Intangible Investment, Skilled Labor, and the Value Discount*

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Abstract

Composition matters. The composition of a firm's assets in place, and the composition of a firm's growth opportunities both affect risk and expected returns. In this paper, we study the effects of varying these compositions and show one must go beyond simple valuation ratios, namely, the book-to-market ratio, to understand firm risk. We develop a production-based asset pricing model which includes intangible and tangible assets and investment rates. The model shows that installed intangible capital and investment provide different information. The first tells us about current displacement risk, and the second tells us about future displacement risk. We take the model implications to the data and show that, indeed, high intangible investment firms are risky. The intangible investment effect is larger than the physical investment effect. Failing to account for the differential risk of intangible investment compared to physical investment can explain why recent attempts to "save" the value premium have not been wholly successful. We propose a new value factor that does not suffer a downturn in 2000 or since 2010. We rationalize the positive price of risk of intangible investment in a general equilibrium model with skilled labor and forward-looking labor demand. We validate the model's assumptions in the data using high-quality skilled labor demand data from Burning Glass Technologies. Intangible investment and skilled labor demand are intimately related, skilled labor demand is sensitive to firm exposure to displacement risk, and skilled wages reflect the marginal value of intangible capital.

1 Introduction

Intangible investment positively predicts stock returns, but physical investment negatively predicts stock returns. In conjunction, these two facts raise two questions. First, why is

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there a difference in the relation between these investments and stock returns? Second, how does this difference matter for existing theories of the firm and asset pricing? In this paper, we answer both questions

We begin with the second question by setting up a simple model of the firm, which we decompose into assets in place and the present value of growth opportunities. The assets in place are comprised of tangible (physical) assets and intangible assets. Examples of tangible assets are factories or machinery, and examples of intangible assets are patent portfolios or brand value. The present value of a firm's growth opportunities are related to its investment rates (tangible and intangible). The firm optimally chooses its investments subject to technology and productivity shocks and idiosyncratic risk. Intangible capital in our model represents a catch-all variable that captures the flow of output firms can generate that their physical capital stocks cannot explain. This could be called rents (Crouzet and Eberly (2021)) or firm-specific efficiencies (Lev and Radhakrishnan (2005)).

Our key insight here is that intangible capital is inherently "fragile."[1] We combine the insights from Kogan et al. (2020) and Eisfeldt and Papanikolaou (2013) and assume that intangible capital's value is destroyed by frontier technology shocks.[2][3] Intangible capital protects the firm's assets in place. If the firm's products are "displaced" by new technology, then the intangible capital built around them becomes useless. On the other hand, should the products remain in demand or un-displaced, the high intangible capital firms will generate more output per unit of physical capital. So, while the intangible capital can be destroyed by frontier technology shocks, the physical capital cannot be. A factory does not disappear, but a portfolio of patents on an obsolete technology essentially does.

For example, Amazon spends six times as much on selling, general, and administrative expenses and research and development as it does on capital expenditures. Walmart is one of Amazon's biggest competitors since the former is trying to challenge the latter's e-commerce supremacy. When the popular press and financial analysts discuss Amazon's advantages in this competition, they frequently point to the agglomeration effects of having all the sellers already on the Amazon platform. Amazon's Web Services host many sellers' businesses, adding another layer of switching costs.[4]. The investments Amazon has made protect Amazon's dominant position.[5] The other key aspect of these investments that we emphasize is that creating these assets is labor intensive. In particular, these assets require skilled labor (computer engineers, marketing experts) to develop new web services and improve the firm's brand. To use a phrase from the endogenous growth literature, intangible capital is exposed to "creative destruction" risk.[6]

Contrast this with Starbucks. Starbucks spends 10% more on capital expenditures than selling, general, and administrative expenses. They did not report any research and devel-

[1]We use intangible/tangible capital and intangible/tangible assets interchangeably.

[2]We use the phrases frontier technology and displacement technology interchangeably.

[3]Other papers looking at frontier technology risk or displacement risk include Papanikolaou (2011) and Kogan and Papanikolaou (2014).

[4]https://www.nasdaq.com/articles/better-buy%3A-amazon-vs.-walmart-2019-12-03

[5]Research and development (R&D) is a form of intangible investment and may not seem like a defensive action. A lot of R&D actually is defensive: Boldrin and Levine (2013).

[6]Patents, perhaps the most well-known intangible asset, are often to focus of the endogenous growth literature: Aghion et al. (2015).

opment in 2018. Starbucks is also expanding the number of locations it operates.[7]. The development of new stores requires capital expenditures. While demand for Starbucks coffee can wax and wane depending on the efforts of rivals or consumer tastes, new locations are not at risk of being "creatively destroyed."

We solve the firm-level model in closed-form using the model-implied book-to-market ratio (with intangible capital included in book equity). The model-implied expected return on the firm depends on four terms. First, there is the book-to-market ratio. Firms with more assets in place, holding fixed the fraction coming from intangibles (i.e., the composition of assets), have more exposure to disembodied technology shocks,[8] which carry a positive risk premium. The second term captures capital composition risk. For a fixed amount of assets in place, this term tells us how much more or less risky the firm becomes as a larger fraction of those assets in place are attributable to intangibles. The third term is the exposure to future displacement/frontier risk. This is the term associated with intangible investment. Intangible investment also increases the firm's exposure to displacement risk in the form of future intangible capital. The final term is the hedged displacement risk. Firms making more physical capital investments are growing and are in position to take advantage of frontier technology. Note that the model only has two sources of priced risk, but we have four exposure/beta terms. This is because no individual firm characteristic captures all of the firm's exposure to displacement/frontier technology risk. Put differently, if we knew all the parameters of the model, we could construct a single statistic combining multiple firm characteristics. In practice, one does not know the structural parameters of the firm, and researchers try to proxy for risk exposure/beta through individual firm characteristics. We use new insights on measuring intangible capital and investment (Peters and Taylor (2017)) to create proxies for the firm characteristics prescribed in the model.

We find that intangible investment strongly and positively predicts returns. Also, the fraction of installed capital attributable to intangible capital negatively predicts returns (i.e., intangible capital is less risky than physical). However, the magnitude of the investment effect swamps the capital stock composition effect. In annual panel regressions and Fama-MacBeth regressions, the coefficient corresponding to intangible investment risk is 5-6 times larger in absolute value than the coefficient corresponding to composition risk. The results are similar in monthly regressions.

This is important because, in the data, the fraction of assets in place attributable to intangible capital and the intangible investment rate are highly rank-correlated. This makes sense, as firms that make a lot of intangible investments also have a lot of intangible capital. However, we will rely on the investment effect overwhelming the composition effect when we form portfolios.

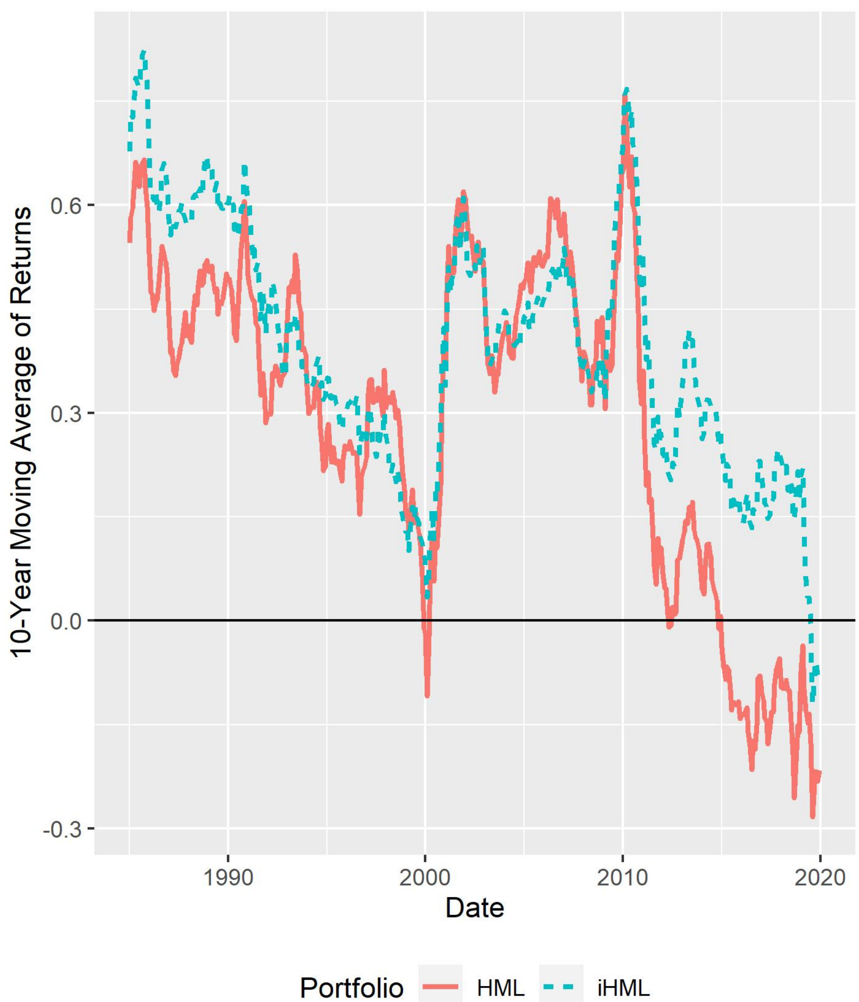
Understanding the differential impacts of different types of investment and capital on expected returns has important implications for the value premium, the idea that firms with high book-to-market ratios should have higher expected returns than firms with low book-to-market ratios. We focus on the decomposition between intangibles and physical assets because of increased awareness in the literature of the decline of the value premium and

[7] https://www.foxbusiness.com/lifestyle/starbucks-expansion-20k-stores-walk-thru-locations-ai

[8] This is the classic productivity shock study in macro models, i.e, total factor productivity (TFP).

the attempts to save the value premium, which depend on capitalizing intangible capital.[9] Figure (1) displays the 10-year moving average of Fama and French (1993)'s HML (high-minus-low) value factor and the "new" value factor, iHML, proposed by the literature based on intangible capital. 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.

Figure 1: The Value Discount



This figure displays the 10-year moving average return of HML and iHML. HML is formed by sorting firms based on their book-to-market ratios. See Fama and French (1993) for more details. iHML is created by sorting firms based on their book-to-market ratios with the book equity corrected to included capitalized intangible capital. See Arnott et al. (2021) for details.

The classic value factor (HML) is formed by sorting firms based on their book-equity-to-market ratio. The factor then goes long high book-to-market firms and short the low book-to-market firms. The new papers cited above have claimed that the book equity of

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

the firm is mismeasured, and econometricians must include installed intangible capital in the assets in place of the firm. This fix faces two key issues. First, it assumes that the risk-profile of intangible assets and physical assets are the same. Put differently, a firm with \$1 of book equity with \$0.50 of physical capital and \$0.50 of intangible capital is treated the same as a firm with \$0.1 of physical capital and \$0.9 of intangible capital. Second, and in a similar vein, this fix assumes that the growth opportunities (i.e., market value minus assets in place) are exposed to similar risk.[10] We show that failing to account for these issues has led to the disappearance of the value premium.

As of the end of our sample in 2019, growth firms and value firms do similar amounts of physical investment as a fraction of their assets in place. However, growth firms undertake much more intangible investment. This speaks to two important facts. First, not only do growth and value firms have different book-to-market ratios, they also have different compositions of growth opportunities. Simple financial ratios mask this. Second, high intangible investment "growth" firms do not conform to our anecdotal idea of a true growth firm. Using our examples above, Amazon is a growth firm under the definition implied by iHML.

To that end, we form double sorted portfolios as a parsimonious way of manufacturing a high expected return portfolio based on the firm characteristics from our firm-level model. We double sort on book-to-market corrected for intangible capital and the difference between the firm's intangible and tangible investment rates. We look at the alphas on these portfolios with respect to leading factor models designed to explain the value premium and other "anomalies." None of the models can explain the returns of the portfolios. In particular, alphas are monotonically increasing within book-to-market portfolios, and the HiLo portfolio (high book-to-market and high intangible investment minus physical minus the low counterparts) also has large and significant alphas. The annualized alphas range from 4 to 8%.

From these sorts, we propose a new value factor, which we call IDiffHML. This factor is a subset of the existing iHML factor. However, it makes two key changes to the long and short legs. First, it keeps only firms doing large amounts of intangible investment relative to physical investment in the long leg. That is, we make sure to focus on firms whose growth opportunities are in the form of future, fragile intangible capital. These are "uber"-value firms. They are betting big on staying entrenched. On the short end, we drop the high intangible investment firms. This stops firms like Amazon from being classified as growth firms.

