

[58]Recall that displacement risk carries a negative price of risk.

[59]The t-statistics are computed using Newey-West (Newey and West (1987)) with 8 lags.

costs. Each year, returns are value-weighted.[60] The five portfolios along the top of the table are based on firm IDiff to adjusted book equity, and the five portfolios alongside are based on the iB/M ratio. The bottom left two cells display the mean return and t-statistic for the Hi-Lo long short portfolio (5.5 minus 1.1). Mean returns are almost monotonic across either portfolio. In particular, the Hi and Lo portfolios always have a positive spread in expected returns, though this difference is not always significant. The HiLo portfolio has an expected return of 8.2% per year (0.682 $\times$ 12) and is highly significant.

Table 13: Mean Returns

iB/M Port \IDiff Port	Lo	2	3	4	Hi
Lo	0.338	0.641	0.562	0.931	0.803
	(1.279)	(2.811)	(2.143)	(3.348)	(2.126)
2	0.607	0.783	0.69	0.596	0.951
	(2.408)	(3.682)	(3.084)	(2.005)	(2.646)
3	0.612	0.77	0.999	1.075	1.003
	(2.533)	(3.568)	(5.005)	(4.530)	(3.138)
4	0.795	0.884	0.811	0.907	1.05
	(3.552)	(4.288)	(3.685)	(3.725)	(3.662)
Hi	0.834	0.983	1.028	1.17	1.02
	(3.370)	(4.824)	(4.483)	(4.272)	(3.442)
HiLo	0.682				
	(2.807)				

This table displays mean returns for each portfolio in the iB/M-IDiff double sort. Newey-West t-statistics using 8 month lags are in parentheses beneath mean returns. The final two rows display the mean return of the long short portfolio where the long leg is the 5.5 portfolio and the short leg is the 1.1 portfolio.

Next, I study whether leading existing factor models can price the portfolios in the double-sort. A priori, it is not clear what the answer should be. On the one, the model in this paper depends on two risk factors. Therefore, a correctly specified two factor model should be able to remove or reduce pricing errors. However, none of the factor modes I consider are based on the firm model presented here, which shows that multiple firm characteristics load on a common risk factor (displacement risk) in different ways. Thus, whether these portfolios are priced by the models is an empirical question.

Tables 14 through 18 display alphas and Newey-West standard errors for the portfolios against the factor models. The tables are as follows. Table 14 displays CAPM (Sharpe

[60] Results are even stronger with equal-weighting.

(1964)) alphas. This model uses the value-weighted market return as the single factor. Table 15 displays Fama-French three factor model (Fama and French (1996)) alphas. This model use the value-weighted market factor, a size factor, and the book-to-market factor. I create the book-to-market factor using the iB/M ratio instead of the standard B/M ratio. Table 16 Fama-French five factor model (Fama and French (2015)) alphas. This model uses the same three factors as the Fama-French three factor model. It also adds a tangible investment factor and a profitability factor. Once again, I use the iB/M ratio to create the book-to-market factor. Table 17 displays Q-Factor model (Hou et al. (2015)) alphas. The factors are the market factor, a size factor, an investment factor, and a return on equity factor. Table 18 displays EP factor model (Eisfeldt and Papanikolaou (2013)) alphas. This model is most closely related to firm-model in this paper. It uses the market factor and a factor constructed by sorting firms based on the ratio of their organization capital (a subset of intangible capital) to tangible capital.

Table 14 shows that the CAPM cannot explain the dispersion in the portfolio returns. The HiLo portfolio return has a statistically significant alpha of nearly 10% per year. Similar results can be seen in the other tables. The HiLo alphas range from 7-9% annual and all are statistically significant. Note that alphas are not monotonic across portfolios, though the HiLo difference *within* portfolio is usually positive. The firm-model presented earlier is stylized and written under assumptions to provide closed form solutions. Further research could do away with these assumptions, perhaps leading to an explanation for these non-montonicities.

In the next section, I provide an application of this double sort to the value premium.

5 The Value Discount

The value premium is the idea that firms with high book-to-market ratios should have higher expected returns than firms with low book-to-market ratios. A well-known empirical validation of this idea is espoused in Fama and French (1993) and Fama and French (1996). In particular, the latter paper's "High Minus Low" (HML) factor returns, which cannot be

Table 14: CAPM Alphas

iB/M Port \IDiff Port	Lo	2	3	4	Hi
Lo	-0.394	-0.013	-0.078	0.225	0.001
	(-2.643)	(-0.072)	(-0.373)	(1.110)	(0.003)
2	-0.124	0.125	0.019	-0.176	0.187
	(-0.863)	(0.913)	(0.118)	(-1.001)	(0.698)
3	-0.065	0.151	0.354	0.377	0.252
	(-0.501)	(1.284)	(2.741)	(2.338)	(1.265)
4	0.154	0.223	0.169	0.209	0.328
	(1.236)	(2.082)	(1.266)	(1.316)	(1.499)
Hi	0.117	0.318	0.37	0.403	0.223
	(0.868)	(2.654)	(2.063)	(2.514)	(1.058)
HiLo	0.759				
	(2.986)				

This table displays CAPM alphas for each portfolio in the iB/M-IDiff double sort. Newey-West t-statistics using 8 month lags are in parentheses beneath mean returns. The final two rows display the CAPM alpha of the long short portfolio where the long leg is the 5.5 portfolio and the short leg is the 1.1 portfolio.

priced by the CAPM, have been used as evidence of the value premium.[61] Over the last two decades, the value premium has disappeared, and a new literature has sought to resuscitate it by including intangible capital in the book equity of the firm.[62] I refer to this new value factor as iHML following Arnott et al. (2021). The classic HML factor has suffered from low or negative average returns since approximately 2005. The new iHML fares better, but since 2010, this has also turned negative. Both sorting procedures assume that the growth opportunities of the firm are less risky than the assets in place, but as the model in this paper shows, that need not be the case. One must track the fraction of growth opportunities coming from intangible investment and the fraction coming from physical investment.