Our factor tracks the existing HML and iHML factors quite closely during "normal times." During the two significant downturns of the HML/iHML, 2000 and over the last decade, IDiffHML continues to perform well. Therefore, forgetting to account for intangible investment can explain the sharp declines in HML and iHML, as both 2000 and the current period are characterized by large technological changes. These are precisely the periods where we expect entrenched firms investing in fragile intangibles to be at their riskiest.

The second part of the paper answers the question: '"Why does intangible investment positively predict returns?" We take the assumptions of the firm-level model to general equilibrium. Our central hypothesis is that physical investment requires the purchase of investment goods, but that intangible investment requires hiring skilled labor. That is,

[10] In particular, the growth opportunities must all have negative prices of risk.

labor hiring and investment are one and the same for intangible capital.

There are frictions in the labor market. In particular, firms must post vacancies for skilled workers who meet with firms via a matching function.[11] Wages are then set via Nash Bargaining. Since intangible capital is created by skilled labor, some of the intangible capital is "embodied" in the human capital. For example, a scientist doing research has accumulated knowledge that, while he works for the firm, is part of the firm's intangible capital. To take this fact to the model, we assume that skilled labor's outside option increases in the stock of intangible capital as in Sun and Xiaolan (2019). We assume that there are two types of agents in the economy: Skilled workers and shareholders. The skilled workers consume either the wage or the outside option. Shareholders consume dividends from the firm and, therefore, it is their marginal utility that prices the firm. Following Kogan et al. (2020), shareholders have Epstein-Zin (Epstein and Zin (1989), Epstein and Zin (1991)) preferences combined with "Keeping up with the Joneses" (Abel (1990)) preferences, which make agents care about their consumption relative to the aggregate. Both agents benefit from disembodied technology (read: TFP). However, the story is different following displacement shocks. Shareholders' consumption declines, and skilled labor's consumption increases, increasing shareholders' marginal utility increase.[12]

The mechanism is as follows. Following displacement shocks, the firm's intangible capital produces less output (e.g., some technology is less valuable than one thought, a patent is rendered obsolete, etc.). The marginal value of intangible capital also drops, which pushes skilled wages down. However, the skilled worker's outside option prevents wages from dropping as much as the marginal value of intangible capital: His services are still "in demand" and he can walk away or start/join a different firm (Eisfeldt and Papanikolaou (2013)). Shareholders are residual claimants after investment costs and wage payments, and since the skilled capital stock cannot be adjusted right away due to search frictions, shareholder dividends coming from intangibles decrease sharply: Flow output decreases more than costs.

Though the firm cannot adjust its skilled labor stock instantaneously, in the face of displacement shocks, both vacancies for skilled workers and intangible investment decrease as well. Combining this observation with the shareholders' increase in marginal utility, we see that intangible investment is pro-cyclical in the model: It increases in "good times" and decreases in "bad times." Intangible investment, therefore, is associated with higher expected returns. The model also replicates the existing counter-cyclicality of physical investment. Periods of high displacement shocks are periods when the costs of physical investment are lower and the benefits of adopting frontier technology are higher. Therefore, high physical investment is associated with lower expected returns

To test the key model assumptions about the links between skilled labor demand and intangible investment, we employ high-quality skilled labor data from Burning Glass Technologies. This firm collects data on online vacancy postings. They have up to 80% of all online postings, and, most importantly for us, they have an extensive data set of standardized skill measures. Each posting is assigned several "desired skills," so we can map jobs postings to skill level. From that, we can define the skilled labor demand of the firm. Our classifi-

[11] Diamond (1982), Mortensen and Pissarides (1994).

[12] This is not the only reason shareholder marginal utility increases. The forward-looking Epstein-Zin effect matters as well.

cation method of skills is subjective. We ask, "Which skills are related to idea generation?" Approximately 11% of total skills are classified as high skill by us.

We combine the Burning Glass Data with skill indexes from Belo et al. (2017) to create a time series of skilled labor demand stretching back to 1995.[13] We show that our general equilibrium model assumptions are verified. A one standard deviation increase in skilled labor demand is associated with a 0.05 standard deviation increase in intangible investment in the next period. The magnitude of this effect is in line with other investment-forecasting regressions.[14] The relationship between installed intangible capital and skilled labor which the literature[15] has emphasized, disappears once we control for investment.

We consider proxies for a firm's exposure to displacement/frontier risk and try to forecast the firm's demand for skilled labor. We use three different proxies. First, we create a long-short portfolio based on firms' intangible investment rates. We go long high intangible investment firms and short low intangible investment firms. We then compute rolling-window betas of firm stock returns on this portfolio. The idea here is that the portfolio is a tracking portfolio of the frontier shock. In fact, they should move in opposite directions: The portfolio should do well in periods in displacement shocks are small. The firm beta on this portfolio proxies for the firm's exposure to the underlying shock. We find that, controlling for other firm characteristics and fixed-effects, this "exposure times shock" does indeed predict firm demand for skilled labor.

Second, we use a model implied measure of frontier shocks. We run cross-sectional regressions of the firm's sales to intangible capital ratio on firm characteristics dictated by the model. As we explain, the ratio of two regression coefficients identifies the frontier technology level. Once again we find that the firms with more employed skilled labor post fewer vacancies for skilled workers in the year following a displacement/frontier shock.

Our final measure of displacement risk uses the patent data from Kogan et al. (2017). Their dataset provides economic values for patent filings by firm and year. We compare a firm's filed patent values within a year to its industry peers in the same year. The result is an industry level, as opposed to aggregate level, measure of displacement risk. Indeed, the more a firm's patent values lag its industry peers, the less skilled labor that firm demands in the future.

Our final exercise uses wages for high-skill workers. Using data from Occupational Employment Statistics (OES) we create an index of high skill versus low skill wages. We find that this index is negatively correlated with measures of our displacement shock. We then move from the aggregate to the firm-level. Burning Glass has posted wages for a subset of vacancies. For each firm we compute the average high and low skill wage. The general equilibrium model implies that wages depend on the marginal value of intangible capital. In an economy with many firms, this could be heterogenous. Thus, firms posting lower relative high skill wages compared to our aggregate index should have lower marginal values of intangible capital. Indeed, we find that these firms have less valuable patents the next year compared to their industry peers.

In summary, we make the following contributions. First, we show that intangible invest-

[13] The Burning Glass extends back to 2010.

[14] Kogan and Papanikolaou (2014)

[15] Lustig et al. (2011), Eisfeldt and Papanikolaou (2013), Atkeson and Kehoe (2005), Bresnahan et al. (2002), Caroli and Van Reenen (2001), Becker (1975)

ment strongly predicts returns. The economic magnitude of this effect is larger than the physical investment effect.[16] Second, intangible capital is less risky than physical capital. Third, accounting for intangible investment can improve the performance of value strategies and deliver a more realistic set of "value firms" and "growth firms." Fourth, we show skilled labor and intangible investment are intimately related and that skilled labor demand reacts strongly to predictors of future intangible investment risk, and skilled wages reflect the marginal value of intangible capital.

Our 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, we rely heavily on the data construction and cleaning procedures put forth in Peters and Taylor (2017) when building our 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 generally ignore intangible investment.

The relationship between intangible capital and skilled labor/human capital has been proposed often (Lustig et al. (2011), Eisfeldt and Papanikolaou (2013), Atkeson and Kehoe (2005), Bresnahan et al. (2002), Caroli and Van Reenen (2001), Becker (1975)). However, we show that the relationship is truly about investment and skilled labor, not the installed intangible capital stock.

Finally, our 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)), and in particular, is closely related to the subset of the literature that has studied production models to explain the value premium (Kogan and Papanikolaou (2013), Ai and Kiku (2013), Kogan et al. (2020), Papanikolaou (2011), Xing (2008)).

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 looks at aggregate trends and summary statistics. Section 5 looks at asset pricing results: Fama-MacBeth and panel regressions and portfolio sorts. Section 6 develops a general equilibrium model to rationalize the positive price of risk of intangible investment. Section 7 tests the general equilibrium model's implications in the data. Section 8 concludes.

[16] Liu and Nguyen (2020) and Gu (2016) study the asset pricing implications of intangible investment and R&D. They do not relate their findings to the value premium or contrast with other firm-characteristics. The former paper does not look at general equilibrium. The argument in the latter is consistent with our interpretation.

2 Firm-Level Model

In this section we develop a model of the firm in continuous-time.[17] The firm has both tangible (physical) and intangible capital. It also chooses its investment in each of these forms of capital. Physical capital is exposed disembodied productivity shocks. These are similar to the classic macro productivity like TFP. Intangible capital creates a wedge between the "average product and marginal product" of physical capital.[18] We use Coca-Cola as a recurring example. That firm, for a fixed amount factories, assembly lines, and soda bottles, can sell more soda than an equivalently sized firm because of Coca-Cola's brand capital and name recognition. Intangible capital is exposed to displacement/frontier technology shocks. We show that the firm's investment rates and capital stocks load on the two productivity shocks in different ways. Therefore, firm composition matters in determining expected returns. It is not sufficient to simply study the assets in place relative to market value.

The model is partial equilibrium, so we take stochastic discount factor (SDF) as exogenous. Our goal is to provide an expression for the expected return on a firm which depends on both the underlying risk-premia of the shocks and the characteristics of the firm, like the book-to-market (B/M) ratio and the intangible and physical investment rates. In general, the main results of this model will be referenced throughout the empirical sections that follow.

Our main proposition will show that the expected return can be written as:

$$\mathbb{E}_t\left[R_{ft}\right] - r_F = b_{ft} BM_{ft}$$

where BM_{ft} is the B/M ratio of the firm, r_F is the exogenous, constant short rate, and b_{ft} is a function of model parameters.

Note that b_{ft} is time-varying. That is, the "price of risk" associated with the B/M ratio is time-varying. We do not assume that the prices of risk in the SDF are time-varying: The variation is endogenous. This dynamic nature of the loading, b_{ft}, arises from the firm's investment decisions and capital composition. A fortiori, the risk-premium of the book-to-market is not necessarily positive. In fact, an underlying argument of this paper can be summarized succinctly as saying that b_{ft} has shrunk from a positive to a negative number over the last 20 years.

2.1 The Set-Up

The model is partial equilibrium and set in continuous time. Throughout, we assume an SDF, M_t, which obeys the following stochastic process:

$$\frac{\mathrm{d}M_t}{M_t} = -r_F \mathrm{d}t - \gamma_X \mathrm{d}B_t^X - \gamma_Z \mathrm{d}B_t^Z. \tag{1}$$

where the B_t^i are independent Brownian motions and $r_F > 0$ is the exogenous, constant short-rate. The γ_i are the risk premia for the Brownian motions. We discuss the signs of

[17] This is a debt and cash free model. These two ingredients change the investment choices of firms in ways unrelated to growth opportunities. See Bolton et al. (2011).

[18] This is the phrasing used by Crouzet and Eberly (2021).

these as they become relevant below.

We follow a certain strand of the production-based asset pricing literature in decomposing firm value. This literature has written the firm's value as the sum of assets in place (VAP) and the present value of growth opportunities (PVGO). This method maps the model into the empirical measures of B/M ratios we are interested in.[19]

The value of a firm, V, can be written as:

$$V = VAP + PVGO.$$

The VAP can be thought of as the accounting value of a firm. It does not take into account future investments the firm may make. Therefore, the simplest way to think of VAP is as the value of the firm following the investment policy "invest 0 forever." That is, we account for capital depreciation and the expected future productivity of the installed capital.

In light of the previous paragraph, we equate VAP with the firm's book equity (= book value in our model). The market value of the firm is V and it incorporates the present value of future cash flows created by new investments In terms of theory, this is the value function of the firm evaluated at the current state. Finally, our decomposition implies that:

$$PVGO = V - VAP.$$

As the name implies, PVGO is the part of the firm's value which is attributable to optimal future investments.[20] Therefore, the model equivalent of the B/M ratio is:

$$\frac{\text{Book Equity of Firm}}{\text{Market Value of firm}} \approx \frac{VAP}{VAP + PVGO} \tag{2}$$

The firm produces output (Y_{ft}) using intangible capital (O_{ft}) and physical capital (K_{ft}):

$$Y_{ft} = X_t K_{ft} + \frac{O_{ft}}{Z_{ft}}. \tag{3}$$

X_t represents a disembodied productivity that benefits all tangible capital equally. Z_{ft} represents a frontier technology or a displacement technology.[21] Firms that have invested and built up a large intangible capital stock have built a large defensive position. For example, when a new beverage is invented that displaces soda, Coca-Cola's large stock of brand capital becomes much less valuable. That is, when Z_{ft} **increases** the flow output from intangibles **decreases**. This additive form is in the spirit of Van Rens (2004) and Eisfeldt and Papanikolaou (2013). We will see that the functional form above vastly simplifies computation and allows for closed-form solutions.