Recall that the model shows that the B/M ratio informs us about the firm's exposure to general productivity risk. Conditional on the B/M ratio, the ratio of intangible capital to market value and the two investment rates provide information about exposure to displacement risk. I claim that within each HML or iHML portfolio, the exposure to displacement risk has changed. In particular, value firms are now longer displacement risk than they once were and growth firms are shorter displacement risk. To that end, I use the coefficients from column (1) of Table 12 to estimate the expected return on the firm attributable to its

[61] I present within-industry CAPM alphas in the Appendix.
[62] Eisfeldt et al. (2020), Arnott et al. (2021), Park (2019).

Table 15: Fama-French Three Factor Model Alphas

iB/M Port \IDiff Port	Lo	2	3	4	Hi
Lo	-0.399	-0.118	-0.268	0.015	-0.312
	(-2.798)	(-0.736)	(-1.538)	(0.079)	(-1.075)
2	-0.015	0.048	-0.149	-0.353	-0.069
	(-0.117)	(0.433)	(-1.140)	(-2.494)	(-0.339)
3	0.075	0.116	0.326	0.241	0.056
	(0.809)	(1.059)	(2.794)	(1.499)	(0.355)
4	0.254	0.232	0.123	0.126	0.176
	(2.366)	(2.339)	(0.948)	(0.935)	(1.070)
Hi	0.278	0.396	0.339	0.361	0.118
	(2.720)	(3.316)	(2.110)	(2.625)	(0.806)
HiLo	0.694				
	(2.819)				

This table displays the Fama-French three factor model alphas for each portfolio in the iB/M-IDiff double sort. The HML factor includes intangible capital in the book equity used to create the sort. Newey-West t-statistics using 8 month lags are in parentheses beneath the alphas. The final two rows display the alpha of the long short portfolio where the long leg is the 5.5 portfolio and the short leg is the 1.1 portfolio.

exposure to displacement risk. The expected return is the fitted value from that regression, zeroing out the book-to-market ratio and ignoring firm-fixed effects.

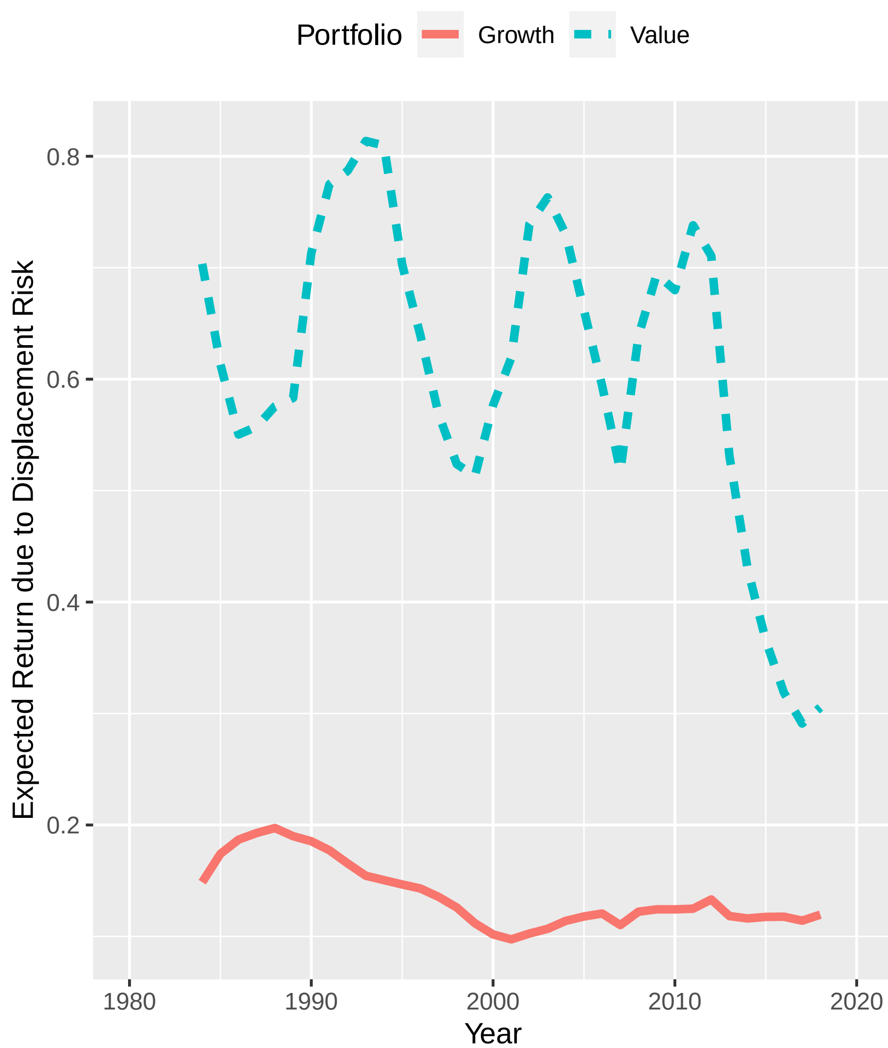
Figure 2 displays the results for the HML portfolios, and Figure 3 displays results for iHML portfolios. For both figures, the value portfolio's expected return due to displacement risk has dropped. For the HML value portfolio, the expected return due to displacement risk peaked right after the Dot-Com boom after the year 2000. It has steadily declined since then, and after 2011-2012 it is actually lower than the expected return for the growth portfolio. Figure 3 shows that the iHML value portfolio has a larger expected return due to displacement risk than the growth portfolio for the whole sample. However, the value portfolio's expected return has dropped sharply since 2010, while growth's has remained steady. The iHML value portfolio's drop occurs about a decade after the HML value portfolio's.

To see why this change in expected returns has occurred, I study the trend in IDiff across the value and growth portfolios. For each year, I calculate the fraction of firms in the top tercile of IDiff to market value that are simultaneously growth or value firms. These results are displayed in Figures 4 and 5. For the HML portfolio, in Figure 4, there is a clear divergence between value and growth which starts after the year 2000. Since then, the share of high IDiff firms that are also growth firms has steadily climbed, while the share of value

Figure 2: Expected Return Due to Displacement Risk: HML Portfolios

This figure displays the expected return due displacement risk for the value and growth portfolios as defined by HML. The expected return due to displacement risk is the fitted value from column (1) of Table 12 with the book-to-market ratio zeroed out and ignoring firm fixed-effects. The expected returns are value-weighted within portfolios. The values in the figure are 5-year moving averages of the underlying series.

Figure 3: Expected Return Due to Displacement Risk: iHML Portfolios



This figure displays the expected return due displacement risk for the value and growth portfolios as defined by iHML. The expected return due to displacement risk is the fitted value from column (1) of Table 12 with the book-to-market ratio zeroed out and ignoring firm fixed-effects. The expected returns are value-weighted within portfolios. The values in the figure are 5-year moving averages of the underlying series.

Table 16: Fama-French Five Factor Model Alphas

iB/M Port \IDiff Port	Lo	2	3	4	Hi
Lo	-0.521	-0.134	-0.243	-0.158	-0.374
	(-2.521)	(-0.812)	(-1.282)	(-0.900)	(-1.803)
2	-0.089	0.052	-0.327	-0.258	-0.071
	(-0.905)	(0.495)	(-2.500)	(-1.725)	(-0.375)
3	0.219	0.103	0.232	0.053	-0.098
	(2.683)	(1.135)	(1.795)	(0.305)	(-0.399)
4	0.232	0.36	0.244	0.056	0.073
	(1.598)	(3.656)	(1.855)	(0.342)	(0.418)
Hi	-0.548	0.099	0.222	0.183	0.059
	(-1.129)	(0.529)	(1.298)	(1.497)	(0.534)
HiLo	0.579				
	(2.443)				

This table displays Fama-French five factor model alphas for each portfolio in the iB/M-IDiff double sort. The HML factor is constructed including intangible capital in the book equity used to define the sort. Newey-West t-statistics using 8 month lags are in parentheses beneath mean returns. The final two rows display the alpha of the long short portfolio where the long leg is the 5.5 portfolio and the short leg is the 1.1 portfolio.

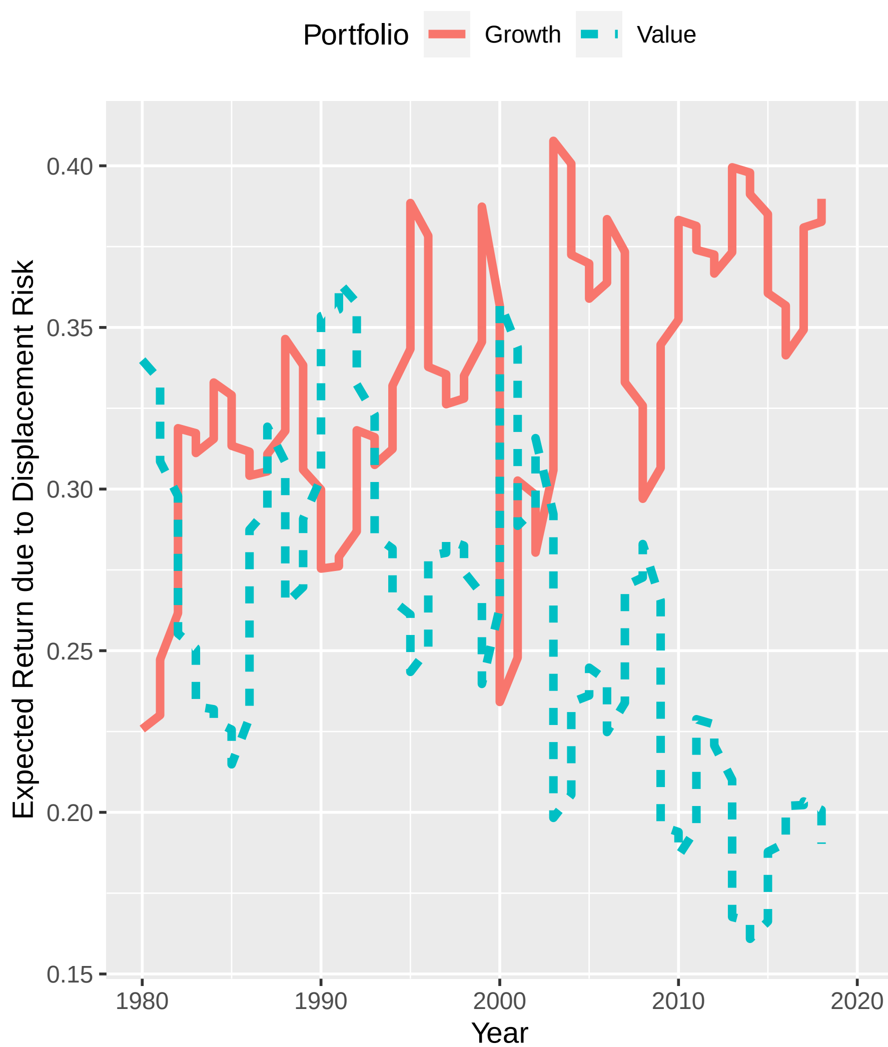
firms has declined. The story is a bit different for the iHML portfolios. Value firms still make up a larger fraction of the high IDiff firms than growth firms. However, similar to the HML trends, that fraction has steadily declined. In 1980, value firms made up around 40% more of the high IDiff portfolio. By 2020, this difference has halved to around 20%.

Given these trends in investment rates, I use the double sort from the previous section to "fix" the value factor, by selecting subsets of the long and short legs of the double sort. Essentially, I use the HiLo portfolio as the new value factor.[63] Note that this is a strict subset of the existing iHML portfolio.