[19]See Berk et al. (1999) for the canonical treatment of this breakdown.

[20]When the firm has tangible and intangible capital, some of the future investments capitalized in PVGO may be future rents, and therefore, different than what has traditionally been called growth opportunities. We retain the PVGO moniker since this is standard in the literature. Regardless, PVGO capitalizes future investments.

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

Both technologies are assumed to follow geometric Brownian motions:

$$\frac{\mathrm{d}X_t}{X_t} = \mu_X \mathrm{d}t + \sigma_X \mathrm{d}B_t^X$$
$$\frac{\mathrm{d}Z_{ft}}{Z_{ft}} = \mu_Z \mathrm{d}t + \sigma_Z \mathrm{d}B_t^Z + \sigma_{fZ} \mathrm{d}B_{ft}^Z$$

The parameters μ_i are the positive drifts, and the first Brownian motion for each process is the aggregate shock. Recall that both of these Brownian motions appeared in the SDF specification, equation (1). Thus, holding either type of capital stock increases the firm's exposure to two different priced risks. Finally, the Z process is exposed to idiosyncratic risk, as mentioned above. The second Brownian motion captures this. This Brownian does not appear in the SDF: It is not priced.

The idiosyncratic component captures luck and firm-specific organizational efficiencies. The fact that Facebook is the dominant social media firm stems partly from the "idiosyncratic" shock of having Mark Zuckerberg at the helm and at coming along at the "right place, right time."

If the priced risks have negative risk premia, then the more physical and/or intangible capital the firm has, the lower its expected return will be. The opposite is true if these risks carry positive risk premia. The risk premias' signs are summarized by the γ_is which appear in the SDF.

The general productivity shock, X_t, is expected to carry a positive risk premium ($\gamma_X > 0$). This is the basic shock in standard real business cycle models, consumption based asset pricing models, and other baseline models. We can think of this as a proxy for market risk. The intuition for the positive risk premium is simple: When X_t is larger, there is more output, leading to "good times" (i.e., a lower marginal utility of wealth).

A large asset pricing literature has studied the properties of Z_{ft} or related technologies. We take the view of Eisfeldt and Papanikolaou (2013) and Kogan et al. (2020) and think of Z_{ft} as a displacement technology or "frontier technology". These papers have shown that this technology carries a negative price of risk: $\gamma_Z < 0$.

The firm invests in both types of capital to regulate the optimal level of its capital stocks. We choose nearly symmetric investment functions for both types of capital. This allows us to focus on the effects of the risk-premia and not on specific functional forms.

For physical capital, the firm pays $X_t I_{ft}$ today. The assumption that the cost of physical investment is increasing in the physical capital productivity is consistent with general equilibrium, under certain assumptions (Papanikolaou (2011)). The evolution of K_{ft} follows:

$$\mathrm{d}K_{ft} = \left((Z_{ft} I_{ft})^{p_2} - \delta_K K_{ft}\right) \mathrm{d}t. \tag{4}$$

The positive parameter p_2 is a returns to scale parameter which is less than 1, and $0 < \delta_K < 1$ is the depreciation rate. The displacement technology, Z_{ft}, which appeared in the output of the firm, also appears here. As Kogan et al. (2020) show, firms that are growing their physical capital stocks benefit from shocks to the frontier technology. They are the "displacers" the technology refers to. Thus, in this model, Z_{ft} plays two roles: It decreases the value of defensive positions of existing firms by reducing the value of their installed intangible capital, and it makes physical investment more efficient: firm's get more "bang for the buck."

Intangible investment is S_{ft}, and the cost of intangible investment is $Z_{ft}^{-\alpha}$ for $\alpha < 1$. As we will see in the general equilibrium model later in the paper, this assumption is consistent with equilibrium. There we show that both the costs and benefits of intangible investment are decreasing in the frontier technology. However, on net, the benefits are more sensitive to Z_{ft}, so increases in Z_{ft} lead to decreases in S_{ft}. This will be the case when $\alpha < 1$.

The accumulation of intangible capital follows:

$$\mathrm{d}O_t = \left((S_{ft})^{p_1} - \delta_O O_{ft}\right)\mathrm{d}t \tag{5}$$

The parameters are analogous to their physical investment counterparts.

The objective function of the firm is:

$$V_{ft} = \sup_{S_{fs}, I_{fs}} \mathbb{E}_t \int_t^\infty \frac{M_s}{M_t}\left(Y_{fs} - X_s I_{fs} - Z_{fs}^{-\alpha} S_{fs}\right)\mathrm{d}s \tag{6}$$

subject to the capital accumulation equations and the laws of motion for the productivities. We can see the implications of constant returns here: The firm's intangible and physical capital investment decisions can be split up into two separate "value functions" and then added back together. That is, we can solve:

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

and

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

with the result that:

$$V_{ft} = V_{ft}^P + V_{ft}^I.$$

For intangible investment, the optimal investment rate is given by:

$$S_{ft} = \left(\frac{p_1}{r + \delta_O - \mu_U}\right)^{\frac{1}{1-p_1}} Z_{ft}^{\frac{-p_1 + p_1\alpha}{1-p_1}} = C_1 Z_{ft}^{\frac{-p_1 + p_1\alpha}{1-p_1}} \tag{7}$$

where C_1 is simply a constant. Since $p_1 < 1$ and $\alpha < 1$, the exponent on Z_{ft} is negative. For physical capital investment, we have analogously:

$$I_{ft} = \left(\frac{p_2}{r + \delta_K - \mu_X}\right)^{\frac{1}{1-p_2}} Z_{ft}^{\frac{p_2}{1-p_2}} = C_2 Z_{ft}^{\frac{p_2}{1-p_2}} \tag{8}$$

The equations also have a constant in front of them. This constant is a transformation of the Gordon Growth Formula's discount rate. Finally, we see, since the investments are functions of Z_{ft}, that idiosyncratic risk Z_{ft} will generate cross-sectional dispersion in investment and, hence, in capital stocks.

The value function is:

$$V_{ft} = X_t \left[\frac{K_{ft}}{r + \delta_K - \mu_X} + C_2 Z_{ft}^{\frac{p_2}{1-p_2}} \right] + \frac{Z_{ft}^{-1} O_{ft}}{r + \delta_O + \mu_Z} + C_1 Z_{ft}^{\frac{-p_1 + p1\alpha}{1-p_1}} \tag{9}$$

We see clearly the effects of the installed capital stocks and the effects of the "growth opportunities" embodied in the investment shocks. If $\alpha = 1$, then intangible investment is constant, and the final term collapses to the capitalized value of this constant policy. The first two terms of this expressions are the parts of firm value related to physical capital and investment. The second two components are the parts related to intangible investment capital. Note that if we assume the firm has no intangible capital or investment, the model and value function collapse to that of Kogan and Papanikolaou (2014), a canonical model.

Now we must compute the VAP of the firm. Recall that this is defined as the "accounting value" of the firm, or, the value of its installed capital stock. Since the turn of the 20th century, researchers and policy makers have been concerned with capitalizing intangibles on balance sheets to provide a more accurate picture of a firm's value (Blair and Wallman (2000)). In a similar vein, as we discussed in the Introduction, many papers have argued that the disappearance of the value premium can be attributed to the misclassification of intangibles. That is, by failing to include intangible capital in the firm's VAP or book value, the numerator in the B/M ratio is misspecified. This leads to an incorrect sorting based on the measured B/M ratio. These papers argue that once the B/M ratio is corrected, the value premium should be restored.

Given this extant literature, we work on the assumption that the modeler can measure the intangible capital of the firm and therefore, we include O in the measurement of the capital stock. The VAP of the firm is defined as:

$$VAP_{ft} = \mathbb{E}_t \int_t^\infty \frac{M_s}{M_t} \left(Z_{fs}^{-1} O_{fs} + X_s K_{fs} \right) \mathrm{d}s \tag{10}$$

subject to:

$$\mathrm{d}K_{ft} = -\delta_K K_{ft} \mathrm{d}t \tag{11}$$

$$\mathrm{d}O_{ft} = -\delta_O O_{ft} \mathrm{d}t \tag{12}$$

and the laws of motion of Z_{ft} and X_t.

That is, we calculate the value of the installed capital stock, assuming no further investments. Those investments, technically, lead to future capital stocks and therefore are not assets in place. We do assume that the future improvements in technologies, X_t and Z_{ft}, are taken into account

We can take a similar approach to the one we used to derive the value of the firm to derive the VAP. Once again, we can split the VAP into a part from physical capital and a part from intangible capital. We end up with familiar terms:

$$VAP_{ft} = \frac{X_t K_{ft}}{r - \mu_X + \delta_K} + \frac{Z_{ft}^{-1} O_{ft}}{r + \mu_Z + \delta_O} \tag{13}$$

These are simply Gordon Growth Formulas for the two installed capital stocks. The dividends are "productivity times capital stock" per period ("AK" technology) and the growth rate is the growth of the productivity net of depreciation. Note that there is no positive growth in the capital stocks because we exclude investment in this calculation.

Now, we can determine the PVGO using the identity: $PVGO = V - VAP$. Doing this yields:

$$PVGO_{ft} = C_2 X_t Z_{ft}^{\frac{p_2}{1-p_2}} + C_1 Z_{ft}^{\frac{-p_1+p_1\alpha}{1-p_1}} \tag{14}$$

Intuitively, the shocks which affect the productivity of investment alter the present value of growth opportunities. We can use the optimal investment rates to write this as:

$$PVGO_{ft} = X_t I_{ft} + S_{ft}. \tag{15}$$

The present value of growth opportunities is increasing in the investment amounts.

We are ready to calculate the expected return on the firm. We use the classic asset pricing formula:

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

Applying Ito's Lemma yields the result. Before presenting it, it will be useful to define some ratios.

First, define the B/M ratio of the firm as:

$$BM_{ft} = \frac{VAP_{ft}}{V_{ft}} \tag{16}$$

Since there is no debt in the model, the firm's book value is the same as the firm's book equity. From an accounting standpoint, the firm's book assets are the installed capital stocks. The value of these is simply the VAP. We have also assumed that the firm's value is the firm's market value. If the SDF is that of a marginal trader, then these two values should be the same.

There are three other useful ratios. These relate to the compositions of VAP and PVGO, respectively. These ratios are related to an overarching theme of this paper: With two types of capital and two types of investment, the B/M ratio is no longer sufficient for determining expected returns. Composition matters. Define:

$$g_{ft}^{I} = \frac{C_1 Z_{ft}^{\frac{-p_1+p_1\alpha}{1-p_1}}}{VAP_{ft}}$$

$$g_{ft}^{P} = \frac{X_t C_2 Z_{ft}^{\frac{p_2}{1-p_2}}}{VAP_{ft}}$$

and

$$\omega_{ft} = \frac{\frac{U_t O_{ft}}{r+\mu_Z+\delta_O}}{VAP_{ft}}$$

These are, in order, the value of PVGO attributable to intangible investments, the value of PVGO attributable to physical investments, and the fraction of the assets in place coming from intangible capital. We normalize all quantities by VAP because this will allow us to interpret these ratios as betas *in book-to-market units.*

Result 1 *The expected return on the firm under the no arbitrage condition:*

$$\mathbb{E}_t\left[\frac{dM_t}{M_t}\frac{dV_{ft}}{V_{ft}}\right] = 0 \tag{17}$$

is

$$\mathbb{E}_t\left[R_{f,t} - r_F\right] dt = b_{ft} BM_{ft} \tag{18}$$

where BM_{ft} is the B/M ratio, and:

$$b_{ft} = a_1 + a_2\omega_{ft} + a_3 g^I_{ft} + a_4 g^P_{ft}. \tag{19}$$

The $a_i, i = 1, 2, 3, 4$ are constants which depend on the prices of risk in the SDF:

$$a_1 = \sigma_X\gamma_X;\;\; a_2 = -\sigma_Z\gamma_Z - \sigma_X\gamma_X; a_3 = \frac{-p_1 + p_1\alpha}{1-p_1}\sigma_Z\gamma_Z;\;\; a_4 = \frac{p_2}{1-p_2}\sigma_Z\gamma_Z$$

The components of b_{ft} are betas in B/M units. They are percent changes in the value of the firm with respect to productivities divided by the B/M ratio.

We know from the existing literature that the signs on a_1 and a_3 should be positive, while the sign on a_4 should be negative. The empirical results in Eisfeldt and Papanikolaou (2013) imply that $a_2 < 0$, though this is not explicitly discussed in the paper. In our empirical results below, we confirm this. We explain the interpretations of each component in b_{ft} below.

Note that even though there are only two priced shocks, we have four different characteristics which provide information about a firm's exposure to these risks. For example, growing firms undertaking more physical investment have positive exposure to Z_{ft}. Firms undertaking more intangible investment have negative exposure to this technology. In this model, the two investment rates are perfectly negatively correlated.[22] In the data, we will see these variables are indeed negatively correlated.

The interpretations of the components of b_{ft} are as follows. The first term, a_1, captures the riskiness of disembodied general productivity. Firms with more assets in place, holding fixed the fraction coming from intangibles, have more exposure to this technology through K_{ft}. The second term, $\omega_{ft}a_2$, captures capital composition risk. For a a fixed amount of assets in place, this term tells us how much more or less risky the firm becomes as a larger fraction of those assets in place are attributable to intangibles. The third term, $g^I_{ft}a_3$, is the exposure to future displacement risk. This is the term associated with intangible investment. Firms doing more intangible investment will, by definition, have more installed intangible capital in the future. This installed capital generates extra output beyond what their physical capital can explain: It is a defensive position that builds a "moat" around firm's assets in

[22]This could easily be changed by making the idiosyncratic components of the Z_{ft} different for the different roles it plays. It is immaterial.

place.[23] However, this increased output is fragile: it is susceptible to displacement when Z_{ft} is large. The final term, $g^P_{ft} a_4$, is the hedged displacement risk. Firms doing more physical capital are growing and are in position to take advantage of frontier technology.

With the signs of the parameters in hand, we can consider which firm characteristics are associated with a value discount.

Result 2 *For a given B/M ratio, expected returns are increasing in intangible investment as a fraction of VAP, decreasing in the fraction of VAP coming from intangible capital, and decreasing in physical investment as a fraction of VAP.*

The main message of this paper is that composition matters. Composition of the assets in place is captured by the ratio of intangible assets to total assets in place. Composition of growth opportunities is captured by the amount of physical investment the firm is undertaking **and** the amount of intangible investment it is undertaking. This last element, inangible investment, has been ignored by the existing literature. We will devote a simple GE model to explain why we expect intangible investment to capture variation in future exposures to displacement/frontier shocks. Thus, even though the overarching message of this paper concerns all the firm characteristics mentioned, the novel asset pricing results come from the intangible investment rate of the firm.

In the empirical sections that follow, we will map firm characteristics and predictions presented above to the data.

3 Data

In this section, we describe our data construction. We use many different data sources. However, in this section we will discuss our Center for Research in Securities Prices (CRSP) and Compustat sample and the Burning Glass Technologies (BGT) data. It will be easier to discuss the other data sources as they come up later.

3.1 CRSP/Compustat Data

We use data from CRSP and Compustat for our main firm financial variables. 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 data. Our sample runs from January, 1950 through December, 2019. However, to remove the effects of initial normalizations, we use data from 1975 onward.

We 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 a number of checks which we also use. First, we make sure the industry and data formats are "standard."[24] Second, we use only valid links (from CRSP to Compustat).[25] Finally, we make sure the link is still active.[26]

[23]For example, this could be a firm building up barriers to entry.

[24]indfmt = INDL and datafmt = STD.

[25]linktype either equal to LU or LC.

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

We construct two variables from CRSP: Market capitalization (market cap.) and stock returns. For market cap. we simply compute shares outstanding times the stock price.[27] Returns are collected from CRSP and corrected for delisting bias using the method from Shumway (1997).

We follow Peters and Taylor (2017) and Belo et al. (2017) for much of our data construction. First, as in those two papers, if any of the following are missing, we 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)), we create a cleaned version of Selling, General, and Administrative, which we will call SGA. First, if xrd is larger than xsga and if xrd is less than cogs, we simply set SGA equal to xsga. Otherwise, we set it equal to xsga - cogs - rdip.

With these measures in hand, we 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. We use a depreciation rate of 0.15 following Peters and Taylor. That is, knowledge capital evolves according to:

$$K_t^K = 0.85 \times K_{t-1}^K + R\&D_t.$$

Organization capital is defined similarly, except instead accumulating R&D expenses, we accumulate $0.3 \times SGA$.[28] The depreciation rate here, again from Peters and Taylor (2017), is 0.2. Thus:

$$K_t^O = 0.8 \times K_{t-1}^O + 0.3SGA_t$$

Then, the intangible capital stock is simply the sum of these two capital stocks:[29]

$$K_t^I = K_t^K + K_t^O.$$

Define the total book assets of the firm as:

$$TA_t = K_t^I + Assets_t$$

That is, this is the sum of the intangible capital stock plus the total assets (Compustat code: AT) of the firm. The latter excludes internally generated intangibles, but includes purchased intangibles. By adding our measure of internally generated intangibles, we are able to get a better picture of the total asset of the firm. We will use this to normalize some of our control variables.

Our measure of intangible investment follows directly from the construction of the intangible capital stock above. We add R&D expenditures to 0.3×SGA. We normalize this by

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

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

[29] 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).)

the total assets of the firm:

$$IntInv_t = \frac{R\&D_t + 0.3 \times SGA_t}{TA_t}$$

The analogous definition for physical investment is:

$$PhyInv_t = \frac{CAPX_t}{TA_t}$$

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

The last two important variables we construct are the B/M ratio and, what we call ω_t. The B/M ratio is computed in the standard way (see the textbook by Bali et al. (2016)). We also create a measure of the B/M ratio which has been corrected for intangible capital. That is, we simply add K_t^I to the book equity of the firm, and then we take the ratio of this sum over the market value of the firm. We call this the iB/M ratio.[30] Finally, we will be interested in the composition of the total book equity (BE + Intangible Capital) of the firm. Define ω_{ft} to be the fraction of the total book equity attributable to the intangible capital stock. That is:

$$\omega_{ft} = \frac{K_{ft}^I}{K_{ft}^I + BE_{ft}}.$$

There are a number of other control variables which will appear in regressions. However, it will be simpler to discuss them as they come up.

When it comes to merging the annual Compustat data with the monthly CRSP data, we follow Fama and French (1993). That is, we assume all financial information about a firm in year t is public information by the end 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 held through the following June. Thus, whenever we discuss annual returns, unless stated otherwise, we are assuming a July-to-July year.

For industry classification, we use the SIC class for all years prior to 2002 and NAICS thereafter. We exclude Transportation, Finance, and Public firms. Our other filter is a size filter. Each June, we calculate the 20th percentile market cap of NYSE firms. We then drop firms below this size. This is the same cutoff used by Fama and French (2015).[31]

3.2 Burning Glass Technologies (BGT) Data

The firm Burning Glass Technologies (BGT), among other activities, collects data on job postings. It does this by using an electronic "spider" which walks over company web sites and job boards. This is a continual process, so the job posting information is updated close to real-time, or as fast as the spider can return to the site.

The data that is collected needs to be cleaned and standardized. One of the key products BGT sells are these series of cleaned data sets. We are interested in two types of these.

[30] Park (2019)

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

The first data set we use is the raw job posting data. The unit of observation here is a job posting. Consequently, firms can and do appear many times per unit of time. In order to match our financial data, we aggregate firm data to an annual frequency.[32] Each observation has a unique ID (BGTID), an associated firm, a job title, as well as a great deal of information on the job's location, required education, and posted wage. Note all of these variables are available for every posting. For example, around 5% of postings have wage information. However, the BGTID and firm are available for all posts. This data set contains both public and private firms, and we retain only the former. Similarly, we drop all jobs which are actually internships.

We use BGTIDs to link our first BGT data set to our second. This second data set is the skills data set. Each job posting is associated with a set of skills the prospective employer would like in a candidate.[33] Of course, it is hard to categorize so many distinct and disparate sources of data. This is where BGT's standardization comes in.

The BGT skill data are sorted in three lists, each more granular than the previous one. We use skills from the middle list called the Skill Cluster. For the least broad group, Skill Cluster Family, there are less than 30 possible levels. Some of these levels, like IT, include skills we would include as high skill (e.g., Artificial Intelligence) but others we would not (e.g., Advanced Microsoft Excel). The most granular level, Skill, could be used, but we find that every Skill under a Skill Cluster that we mark as High Skill would also be marked. Therefore, we think the marginal gain from going deeper is small.

The Skill Cluster level has hundreds of titles. Some examples include Big Data, Mathematics, Laboratory Research, and Data Wrangling. There are 663 Skill Cluster names, and we classify 73 of them as high skill.

Our classification method is subjective. We consider the question, "Which skills are used to develop new ideas and products?" There are many skills based on factors like required education, specificity, or on-the-job-training which are "high skill" in a more general sense. The health care industry provides a good example. Medical doctors are highly skilled by almost all measures, but they would not be considered high skill in our context. Even a specialty like neurosurgery does not contribute to innovation and creation of new products at, say, the level of the hospital network where the doctor is employed.

Whenever a job posting has any "high skill," we label it as a high skilled job. Otherwise, we label it as an unskilled job.

The BGT data extends from 2010-2018. The raw BGT data has 174,226,357 jobs. After matching to Compustat (i.e., public firms), we have 36,270,982 jobs. As stated in a footnote above, we drop jobs that cannot be matched to any skills. This leaves us with 36,106,143 jobs. In the Appendix, we provide more information on the fraction of matches, the aggregate skilled labor posting rate, and the correlation between posting and employment.

[32] We could also use a monthly frequency, but then the interpretation of when information is available to investors becomes difficult. For example, it may be that investors do not know a firm is hiring many new researchers the month they make these postings. We use an annual frequency and match data the same way as Compustat, by assuming information in year $t-1$ becomes known at the end of June of year t.

[33] 7% of postings have no match between the two data sets. We drop these.

3.3 Overview

After employing our filters, we are left with 1,667,087 firm-month observations across 19,307 different firms. There are 103,555 observations with non-missing BGT data. When we restrict the data to being between 2010-2018, we have 150,660 observations, meaning that for years where BGT is available, 68.7% of our observations have non-missing vacancy data, and 18% of all postings are high skill.

4 Summary Statistics and Stylized Facts

This section will show some trends in the firm characteristics we descried above. In particular, we will look at the trends within the "growth" and "value" portfolios which form the value factor. Our goal is to show considerable variation across portfolios. We will also discuss summary statistics by intangible investment portfolio sorts.

We begin with the total investment rate. We define this as the sum of intangible and physical capital investment divided by total assets.[34] We also split our data into the familiar value and growth portfolios which comprise Fama and French (1993)'s HML portfolio. We also create "iHML" portfolios.[35] These are constructed in exactly the same way as the HML portfolio, except instead of sorting on the B/M ratio, we sort on the iB/M ratio, which corrects for intangible capital in the book equity of the firm.

The top row of figure 2 displays the results. The averages are value weighted within portfolio. The left panel shows investment rates for the HML portfolios, and the right panel shows investment rates for the iHML portfolios. The immediate takeaway is that investment rates have been declining for both the value and growth portfolios. This phenomenon has been commented on before (Gutiérrez and Philippon (2016)). Second, as the production-based asset pricing literature predicts, growth firms have higher investment rates than value firms. However, this difference has almost completely disappeared since 2015.

The middle row of figure 2 displays the fraction of total book equity coming from intangible capital, which we call ω_{ft}. First look at the left panel. We see that growth firms, as defined by HML, have always had a larger fraction of their book equity coming from intangibles. This is partly by construction as the denominator, book equity, excludes intangibles. While the growth portfolio's fraction has leveled off since 2000, the value portfolio's fraction plummeted after 2002. This has caused the gap in intangible composition across the portfolios to be at its largest yet.