Figure 6 displays the 10-year moving average of IDIffHML on top of that of HML and iHML. The three series all comove closely for much of the sample period. In the two notable periods of decline in HML and iHML, 2000 and since 2010, IDiffHML continues to perform well. Both 2000 and the current period are classified by tech booms and busts. They are periods where the frontier technology is rapidly changing and displacement risk is plausibly high, and it is not clear which firms will emerge as winners. Firms doing more intangible investment are precisely those who will be most at risk of being displaced.

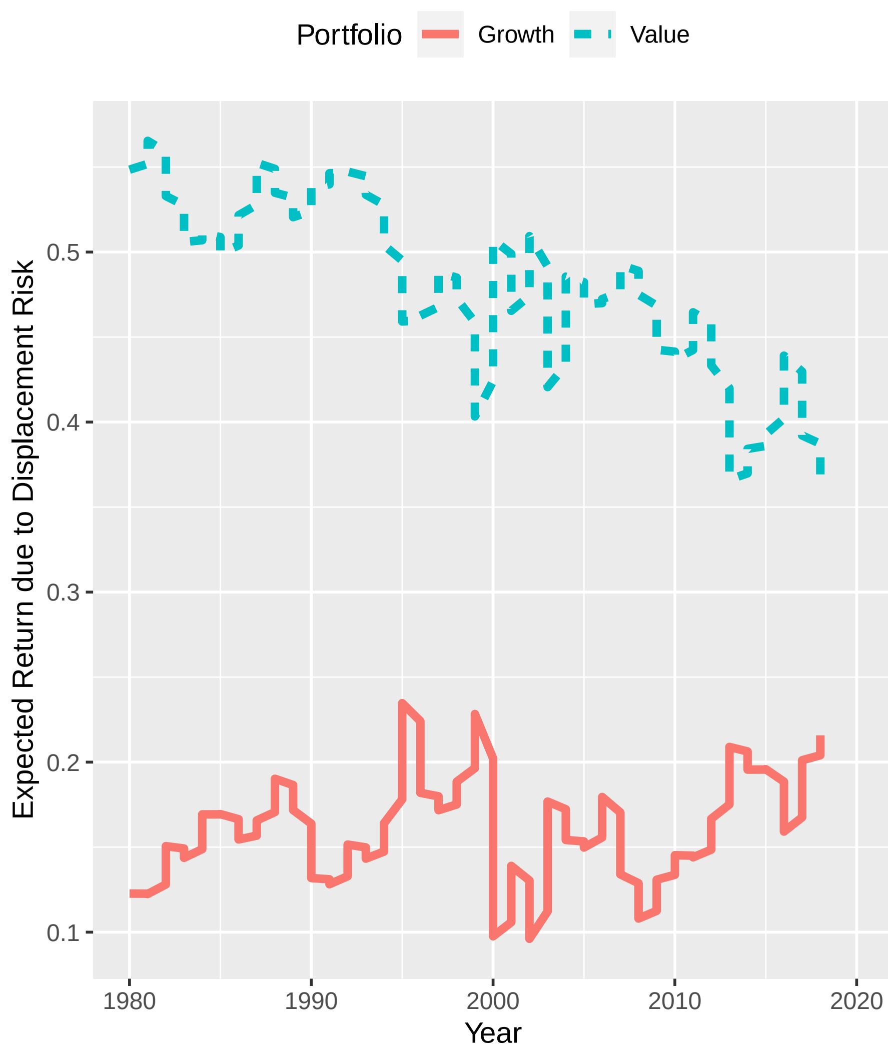
[63]The only difference is that I, like in the construction of HML, first form value-weighted averages within size, IDiff, and iB/M portfolios. Then I take equal weighted averages across size portfolios within each iB/M by IDiff portfolio.

Figure 4: Fraction of High IDiff Firms in Growth or Value: HML Portfolios



This figure displays the fraction of firms in the top IDiff to market value tercile that are also in either the growth or value portfolios according to HML. The values in the figure are 5-year moving averages of the underlying series.

Figure 5: Fraction of High IDiff Firms in Growth or Value: iHML Portfolios



This figure displays the fraction of firms in the top IDiff to market value tercile that are also in either the growth or value portfolios according to iHML. The values in the figure are 5-year moving averages of the underlying series.

Figure 6: Value Factor Returns

This figure displays the 10-year moving average returns of HML, iHML, and IDiffHML. The descriptions of how these factors are formed can be found in the body of the paper.

Table 17: Q-Factor Model Alphas

iB/M Port \IDiff Port	Lo	2	3	4	Hi
Lo	-0.509	-0.287	-0.251	0.172	0.174
	(-2.398)	(-1.859)	(-1.526)	(0.987)	(0.627)
2	-0.15	-0.097	-0.412	-0.189	0.078
	(-1.366)	(-0.897)	(-2.557)	(-0.951)	(0.335)
3	0.309	0.036	0.174	0.12	-0.016
	(2.954)	(0.340)	(1.372)	(0.563)	(-0.050)
4	0.277	0.327	0.214	0.159	0.15
	(1.643)	(2.895)	(1.635)	(0.756)	(0.849)
Hi	0.14	0.263	0.264	0.404	0.262
	(0.278)	(1.268)	(1.257)	(2.156)	(1.397)
HiLo	0.772				
	(2.517)				