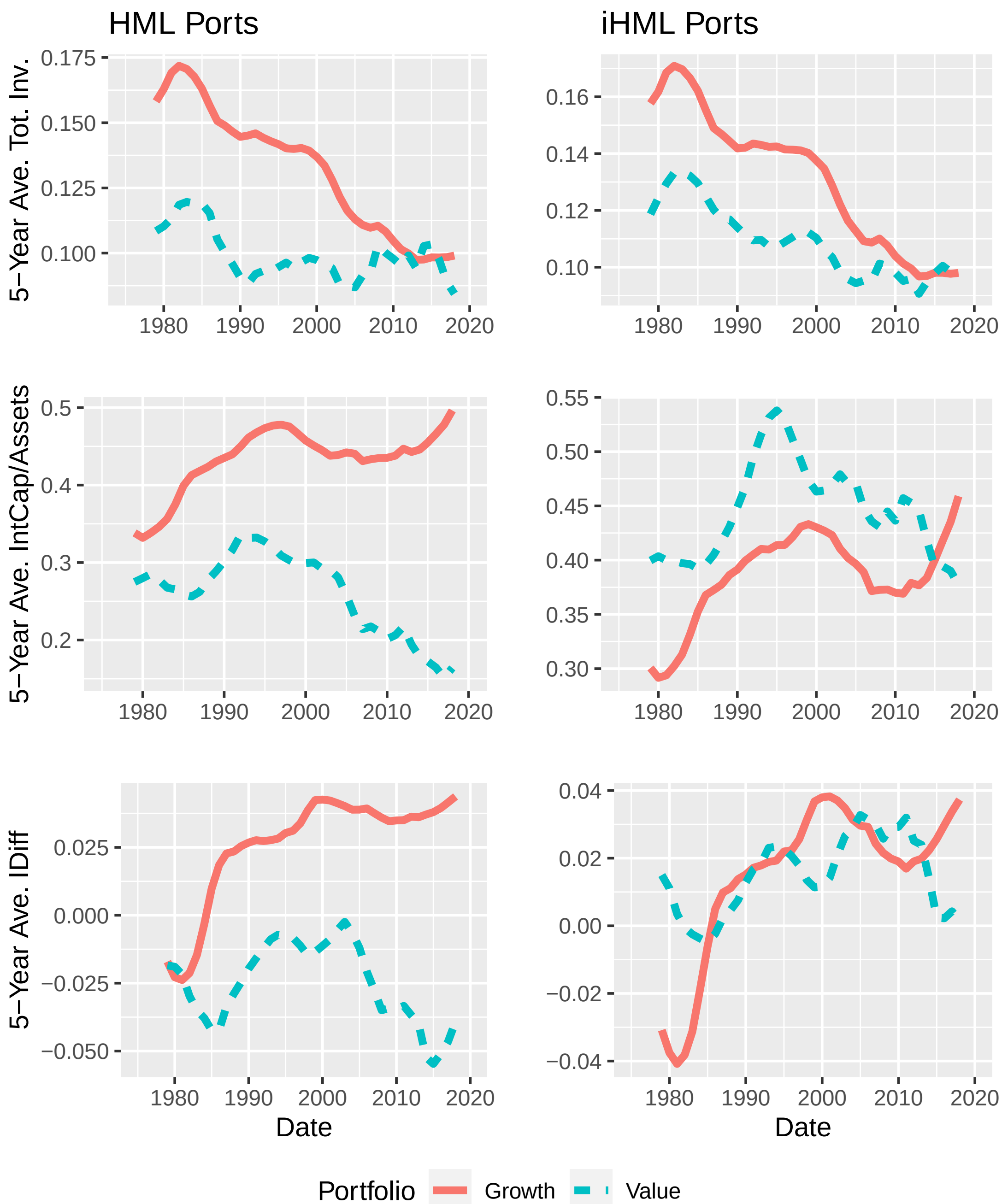
The right panel shows the same variables for the iHML portfolios. The iHML sort has successfully re-allocated high intangible capital firms but low physical capital firms to the value portfolio. Thus, ω_{ft} is not higher in the growth portfolio for much of the sample compared to value. However, value's level of ω_{ft} has been on a steady decline since the mid-1990s. After 2010, growth has experienced a surge in ω_{ft}. This has caused growth to have a larger average ω_{ft} than value by the end of the sample.

Recall that ω_{ft}, we assume (and show later), is associated with lower expected returns. Thus, the middle panel has the counterintuitive implication that the original HML value

[34]These variables were defined in the last section.

[35]This terminology is from Arnott et al. (2021).

Figure 2: Investment by Portfolio



This figure displays investment rates for different portfolios. The left column uses the value and growth portfolios as defined by the classic HML sort. The right column defines value and growth using the newer iHML sort. The top row displays the total investment rate by portfolio. The total investment rate is the sum of intangible and tangible investment divided by total assets. The middle row shows the fraction of total book equity coming from intangible capital. The final row displays the difference between the investment rates. All series are computed by taking value-weighted means and are 5-year moving averages of the underlying series.

premium should still exist and iHML should be experiencing a value discount. HML has underperformed iHML in the data. This counterintuitive explanation comes from the fact that we have ignored the composition of investment rates. That is, the first row showed the sum of the investment rates. However, given our assumption of different signs on the prices of risk of intangible and tangible investment, we should truly be interested in the difference between these rates.

The final panel of table 2 displays the variable IDiff = intangible investment - physical investment by portfolio. On the left, we see that the HML growth portfolio has had a larger IDiff than value for almost the entire sample. The sharp drop in IDiff in the value portfolio from 2002 onward has lead to the largest gap in IDiff between the two portfolios. The story is different in the right panel, which shows iHML portfolios. The value and growth portfolios have had IDiff means which were fairly close to each other for most of the sample. Since 2010, however, the value portfolio has experienced a steady decline while the growth portfolio has experienced an increase in IDiff.

When we compare the middle and bottom rows, we can see that it is not clear whether we should have a value premium or a value discount. That is, the middle row shows surging ω in the growth relative to value portfolios. This should increase the value spread. The bottom panel shows the same dynamics but with IDiff in place of ω. This should decrease the value spread. Thus, without more detail, it is hard to say which effect is dominating.

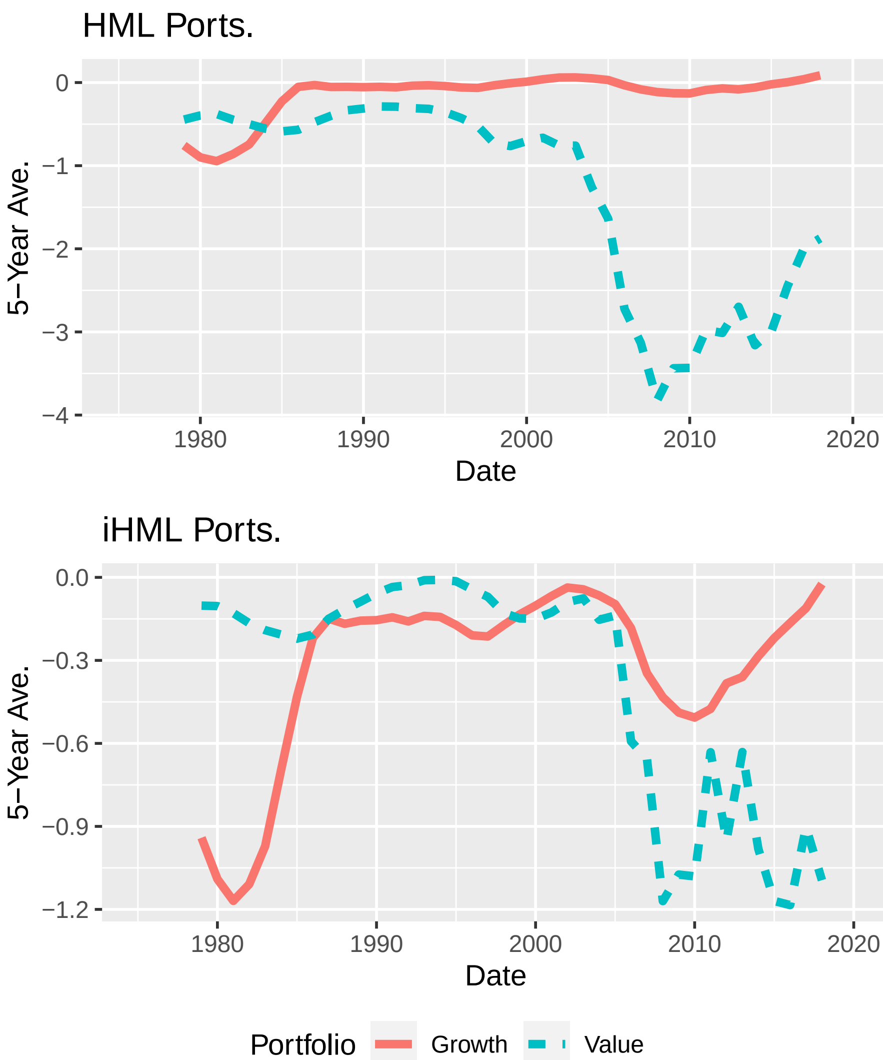
We will look at Fama-MacBeth (Fama and MacBeth (1973)) regressions and panel regressions, and we will be able to control for all characteristics simultaneously. Those results will lead to portfolio sorts which will indeed show by around 2010, the intangible investment effect starts to dominate, and the value premium turns to a discount. However, before we get to that, we present one more graph. This graph is a succinct way of capturing the effects of intangible investment, physical investment, and ω_{ft}, the capital composition. We plot $IDiff/\omega_{ft}$. This ratio will be large for firms doing more intangible investment, less physical investment, and a lower fraction of their assets in place attributable to intangible capital.

Figure 3 displays the value-weighted average of the ratio within growth and value portfolios for HML and iHML. First consider the top panel, which is for HML. The ratio is mostly constant for both growth and value till 2002. Not only that, but the levels are similar across the two portfolios. After 2002, the value portfolio average plummets, but the growth portfolio average stays roughly constant. Despite a rebound after 2008, the value portfolio's average is still far below the growth portfolio's.

The bottom panel shows a similar pattern with a few differences. First, the growth portfolio started with a low value of the ratio, but from 1985 to 2005, both the value and growth portfolios had similar, steady ratios. Both portfolios experienced a drop in the average around 2005. However, after this, they diverge. Since 2010, the gap between the two portfolios' averages has expanded.

It is worth noting that HML turns negative around 2002-2005, depending on how one computes the average. iHML turns negative around 2010. These dates also correspond to the divergences in the IDiff/ω ratio across value and growth. While this is not conclusive, it is suggestive and interesting evidence.

Figure 3: Investment and Capital Composition



This figure displays the ratio of intangible investment minus physical investment divded by the fraction of the firms assets in place attributable to intangibles (called ω_{ft}) by portfolio. IDiff is the difference between intangible and physical investment. ω_{ft} is the ratio of intangible capital to total book equity. The top panel displays the value-weighted mean within the growth and value portfolios, as defined by HML. The bottom panel shows the value-weighted average within growth and value as defined by the new iHML factor. The ratios are presented as 5-year moving averages.

4.1 Summary Statistics

This subsection provides summary statistics of portfolios based on sorting using intangible investment. These tables will reveal similar trends to the ones presented graphically.

Portfolios are formed using the standard methodology. Each year, we compute quintiles based on the sorting variables using NYSE breakpoints. Then, for each year-portfolio, we compute the cross-sectional median. Finally, the values in the tables are the time-series averages of these medians.

Table 1 displays summary statistics of firm characteristics by intangible investment portfolio. Physical investment is decreasing in the intangible investment portfolio. Note that this is not by construction. Sorting on intangible investment does not necessarily imply sorting on physical investment. It follows that IDiff is increasing in intangible investment portfolio. The B/M ratio is decreasing by portfolio. We saw this phenomenon in the graphs above. Note that the "corrected" iB/M ratio is not monotonic in portfolio. This is partly by construction as many high intangible firms were previously classified as growth firms. Neither market betas nor hiring are monotonic in intangible investment portfolio. The second to last column displays the ratio of skilled vacancies to total vacancies. This is our first piece of empirical evidence linking intangible investment firms to human capital. This ratio is increasing in intangible investment portfolio. The final column displays the ratio of intangible capital to total book equity. This is also increasing in intangible investment portfolio. This was also evident in the graphs above. In general, high intangible capital (as a fraction of assets in place) firms are high intangible investment firms. This is logical, as firms undertaking a lot intangible investment will also have a lot of intangible capital.

Table 1: Firm Characteristics by Intangible Investment Portfolio

Portfolio	Int. Inv.	Phy. Inv.	IDiff	B/M	iB/M	MKT Beta	Hiring	Skill Rate	Omega
1	0.01	0.07	-0.05	0.76	0.86	1.11	0.03	13.95	0.09
2	0.03	0.04	-0.01	0.76	1.05	1.08	0.02	18.54	0.23
3	0.06	0.03	0.02	0.70	1.12	1.10	0.02	28.18	0.34
4	0.08	0.03	0.05	0.63	1.13	1.12	0.03	32.97	0.42
5	0.12	0.03	0.09	0.48	1.05	1.26	0.05	45.16	0.53
HiLo	0.11	-0.04	0.14	-0.28	0.19	0.15	0.02	31.21	0.44
HiLo t-stat	95.40	-19.07	71.30	-15.58	4.26	3.17	8.89	25.31	89.48

This table displays average firm characteristics by intangible investment portfolio. The portfolios are based on NYSE cutoffs each July. See body of paper for details. The HiLo row is the difference between the 5 and 1 portfolio, and the row underneath is the t-stat on the sample mean of the HiLo difference being different from 0. The columns are, in order, intangible investment, physical investment, the difference between the two rates, the book-to-market ratio, the total book-to-market ratio that includes intangible capital in book equity, market beta, the hiring rate, the proportion of total vacancies posted which are high skill, and the ratio of intangible capital to total book equity. The variables are computed by first taking the cross-sectional median within each portfolio-year and then computing the time-series average of these medians.

Table 2 displays summary statistics of firm characteristics by IDiff. As expected, physical investment and intangible investment move in opposite directions as we move along the portfolios. The B/M ratio is decreasing by portfolio. On the other hand, the iB/M ratio is increasing by portfolio. Recall that this was true until the end the sample. As of 2019, high iB/M firms have lower IDiff on average. Neither market betas nor hiring are monotonic in intangible investment portfolio. Just like the intangible investment sorts, both the skilled posting rate and ω are increasing by portfolio.

Table 2: Firm Characteristics by Intangible IDiff Portfolio

Portfolio	IDiff	Int. Inv.	Phy. Inv.	B/M	iB/M	MKT Beta	Hiring	Skill Rate	Omega
1	-0.08	0.02	0.11	0.66	0.79	1.13	0.05	13.78	0.13
2	-0.01	0.04	0.05	0.73	1.01	1.10	0.03	21.29	0.24
3	0.02	0.05	0.03	0.69	1.09	1.08	0.03	25.73	0.34
4	0.04	0.07	0.03	0.65	1.15	1.10	0.03	28.91	0.41
5	0.09	0.11	0.02	0.55	1.19	1.25	0.04	46.34	0.53
HiLo	0.17	0.09	-0.10	-0.11	0.39	0.12	-0.01	32.55	0.39
HiLo t-stat	62.66	102.79	-35.99	-3.77	5.81	2.46	-3.60	33.30	81.34

This table displays average firm characteristics by IDiff portfolio. The portfolios are based on NYSE cutoffs each July. See body of paper for details. The HiLo row is the difference between the 5 and 1 portfolio, and the row underneath is the t-stat on the sample mean of the HiLo difference being different from 0. The columns are, in order, IDiff, intangible investment, physical investment, the book-to-market ratio, the total book-to-market ratio that includes intangible capital in book equity, market beta, the hiring rate, the proportion of total vacancies posted which are high skill, and the ratio of intangible capital to total book equity. The variables are computed by first taking the cross-sectional median within each portfolio-year and then computing the time-series average of these medians.

The firm-level model we presented earlier implies certain firm characteristics are important in determining exposure to priced risk. This section has shown trends across portfolios in these key firm characteristics. The evidence points to the **within portfolio** characteristics of growth and value changing over time in a such a way that makes a value discount more likely. Once again, we see our main point: Composition matters. Simply sorting on the B/M, or iB/M, ratio masks heterogeneity in characteristics that can determined pricing.

5 Asset Pricing Results

In the next section, we will use panel regressions, Fama-MacBeth regressions, and portfolio sorts to firmly establish the signs the parameters in the model of the firm. With these signs in hand, we will then create double-sorted portfolios. From these portfolios, we will be able to select a **subset** of the current iHML portfolio which does not follow the same downturn as iHML and HML.

5.1 Fama-MacBeth and Panel Regressions

Recall equations (18) and (19) in the model of the firm. We can map these equations to an empirical specification as:

$$R_{f,t+1} = \alpha_t + BM_{ft} \times (\beta_1 + \beta_2 IntInv_{ft} + \beta_3 PhyInv_{ft} + \beta_4 \omega_{ft}) + \varepsilon_{ft} \tag{20}$$

Here the dependent variable is the annual return on the firm, α_t is an aggregate time-varying parameter which captures the risk-free rate, and ε_{ft} is an error term. Note that the β_i's map to the a_i's, which tell us about the signs of the prices of risk in our SDF specification. We follow the standard timing procedure in empirical asset pricing. That is, the annual return is July of t to July of $t+1$. The right-hand side variables are based on the fiscal year which falls in $t-1$. This procedure allows investors time to learn the firm financial characteristics before forming portfolios.

We first estimate equation (20) in the Fama-MacBeth style. That is, each year (in July) we run cross-sectional regressions of returns on the right-hand side variables. The time-series mean of the estimated parameters are our estimates of the betas.[36] We then estimate Fama-MacBeth regressions with monthly returns instead of annual. That is, the right-hand side variables remain fixed for 12 months, but the dependent variable changes. This method mimics portfolio sorts, since these also hold fixed the sorting variables for a year before re-balancing.

Table 3 displays the results. In the first column, we use annual returns, and in the second we use monthly returns. For all specifications, we use the correct iB/M ratio, which accounts for intangibles. The investment rates and ω_{ft} are as defined in the Data section. We exclude the constant from the results, though it is estimated as well.

Table 3: Fama-MacBeth: Prices of Risk

	Returns	
	Annual	Monthly
	(1)	(2)
iB/M	1.795	0.130^{**}
	(1.184)	(0.064)
iB/M x Int. Inv.	31.277^{**}	2.188^{***}
	(15.693)	(0.841)
iB/M x Phy. Inv.	-10.535	-1.225^{*}
	(10.072)	(0.671)
iB/M x Omega	-4.653^{***}	-0.302^{***}
	(1.308)	(0.107)

This table displays Fama-MacBeth regressions results from estimating equation (20). The first column uses annual returns, and the second column uses monthly returns. iB/M is the total book equity to market ratio, intangibles investment is defined as R&D plus SGA divided by total assets, physical investment is defined as capital expenditures divided by total assets, and ω is the ratio of intangible capital to total book equity. The constant of the regression is estimated but excluded from the table.

The first takeaway from both columns is that the signs of the coefficients are as we expected.[37] The second key takeaway is that the magnitude of the coefficient on intangible investment interacted with the iB/M ratio is large and significant. Firms attempting to

[36] See Fama and MacBeth (1973) for details.

[37] One inconsistency with the model is the magnitude of the coefficient on ω. Taking the model literally, this is the difference between the risk premium of U shocks minus X shocks. The coefficient magnitude implies

increase their intangible capital stocks tend to have larger returns in the future. For example, a firm with $iB/M = 0.5$ undertaking intangible investment which is 10% of the value of its assets is expected to have a 1.55% higher return over the next year. This effect is larger than any other coefficient. This tells us that the accumulating "fragile" intangible capital is viewed as very risky by market participants. In particular, a firm doing equal amounts of intangible and physical investment is still negatively exposed to frontier technology shocks. Finally, the smallest magnitude coefficient belongs to the iB/M ratio uninteracted with any other coefficients. This shows, starkly, how important it is to take into account the composition of assets and growth opportunities.

Table 4: Panel Regressions

	Returns	
	Ann. Ret	
	(1)	(2)
iB/M	2.015***	5.419***
	(0.552)	(0.828)
iB/M x Int. Inv.	23.821***	29.449***
	(4.585)	(8.161)
iB/M x Phy. Inv.	−6.761*	−15.759***
	(3.755)	(4.473)
iB/M x Omega	−4.092***	−5.382***
	(0.915)	(1.434)
Lagged Ret.		−0.034
		(0.023)
Ind. Ret.		0.048**
		(0.024)
FE?	Date	Date + Firm

This table displays pael regressions results from estimating equation (20). The first column uses only year fixed effects, and the second column uses year and firm fixed effects. The second column also includes the firm's lagged return and lagged leave-one-out industry mean return. iB/M is the total book equity to market ratio, intangibles investment is defined as R&D plus SGA divided by total assets, physical investment is defined as capital expenditures divided by total assets, and ω is the ratio of intangible capital to total book equity. Standard errors are clustered at the firm-level.

that the risk premium of U would be just slightly negative, while the coefficient on intangible investment implies it is positive. This inconsistency can be partly chalked up to the AK technology used in the model.

Table 4 shows results from estimating equation (20) using panel data methods. In the first column uses only date fixed effects. The second column includes firm fixed effects and two control variables to account for possible persistent risk that is not captured by our specification: Lagged firm returns and leave-one-out industry returns.[38] The estimated coefficients are similar to the Fama-MacBeth regressions. In particular, controls for fixed effects and lagged returns indicate the results are not just picking up idiosyncratic firm risk.

5.2 Portfolio Sorts

Building on the results of last section, we form portfolios based on firm characteristics. To build the "ideal" portfolio based on the results of last section, we would want firms with high iB/M, low physical investment, high intangible investment, and low fraction of assets in place coming from intangibles. Unfortunately, this sort is not feasible. We would be left with a small number of firms per portfolio, and idiosyncratic risk would dominate. In particular, it is nearly impossible to form portfolios that have high intangible investment and low ω_{ft}, the fraction of assets attributable to intangibles. Naturally, firms doing more intangible investment tend to have more intangible capital, everything else equal.

We rely on the fact that in all specifications of model (20), the absolute value of the intangible investment coefficient is much larger than that of the ω_{ft} coefficient. Thus, our hope is that the intangible investment effect swamps the composition effect. Instead of sorting on each investment rate separately, we sort on IDiff, the firm level difference in investment rates (intangible minus physical). Thus, our final sort is a double sort with respect to iB/M and IDiff.

We take the intersections of the three portfolios for IDiff and iB/M. The methodology is the standard July-to-July holding period described earlier. We compare the ability of leading asset pricing models to explain the returns of these portfolios. None of the models have been created to explain the multi-characteristic composition we are after, so it would be surprising if any of the models succeeded.

The models we consider are the Capital Asset Pricing Model (CAPM, Sharpe (1964), Lintner (1965)), the Fama-French Three Factor Model (FF3, Fama and French (1993)), the FF3 model with the HML factor replaced by iHML, the Q-Factor model (Q-Model, Hou et al. (2015)), and the Organization Factor model (EP, Eisfeldt and Papanikolaou (2013)). We also consider the simple expected return on the portfolios, as well.

[38] This latter value is the value-weighted mean return, excluding the own firm return.

Table 5: Portfolio Sorts

iB/M	IDiff	$\overline{r}^e$	SE	t-stat	Alpha	SE	t-stat	Alpha	SE	t-stat
						CAPM			FF3	
1	1	0.54	0.23	2.36	-0.16	0.10	-1.60	-0.16	0.10	-1.68
1	2	0.69	0.21	3.31	0.04	0.09	0.43	0.12	0.08	1.49
1	3	0.83	0.23	3.68	0.15	0.11	1.29	0.28	0.08	3.45
2	1	0.68	0.24	2.80	0.00	0.17	0.01	-0.17	0.13	-1.30
2	2	0.86	0.20	4.27	0.22	0.10	2.13	0.16	0.10	1.61
2	3	0.97	0.21	4.66	0.30	0.12	2.41	0.29	0.12	2.48
3	1	0.83	0.31	2.66	0.05	0.22	0.23	-0.24	0.17	-1.38
3	2	0.87	0.28	3.14	0.14	0.17	0.82	-0.04	0.14	-0.29
3	3	1.19	0.25	4.72	0.43	0.16	2.75	0.35	0.11	3.08
HiLo	HiLo	0.65	0.16	4.06	0.60	0.17	3.53	0.51	0.14	3.55

iB/M	IDiff	Alpha	SE	t-stat	Alpha	SE	t-stat	Alpha	SE	t-stat
		FF3 w. iHML			Q-Model			EP (2013)		
1	1	-0.15	0.10	-1.58	-0.20	0.10	-2.07	-0.07	0.09	-0.77
1	2	0.11	0.08	1.35	0.14	0.11	1.27	0.00	0.08	0.00
1	3	0.28	0.08	3.30	0.37	0.11	3.31	0.08	0.10	0.82
2	1	-0.20	0.14	-1.35	-0.22	0.14	-1.61	0.18	0.12	1.43
2	2	0.14	0.10	1.34	0.12	0.13	0.93	0.23	0.11	2.14
2	3	0.24	0.11	2.11	0.28	0.14	2.05	0.26	0.15	1.80
3	1	-0.35	0.16	-2.15	0.12	0.20	0.61	0.17	0.19	0.89
3	2	-0.12	0.12	-1.00	0.00	0.18	0.02	0.16	0.18	0.88
3	3	0.26	0.10	2.54	0.49	0.14	3.50	0.38	0.17	2.24
HiLo	HiLo	0.41	0.13	3.07	0.69	0.16	4.22	0.44	0.17	2.63

This table displays alphas, Newey-West standard errors, and associated t-statistics for portfolios double-sorted on IDiff and iB/M ratio. The first two columns indicate the portfolio used. In the top panel, the first three columns (after the portfolio indicators) show the expected return on the portfolios, standard errors, and alphas. The next three show results with respect to the CAPM, and the final three show results with respect to the FF3 model. In the bottom panel, results are shown with respect to the FF3 model with iHML factor, the Q-Factor model, and the Eisfeldt and Papanikolaou (2013) model. All standard errors use 6 lags. The HiLo portfolio at the bottom of each panel is a portfolio long the (3,3) portfolio and short the (1,1) portfolio.