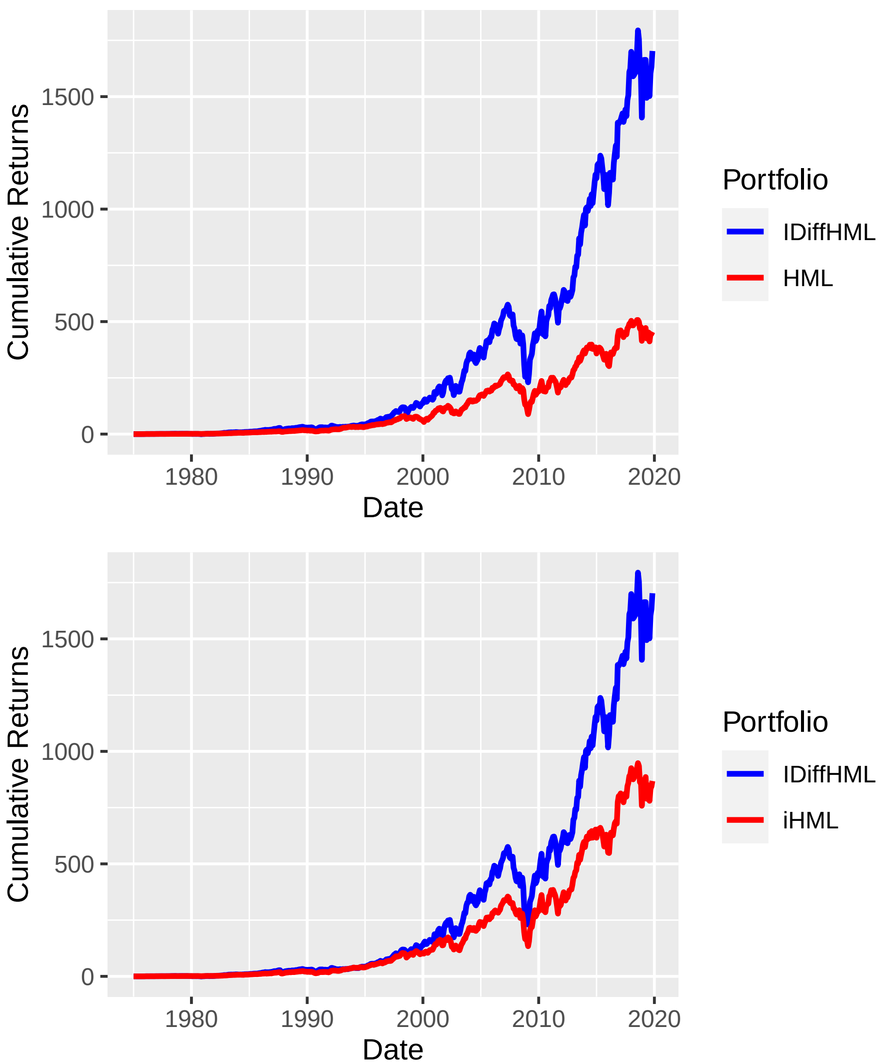
This table displays Q-Factor model alphas for each portfolio in the iB/M-IDiff double sort. Newey-West t-statistics using 8 month lags are in parentheses beneath mean returns. The final two rows display the alpha of the long short portfolio where the long leg is the 5.5 portfolio and the short leg is the 1.1 portfolio.

Figure 7 shows the cumulative returns on IDiffHML versus HML (top panel) and iHML (bottom panel). IDiffHML experiences no leveling off like HML or iHML. Investing the IDiffHML portfolio would have yielded an investor more the three times the amount he would have had from investing in HML and two times his return from iHML.

6 Conclusion

Intangible investment positively predicts stock returns, and tangible investment negatively predict stock returns. Firms with large differences between their intangible and tangible investment rates, what I call IDiff, have large negative exposure to displacement risk shocks. These two empirical facts are rationalized in a production-based asset pricing model that features tangible and intangible capital and investment. Displacement risk connects the tangible and intangible sides of the model, whereby tangible investment benefits from displacement risk shocks, while intangible investment and capital suffer. The predictions of the model are borne in cash flow, investment, and asset pricing data. Based on the model's predictions, I form a double sort based on the book to market ratio, where book equity includes intangible capital, and the firm's IDiff to market ratio. The returns on the difference

Figure 7: Cumulative Returns



This figure displays the cumulative returns of HML, iHML, and IDiffHML. The descriptions of how these factors are formed can be found in the body of the paper.

Table 18: EP Factor Model Alphas

iB/M Port \IDiff Port	Lo	2	3	4	Hi
Lo	-0.367	0.09	0.078	0.226	0.143
	(-2.087)	(0.641)	(0.498)	(1.347)	(0.568)
2	-0.209	0.181	-0.069	-0.035	0.227
	(-1.659)	(1.383)	(-0.420)	(-0.194)	(0.929)
3	0.013	0.143	0.25	0.261	0.16
	(0.134)	(1.222)	(1.843)	(1.454)	(0.497)
4	0.066	0.286	0.318	0.237	0.289
	(0.428)	(2.698)	(1.812)	(1.430)	(1.240)
Hi	-0.769	-0.1	0.183	0.238	0.222
	(-1.621)	(-0.539)	(1.188)	(1.536)	(1.144)
HiLo	0.589				
	(2.605)				

This table displays EP factor model alphas for each portfolio in the iB/M-IDiff double sort. Newey-West t-statistics using 8 month lags are in parentheses beneath mean returns. The final two rows display the alpha of the long short portfolio where the long leg is the 5.5 portfolio and the short leg is the 1.1 portfolio.

between corner portfolios of this double sort cannot be explained by existing factor models. The double sort also suggests a "fix" for the value premium's decline. IDiffHML, based on the corner portfolios of the double sort, tracks existing value factors closely, but continues to perform well during the Dot-Com crash of the 2000s and the tech boom of the 2010s, periods when existing value factor suffered. An investor who purchased the IDiffHML portfolio in 1980 would have gained 2-3 times as much as one who purchased an equal amount of the existing value factors.

More broadly, this paper shows that the composition of a firm's assets in place and growth opportunities matters. In particular, the book-to-market ratio only summarizes the relative levels of assets in place and growth opportunities, not the compositions. As intangible capital and investment have increased in importance in the modern economy (Belo et al. (2021)), it is necessary to consider composition effects when formulating asset pricing theories and models.

Papers such as Eisfeldt and Papanikolaou (2013) have emphasized the connection between intangible capital and human capital. I leave incorporating the links between human capital, intangible investment and capital, and displacement risk to future research. This paper has also focused on first moments, the effects of IDiff on mean expected returns. Anecdotal evidence suggests intangible investments are subject to booms or busts, thus a thorough study of the higher moment effects on returns and cash flows of different types of investment is another area of future research.