Table 5 displays the results from our sorts. The first two columns display the IDiff or iB/M portfolio to which the statistics on the right belong. The HiLo portfolio is a long-short portfolio with long end the (3,3) portfolio and short end the (1,1) portfolio. The first three columns in the top panel, after the portfolio indicators, show the mean return and associated standard error and t-statistic for each portfolio. Within each, iB/M portfolio, mean returns are monotonic, and the HiLo portfolio has a large and statistically significant mean return. Looking at the alphas for each model, we see the same pattern. The alphas are almost perfectly monotonic within iB/M portfolio.[39] The HiLo portfolios all have large, statistically significant alphas, as well. They are also economically significant. The annualized alphas range from 4.92% to 8.28% per year.

Based on these portfolio sorts, we attempt to “fix” iHML (and HML), by selecting subsets of the long and short legs of these portfolios. Essentially, we simply use the HiLo portfolio above as our new value factor.[40] Note that this is a strict subset of the existing iHML portfolio. Let us consider the types of firms that are included and excluded.

The long leg of what we call IDiffHML contains high iB/M firms, as expected, and firms doing more intangible investment relative to physical investment (high IDiff). Having low physical investment firms is in line with the classic definition of a value firm. To see why we want high intangible investment firms, recall the firm model from before. Intangible investment has negative exposure to reallocation or frontier shocks. Firms undertaking more intangible investment are building up a capital stock that is particularly sensitive to this replacement effect. If we think about value firms as the “incumbents” or entrenched firms, then we see that high intangible investment fits in with this definition. This is also why we wish to exclude high intangible investment firms from the short leg of the portfolio.

Figure 4 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. The fact that IDiffHML performs well during the two big downturns tells us that indeed missing intangible investment is a key driver. Both 2000 and the current period are classified by tech booms and busts. They are periods where the frontier technology is rapidly changing, 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.

[39] The only exceptions are in the Q-Model and EP (2013).

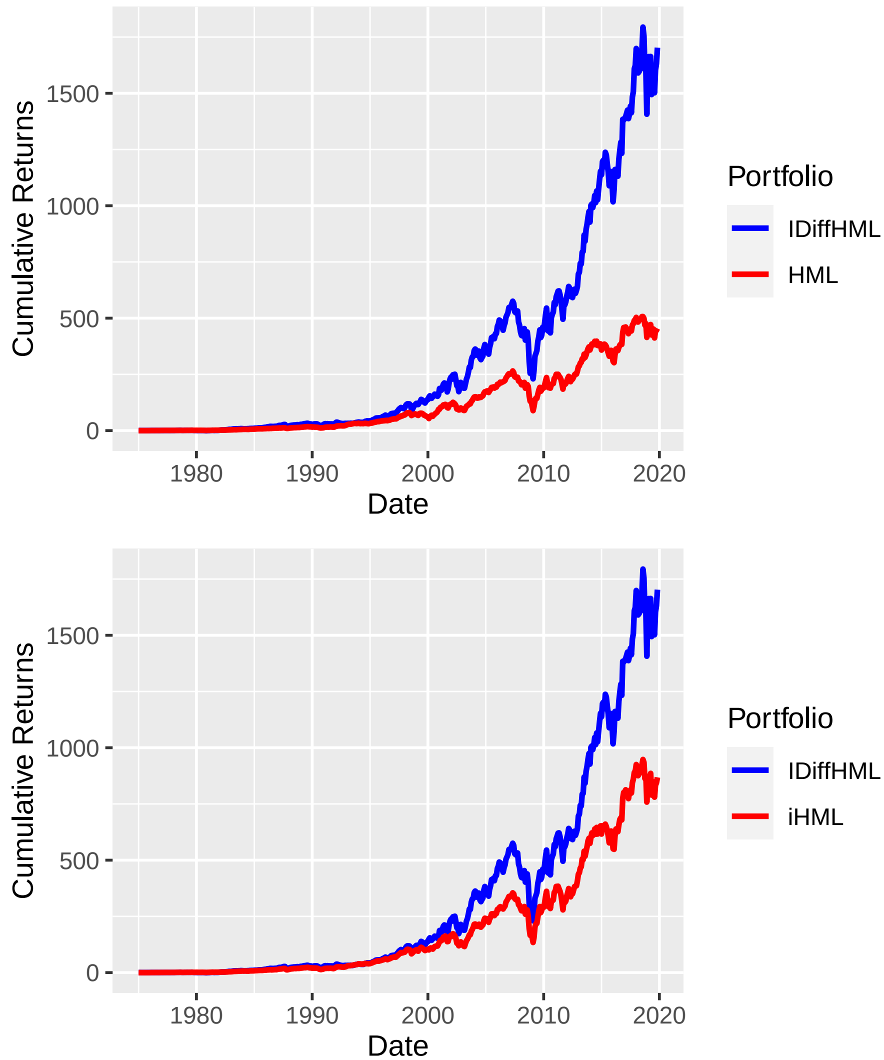
[40] The only difference is that we, like in the construction of HML, first form value-weighted averages within size, IDiff, and iB/M portfolios. Then we take equal weighted averages across size portfolios within each iB/M by IDiff portfolio.

Figure 4: 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.

Figure 5 shows the cumulative returns on IDiffHML versus HML (top panel) and iHML (bottom panel). The results here provide an even more striking view than the moving average graph. 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.

Figure 5: 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.

6 General Equilibrium Model

To interpret the positive association between intangible investment and expected returns, we introduce a general equilibrium model with two types of agents, intangible investment, and labor market frictions. The model also features physical investment and capital, and we emphasize the skilled labor intensity of intangible investment versus physical as a main difference. Our treatment of displacement/frontier risk is based on a combination of Eisfeldt and Papanikolaou (2013) and Kogan et al. (2020).

6.1 Firm

The firm produces output using tangible capital, K_t, and intangible capital, O_t:

$$Y_t = X_t \left[K_t^{\alpha} + \frac{O_t}{Z_t} \right] - f K_t$$

where α is a returns to scale parameter and f is a fixed cost of having physical capital (it scales with physical capital so that it does not become insignificant as the firm grows).[41] X_t is general productivity. Z_t is what we call frontier technology or displacement technology. It is similar to the technology studied in Kogan et al. (2020) and Eisfeldt and Papanikolaou (2013). As in the latter paper, firms with more intangible capital are at risk of being displaced. This can be due to the loss of key executives/talent or changes in technology that make the products firms sell obsolete or due to built up knowledge capital (e.g., patents) being made obsolete.

The firm accumulates physical capital by spending I_t today, which leads to $Z_t I_t^y$ capital tomorrow. That is, physical capital accumulation is:

$$K_t = (1 - \delta_K) K_{t-1} + Z_t I_t^y$$

where δ_K is depreciation. As in Kogan et al. (2020), Kogan and Papanikolaou (2014), and Papanikolaou (2011), frontier technology makes physical investment more efficient. "New idea" make investment goods cheaper and make it easier for firms to increase their physical capital stock. y is a returns to scale parameter. It is positive and less than one, so this represents investment adjustment costs.

Intangible capital is accumulate using skilled labor, S_t:

$$O_t = (1 - \delta_O) O_{t-1} + S_t^u$$

where δ_O is depreciation. u is also an adjustment cost parameter. Intangible investment is not more efficient after a frontier shock. We discuss this more at the end of the section.

There are frictions in the labor market. Therefore, the firm must post vacancies at a cost κ. They match with unemployed skilled workers via the Diamond-Mortensen-Pissarides (Diamond (1982), Mortensen and Pissarides (1994)) matching function:

$$M_t = \phi (1 - S_t)^{1-p} V_t^p$$

where $1 - S_t$ is the level of unemployed[42] and V_t is total vacancies posted. Skilled labor employed evolves as:

$$S_{t+1} = (1 - \delta_S) S_t + u(S_t, V_t) V_t$$

where $u(\cdot, \cdot)$ is the probability of matching a worker, which the firm takes as given, and δ_S is the exogenous quit rate of workers.

Intangible capital is partly embodied in the workers. Also, intangible capital is in general

[41]The constant returns to O_t are for simplicity and because intangible capital is hard to measure, and if O_t had returns to scale α', we could always redefine intangible capital to be $O_t' = O_t^{\alpha'}$.

[42]There is a measure 1 of workers.

harder to make excludable and rival: there are spill-overs.[43] The skilled worker's outside option is therefore increasing the in the level of intangible capital in the economy . That is, we assume the outside option of the worker is bO_t, where b is a positive number less than one capturing the fact that only part of the intangible capital stock is portable. This outside option is consistent with Sun and Xiaolan (2019).

Putting this together, the firm's dividends are:

$$D_t = X_t \left[K_t^{\alpha} + \frac{O_t}{Z_t} \right] - fK_t - I_t - \kappa V_t - w_t S_t$$

where w_t is the wage.

Because of labor market frictions, we need a wage setting procedure. We follow the standard method and assume wages are set by Nash bargaining. The Nash Bargaining wage is:

$$w_t = a\left(\lambda_{1,t} u S_t^{u-1} + \lambda_{2,t}\left(1 - \delta_S\right)\right) + (1-a) bO_t$$

where $\lambda_{i,t}$ are Lagrange multipliers representing the marginal value of intangible capital tomorrow and the marginal value of a skilled worker tomorrow. Finally, a is the skilled worker's bargaining power.

Finally, the productivity processes follow AR(1)s in logs:

$$\log\left(X_t\right) = \rho_X \log\left(X_{t-1}\right) + \sigma_X \varepsilon_{X,t}$$

$$\log\left(Z_t\right) = \rho_Z \log\left(Z_{t-1}\right) + \sigma_Z \varepsilon_{Z,t}.$$

6.2 Shareholders and Workers

There are two types of agents: Skilled labor and shareholders. We assume that skilled workers do not own shares.[44] The skilled workers consumer their wage or outside option:

$$C_{1,t} = w_t S_t + bO_t\left(1 - S_t\right)$$

Shareholders consume the dividends of the firm:

$$C_{2,t} = D_t$$

The shareholders have Epstein-Zin (Epstein and Zin (1989), Epstein and Zin (1991)) preferences mixed with Keeping up with the Joneses (Abel (1990)) habits:

$$U_t = \left[(1-\beta) \left(\frac{C_{2,t}}{C_t} \right)^{1-\chi} + \beta \mathcal{W}_t^{1-\chi} \right]^{\frac{1}{1-\chi}}$$

where

$$\mathcal{W}_t = \left[\mathbb{E}_t \left(U_{t+1}^{1-\gamma} \right) \right]^{\frac{1}{1-\gamma}}$$

[43] See Lev (2000) for a discussion of excludability and rivalry in intangibles.

[44] This is not necessary but amplifies the differences.

The variable C_t is aggregate consumption $C_{1,t} + C_{2,t}$ which the agent takes as given. This the habits part of the preferences. The agent not only cares about his consumption, he also cares about his relative consumption. Thus, as there are transfers between agents, the shareholder's marginal utility may increase or decrease. This utility set up is similar to that in Kogan et al. (2020).

6.3 Parameters

We set parameters based on a number of papers and sources. We estimate the new parameter introduced, u, the intangible investment efficiency of skilled labor.

From Kogan et al. (2020) we draw our preference parameters. We set $\beta = 0.95$, $\chi = 2.5$ and $\gamma = 55$. We draw our firm-level parameters from Belo et al. (2017): $f = 0.1$, $\delta_K = 0.12$, $\rho_X = \rho_Z = 0.95$, $\sigma_X = \sigma_Z = 0.35$, and $\delta_S = 0.36$. Our labor market matching parameters are from Kuehn et al. (2017): $p = 0.8$, $\kappa = 3.5$, and $p = 0.25$.[45] We set $b = 0.25$, which is the midpoint of values considered by Sun and Xiaolan (2019). Finally, we set $\delta_O = 0.15$, which is consistent with our empirical values of this parameter, which we discussed in the data section above.

We calculate u by estimating the intangible capital accumulation equation in the data. That is:

$$\text{Intangible Investment}_t = S_t^u.$$

In the next section, we describe how we calculate S_t using Burning Glass Technologies data and data from Belo et al. (2017). We derive u by estimating:

$$\log\left(\text{Intangible Investment}_{ft}\right) = u \log\left(S_{ft}\right) + e_{ft}$$

We try a number of specifications: With and without fixed-effects to capture unmodeled investment effects and using only high intangible investment firms. Our estimates range from 0.2-0.4. We set the parameter to 0.3, at the midpoint.