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A Comparison of Performance Between Included and Excluded Components of IDiffHML

This section shows more results concerning the new value factor I propose (IDiffHML) and the set of firms excluded from the factor.

The factor portfolios are constructed as follows. At the end of each June, firms are placed into portfolios depending on breakpoints based on certain firm variables. The breakpoints are based on NYSE firms and are set at the 70th percentile and 30th percentile. A firm with a variable above the 70th percentile is in the High (H) portfolio, and a firm with a variable below the 30th percentile is in the Low (L) portfolio. In this way I form portfolios based on the book-to-market ratio, where book equity includes intangible capital and the intangible minus tangible investment rate divided by total assets.

Also, at the end of each June, firms are placed in size portfolios, Big (B) or Small (S), based on the market values. The cutoff depends on the median of NYSE firms. For each portfolio, value-weighting is done using the value of firms at the end of June. The portfolios are rebalanced every 12 months.

To be consistent with the Introduction, I use Inc. iHML in place of IDiffHML. The other factor is Exc. iHML. The factors are formed as follows. I use the following piece of notation. Let $\mathbb{E}^V[A/B/C]$ = Value-weighted mean of firms in size portfolio A, book-to-market portfolio B, and intangible minus tangible investment over total assets portfolio C. Then:

$$\text{Inc. iHML} = \left[\frac{1}{2}\mathbb{E}^V[S/H/H] + \frac{1}{2}\mathbb{E}^V[B/H/H]\right] - \left[\frac{1}{2}\mathbb{E}^V[S/L/L] + \frac{1}{2}\mathbb{E}^V[B/L/L]\right] \tag{54}$$

$$\text{Exc. iHML} = \left[\frac{1}{2}\mathbb{E}^V[S/H/L] + \frac{1}{2}\mathbb{E}^V[B/H/L]\right] - \left[\frac{1}{2}\mathbb{E}^V[S/L/H] + \frac{1}{2}\mathbb{E}^V[B/L/H]\right] \tag{55}$$

$$\text{iHML} = \left[\frac{1}{2}\mathbb{E}^V[S/H/NA] + \frac{1}{2}\mathbb{E}^V[B/H/NA]\right] - \left[\frac{1}{2}\mathbb{E}^V[S/L/NA] + \frac{1}{2}\mathbb{E}^V[B/L/NA]\right] \tag{56}$$

where in the final portfolio, NA means I do not sort on that variable.

Looking at Table 1, one can think of Inc. iHML as "bottom left minus top left firms" and Exc. iHML as "bottom right minus top right firms." iHML does not sort on the investment rates and only sorts on the book-to-market ratio, inclusive of intangibles in the numerator.

Figure 8 displays the cumulative return of Inc. iHML versus Exc. iHML. The former's cumulative return far outpaces the latter's. In fact, the latter has a negative cumulative return since 1980. This means that the investment risk "channel" is dominating the book-to-market channel. To see this, recall that Exc. iHML is still long high book-to-market firms and short low ones. This side of the sort, then, is long a positive price of risk shock. However, the second leg of the sort, on intangible minus tangible investment, is long a negative price of risk shock. This is because the long leg of Exc. iHML is the subset of high book-to-market firms that are also high tangible minus intangible firms. The short leg of the portfolio is the subset of low book-to-market firms that have high intangible minus tangible investment. Tangible investment is long a negative price of risk shock, and the reverse is true for intangible investment. Thus, the investment sort of Exc. iHML is long a negative price of risk shock. The negative cumulative return implies that this end of the sort is dominating the positive return of the book-to-market end.

Is the outperformance of Inc. iHML compared to Exc. iHML due to the value or growth portfolios? That is, it because the long leg of Inc. iHML has outperformed the long leg of Exc. iHML or because the short leg of Exc. iHML has outperformed the short leg of Inc. iHML? I calculate two long-short portfolios as follows:

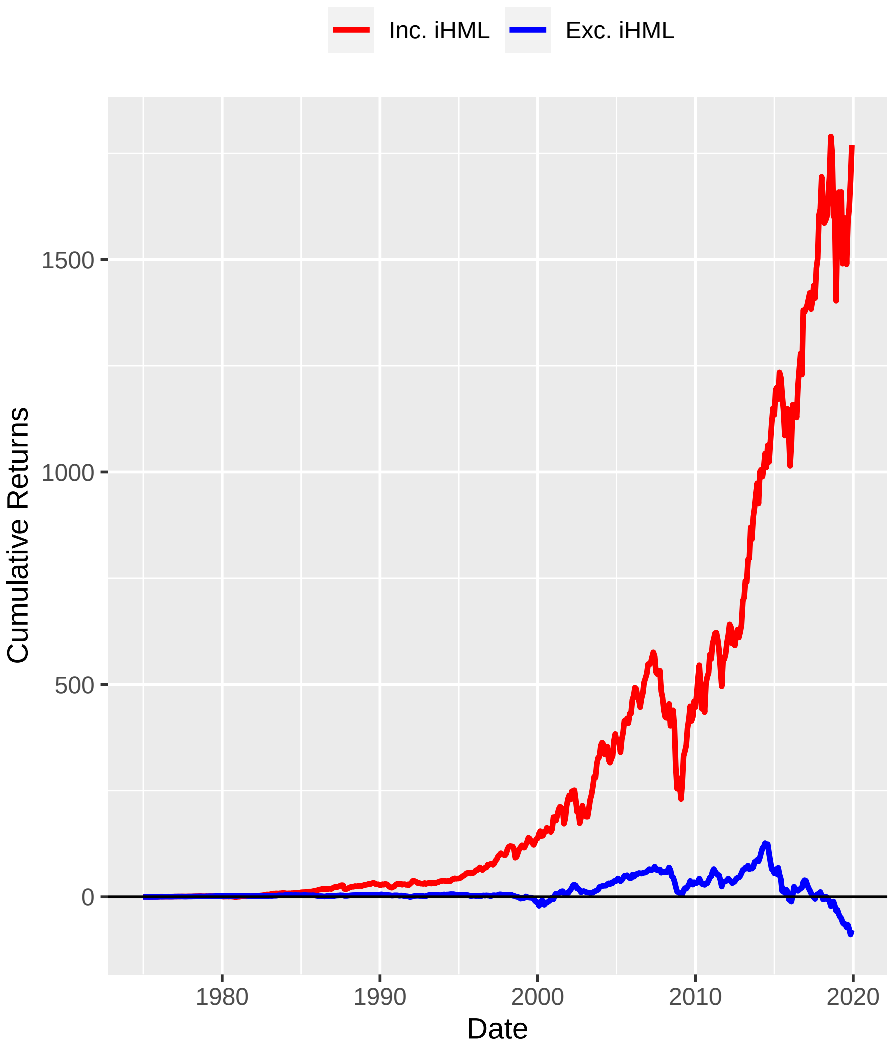
$$\text{Value Difference}_t = \left[\frac{1}{2}\mathbb{E}^V[S/H/H] + \frac{1}{2}\mathbb{E}^V[B/H/H]\right] - \left[\frac{1}{2}\mathbb{E}^V[S/H/L] + \frac{1}{2}\mathbb{E}^V[B/H/L]\right] \tag{57}$$

$$\text{Growth Difference}_t = \left[\frac{1}{2}\mathbb{E}^V[S/L/H] + \frac{1}{2}\mathbb{E}^V[B/L/H]\right] - \left[\frac{1}{2}\mathbb{E}^V[S/L/L] + \frac{1}{2}\mathbb{E}^V[B/L/L]\right]. \tag{58}$$

The Value Difference return is the difference between the Inc. iHML value portfolio and the Exc. iHML value portfolio. The Growth Difference return is the difference between the Exc. iHML growth portfolio and the Inc. iHML growth portfolio. Since the book-to-market portfolio is the same within the Growth and Value difference portfolios, the returns of these portfolios are driven by differences in their intangible minus tangible investment rates.

Figure 9 displays the 10-year moving average returns of these portfolios. The Model

Figure 8: Cumulative Returns: Inc. iHML versus Exc. iHML



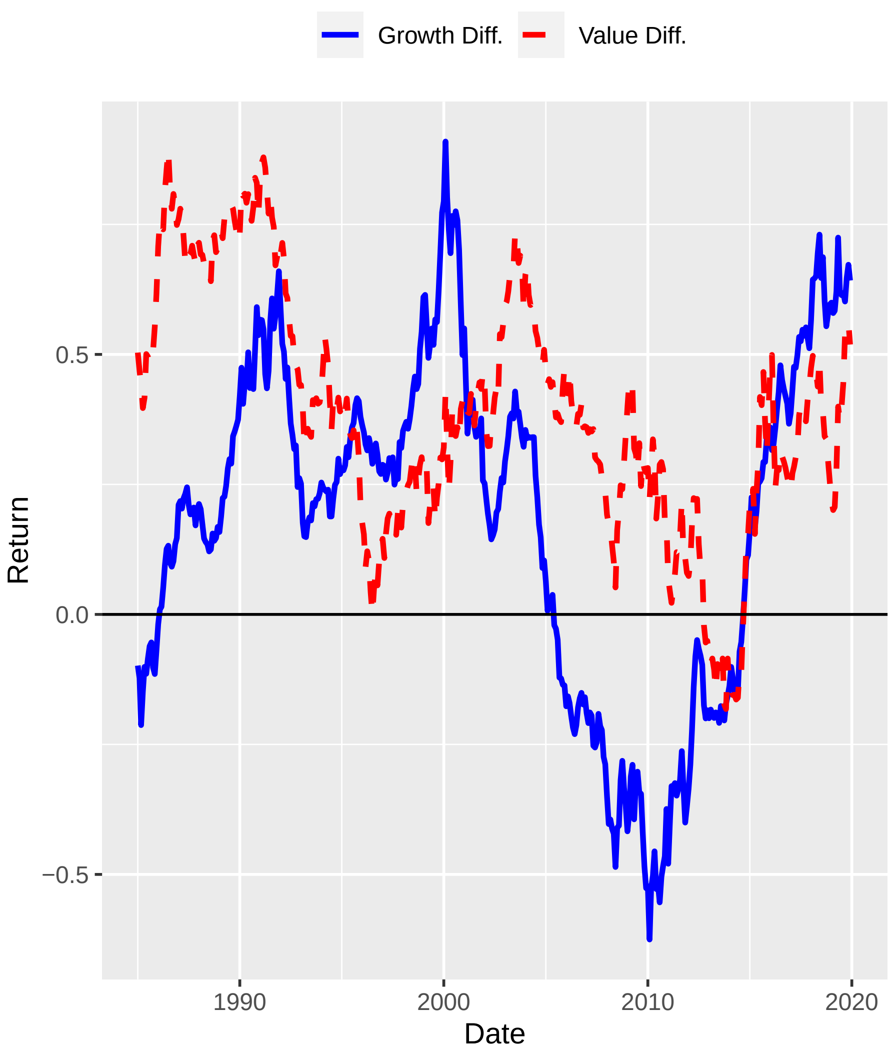
This figure displays the cumulative return of Inc. iHML versus Exc. iHML. See Appendix for details on construction.

section's theory implies that both of these portfolios should have positive average returns. Holding all other firm characteristics constant, these portfolios are short the negative price of risk displacement risk shock.[64] The Value Difference return is positive for almost the entire sample period. The Growth Difference return is negative in the period centered around the Financial Crisis. Incidentally, the period after the Dot-Com crash and before the crisis is precisely when the value premium had a comeback. Aside from that one period in the 2000s, the Growth Difference return is mostly positive as well. In sum, Figure 9 shows that both the value and growth legs of Exc. iHML contribute to its underperformance compared to Inc. iHML.

The discussion to this point has focused on mean returns. I now turn to CAPM alphas. One of the motivations for the original HML factor in Fama and French (1996) was the inability of the CAPM to explain the returns of portfolios sorted by their book-to-market ratios. The HML factor itself had large, positive, and significant alphas with respect to the CAPM. Table 19 displays alphas and betas with respect to the CAPM. The first two columns use the full-sample. Column (1) shows that Inc. iHML has a large and significant alpha of around 0.6% per month (7% per year). On the other hand, Exc. iHML does not have a significant alpha. THe point estimate is negative and close to zero, amounting to a monthly alpha of -0.019% a month (-0.228% annually). Columns (3) and (4) use only the pre-2000 sample to alleviate worries that the results might be driven by the post-2000 tech boom. The Inc. iHML alpha is even larger at 0.7% per month (8.4% per year). The point estimate for Exc. iHML alpha is positive but insignificant. This table shows that any outperformance of the value factor with respect to the CAPM was driven by the Inc. iHML portion of the factor. More broadly, it speaks to the stability of the price of risk of displacement risk shocks.

[64] Of course, forming portfolios does not precisely hold the other firm characteristics fixed, but it is an approximation.

Figure 9: Value and Growth Differences: Inc. iHML versus Exc. iHML



This figure displays the difference between the value and growth portfolio returns of Inc. iHML and Exc. iHML. The solid line is the difference between Exc. iHML growth and Inc. iHML growth. The dashed line displays the difference between the Inc. iHML value return and the Exc. iHML value return. The value and growth portfolios refer to the long and short legs of the value factors, respectively. See body of Appendix for details on their construction.

Table 19: CAPM Alphas

	Dependent variable:			
	Inc. iHML	Exc. iHML	Inc. iHML	Exc. iHML
	Full Sample		Pre-2000	
	(1)	(2)	(3)	(4)
Alpha	0.591***	−0.019	0.705***	0.047
	(0.147)	(0.217)	(0.203)	(0.231)
MKT	0.028	0.009	−0.033	−0.148***
	(0.033)	(0.049)	(0.045)	(0.051)
Observations	540	540	300	300
R^2	0.001	0.0001	0.002	0.027
Adjusted R^2	−0.0005	−0.002	−0.002	0.024
Residual Std. Error	3.361 (df = 538)	4.969 (df = 538)	3.440 (df = 298)	3.930 (df = 298)
F Statistic	0.737 (df = 1; 538)	0.038 (df = 1; 538)	0.552 (df = 1; 298)	8.329*** (df = 1; 298)
Note:				*p<0.1; **p<0.05; ***p<0.01

This table displays CAPM alphas and betas for the Inc. iHML and Exc. iHML portfolios. Columns (1) and (2) use the full-sample, and columns (3) and (4) use only the pre-2000 sample. See body of Appendix for details on the portfolio consturctions. Returns are monthly percentages.

Table 20: Industries Used for Within-Industry Sorts

SIC Code	Industry name
13	Oil and Gas Extraction
20	Food and Kindred Products
28	Chemicals and Allied Products
34	Fabricated Metal Products, except Machinery and Transportation Equipment
35	Industrial and Commercial Machinery and Computer Equipment
36	Electronic and other Electrical Equipment and Components, except Computer Equipment
38	Measuring, Analyzing, and Controlling Instruments; Photographic, Medical and Optical Goods; Watches and Clocks
50	Wholesale Trade - Durable Goods
73	Business Services
87	Engineering, Accounting, Research, Management, and Related Services

This table displays the industries used for the within-industry sorts. The left column shows the two digit SIC code of the industry, and the right column shows the name of the associated industry.

B Within Industry Sorts

In this Appendix, I show that the long-short portfolio proposed in the body of the paper works within industries as well. 50% of industries have positive and significant CAPM alphas for the within industry double-sort. None of them have significant, negative alphas. Since intangible investments and assets can take different forms in different industries, conducting the analysis within industries can alleviate concerns of unspecified heterogeneity.[65] The procedure I use in this Appendix is analogous to the sort described in the body of the paper, where the only change is that everything is done within a two-digit SIC industry.

Table 20 shows the industries used for the within-industry analysis. The table shows their SIC codes (two digit) and the full name of the industry. The industries cover the aggregate groups of Mining, Manufacturing, Wholesale Trade, and Services. I chose these industries because they have at least 100 firm-month observations each. This ensures that the portfolios have a sufficient number of firms in them.

Table 21 shows the CAPM alphas for the double-sort long-short portfolio. The first column gives the SIC code of the industry. The next three columns show the CAPM alpha, standard error of the alpha, and associated t-statistic, respectively. Most of the alphas have positive point estimates, and many are highly statistically significant. This shows that the

[65]This is emphasized by Eisfeldt et al. (2020) and Eisfeldt and Papanikolaou (2013). Cohen et al. (2003) show that the value premium is mostly a within-industry effect.

Table 21: Within Industry CAPM Alphas

SIC	Alpha	SE	tstat
13	0.03	0.50	0.06
20	1.16	0.34	3.40
28	0.89	0.36	2.47
34	0.68	0.38	1.80
35	-0.01	0.42	-0.03
36	1.41	0.36	3.95
38	1.00	0.44	2.27
50	1.30	0.52	2.50
73	0.59	0.40	1.50
87	1.02	0.99	1.03

This table displays the within-industry CAPM alphas for the double-sort described in the body of the paper. That sort is long high adjusted book-to-market firms and high intangible minus tangible investment firms. See body of paper for details. The first column gives the industry's two digit SIC code. The names of these industries are in Table 20. The second column shows the CAPM alpha for the double-sort. The third column shows the standard error of the alpha estimate, and the final column shows the associated t-statistic.

double-sort in the main body of the paper is not just an industry sort: The mechanism proposed in the paper holds within industry, as well.