6.4 Results

This section shows impulse responses to frontier technology shocks. Figure 6, in the left panel, displays the consumption of skilled workers and shareholders. Both suffer consumption drops following displacement shocks. However, the drop experienced by shareholders is much larger. This is because the skilled workers' outside option partially shields them from the full drop. As we will see below, the skilled wage drops, but the residual claim accruing to shareholders drops by more. The second panel shows that the value of the firm also decreases following a shock to frontier technology. Thus, the frontier/displacement shock is decreases returns and consumption. This is consistent with Kogan et al. (2020).

Figure 7 explores the break-down of the dividend payments further. First, we see indeed that the wage drops following a frontier/displacement shock. Second, we see that intangible investment, the stock of skilled labor, declines following a frontier shock. This is because

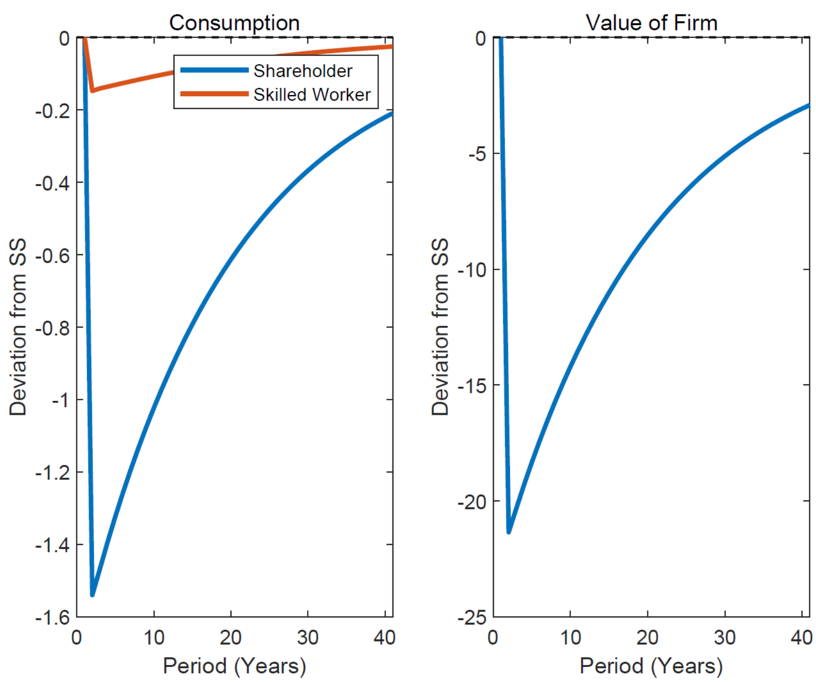
[45] Our value for p is larger than theirs to take into account the fact that skilled labor has more bargaining power than general labor.

the marginal product of intangible capital drops, making investment less attractive. In real-world terms, this corresponds to a firm losing a patent race or finding it's knowledge stock has become obsolete in the face of innovation. Investing further in that knowledge, while not without some gains, is much less attractive. Finally, we consider the dividends from intangible capital:

$$Div_t = \frac{O_t}{Z_t} - w_t S_t$$

As we have seen, all three terms in this expression decrease following the shock, so it is not immediately obvious that dividends should fall. The final IRF shows that this is the case. Essentially, wages and skilled labor do not fall enough to offset the decline in marginal product of intangible capital. Because there are labor market frictions the wage reflects the expected marginal product of intangible capital and the outside option of skilled labor. The former falls, but less than the marginal product.

Figure 6: Consumption and Firm Value

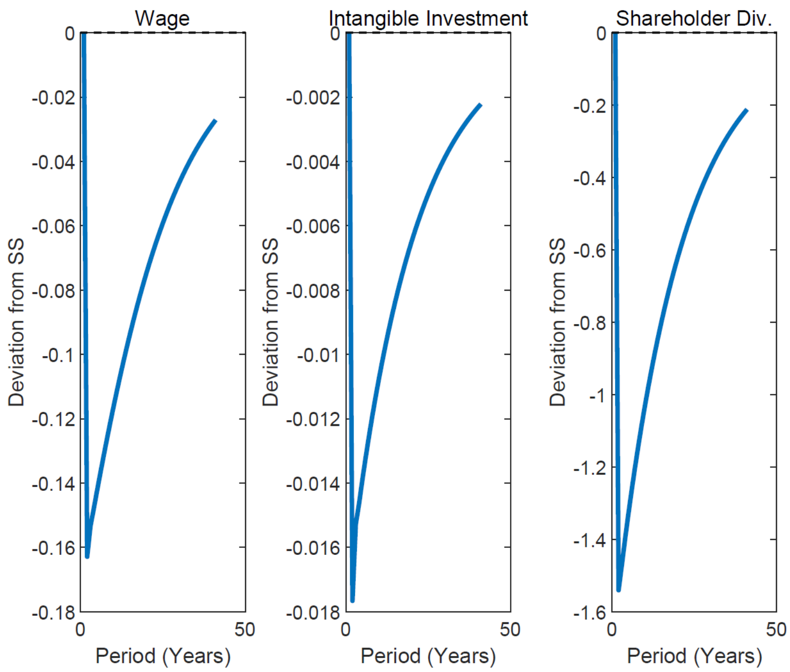


This figure displays impulse responses to a one standard deviation increase in $\varepsilon_{Z,t}$ for consumption and the value of the firm. The frequency is annual and the values are difference from steady state.

7 Taking the Model to the Data

In this section, we test the key assumptions behind the model. In particular, we focus on the relationship between skilled labor demand and intangible investment. First, we show that intangible investment and skilled labor hiring are closely related. Second, we show

Figure 7: Wages and Intangible Investment



This figure displays impulse responses to a one standard deviation increase in $\varepsilon_{Z,t}$ for skilled wages, intangible investment, and dividends coming from intangible capital. The frequency is annual and the values are difference from steady state.

that skilled labor is not related to the installed intangible capital stock, once investment is controlled for. This is in contrast to the assumptions in the extant literature. Third, we show that proxies for displacement risk predict lower demand for skilled labor.

7.1 R&D Versus Organization Capital

Before getting into the model's predictions, we discuss whether both R&D and organization capital should be treated similarly. In particular, we want to know whether both financial expenses are related to similar investment activities, at least along some dimensions.

To do this, we turn to BGT data. We show that R&D is associated with increased demand for research-oriented occupations, as is expected. Organization capital is associated with demand for marketing and logistics/firm-analytics occupations. However, there is a middle category of occupations, which we call computing-occupations, that are associated with both.

To organize these occupations, we use the BGT skill data and group jobs into three groups, research jobs, organization jobs, computing jobs, and the rest. Research jobs include postings for people with skills in the hard sciences, mathematics, and general scientific research. Organization jobs include postings for people with skills in logistics, business analytics, and marking. Finally, computing jobs include skills related to data science, cloud computing, and machine learning, among other things.

We estimate equations of the form:

$$Y_{f,t} = \alpha_j + \alpha_t + \beta_1 \log\left(Comp_{ft}\right) + \beta_2 \log\left(RD_{ft}\right) + \beta_3 \log\left(Org_{ft}\right) + \boldsymbol{X}_{ft}\boldsymbol{\beta} + \varepsilon_{ft}$$

Here Y_{ft} is either R&D expenditures, SGA expenditures, or CAPX, all in logs, and α_j and α_t are industry and date fixed-effects, respectively. The first three regressors are the log of computing postings, log of research postings, and log of the organization job postings. The controls in $\boldsymbol{X}_{ft}$ include the overall hiring rate (standardized to have 0 mean and unit standard deviation), the log book-to-market ratio, the log intangible capital to book equity ratio, logs of the excluded dependent variables, and the log of the employment to total assets ratio.

Table 6 displays the results. The main takeaway concerns the relationship between computing jobs and the two types of intangible investment. The association between research jobs and R&D and organization jobs and SGA is as expected. These two types of intangible investment are closely related to skilled labor demand when the skills are specific to the type of investment. The results concerning computing jobs is more interesting. They also speak to the changing nature of the economy, an underlying theme of this paper. The models and ideas we had about firm structure in the 1990s and early 2000s are no longer appropriate. Firms looking for workers with computing skills increase their R&D and their SGA. However, they decrease their CAPX. Thus, in some sense, computing jobs are the best delineator between tangible and intangible investments. As our economy becomes more intangible focused and digitized the line between R&D and organization capital is becoming more blurred. Thus, we think it is appropriate to consider both R&D and organization capital together as intangible capital.

Table 6: Skill Types and Intangible Investment

	Dependent variable:		
	R&D	SGA	CAPX
	(1)	(2)	(3)
Comp	0.443***	0.128***	−0.096***
	(0.049)	(0.031)	(0.034)
Res	0.505***	−0.188***	0.164***
	(0.040)	(0.025)	(0.024)
Org	−0.697***	0.216***	0.090**
	(0.048)	(0.029)	(0.035)
Hire	0.177***	−0.029	−0.103***
	(0.024)	(0.020)	(0.020)
R&D		0.002	0.105***
		(0.013)	(0.014)
CAPX	0.219***	0.610***	
	(0.028)	(0.019)	
SGA	0.005		0.668***
	(0.029)		(0.026)
IntCap/iBE	4.328***	1.940***	−3.260***
	(0.231)	(0.182)	(0.170)
iBM	−0.384***	0.099**	−0.103**
	(0.080)	(0.045)	(0.051)
Emp / TA	−26.686***	4.181**	−1.038
	(8.367)	(1.918)	(2.814)
Observations	11,546	11,546	11,546
R^2	0.585	0.639	0.665
Adjusted R^2	0.584	0.639	0.665
Residual Std. Error (df = 11521)	1.671	1.105	1.157
Note:			*p<0.1; **p<0.05; ***p<0.01

This table displays results from panel regressions relating various skills to different types of intangible investment R&D, SGA, and CAPX are described in the data section of the paper. The covariates are log computing job postings, log research job postings, log organization job postings, the standardized hiring rate, the three intangible investment rates, intangible capital over total book equity, the the iB/M ratio, and employment to total assets. We included time and industry fixed effects and cluster at the firm level.

7.2 Intangible Investment, Skilled Labor, and Frontier Technology Shocks

In this subsection, we study some of the GE model's implications in the data. First, building on the previous results, we create a skill measure for each firm, which combines Compustat data, data from Belo et al. (2017), and BGT data. We show that skilled labor demand and intangible investment are intimately related. We show that this effect is focused on investment, not capital stocks. That is, intangible capital is not related to skilled labor demand. Second, we use a number of proxies for the frontier/displacement shock to show that firms with more exposure to these shocks indeed do less intangible investment and suffer larger declines in profits. Third, we show that an aggregate index of high skilled to low skilled wages is positively correlated with an intangible investment sorted portfolio and negatively related with a physical investment sorted portfolio. It is negatively associated with proxies for displacement risk. Finally, we show that firms whose posted high skill wages are lower than average are less innovative than their industry peers. This corresponds to the marginal product of intangible capital in the model.

We estimate models of the kind:

$$Y_{ft} = \alpha_t + \alpha_j + \beta_1 Skill_{ft} + \beta_2 Hire_{st} + \boldsymbol{X}_{ft}\boldsymbol{\beta} + \varepsilon_{ft}$$

where Y_{ft} is either the next year's IDiff or contemporaneous intangible capital intensity of the firm (intangible capital over total capital). The variable $Skill_{ft}$ combines Burning Glass Data with the skill index from Belo et al. (2017). Their measure is industry specific whereas ours is firm specific. However, their measure extends to 1997.

We create the skill measure as follows. For years after 2010, we use BGT data by calculating the total skilled postings (computing, organization, and research jobs) by firm-year. For years before 2010, we use simply use the BGT measure. To make the measures comparable, we normalize by the annual sum across firms. That is:

$$\widetilde{Skill}_{ft} = \begin{cases} \frac{\text{Skilled Postings}_{ft}}{\sum_f \text{Skilled Postings}_{ft}}, & \text{if Year} \geq 2010 \\ \frac{\text{Belo Measure}_{jt}}{\sum_j \text{Belo Measure}_{jt}}, & \text{if Year} < 2010 \end{cases}$$

where j is industry. Finally, the measure of skill in the regressions is:

$$Skill_{ft} = \widetilde{Skill}_{ft} \times Hire_{ft}$$

where $Hire_{ft}$ is the hiring rate in Compustat.

The variables in $\boldsymbol{X}_{ft}$ included the contemporaneous IDiff, the iB/M ratio, the intangible intensity, and profits divided by total assets.[46] All variables are standardized to have unit standard deviation and zero mean.

Table 7 displays the results. In the first column we see that intangible investment and skilled labor demand are strongly related. Recall that in the GE model above, skilled labor vacancies predict next period intangible investment (in the form of employed skilled labor).

[46] Profits are defined as the variable OIBDP from Compustat.

Table 7: Skilled Labor Demand and Intangible Investment

	Dependent variable:	
	IDiff(t+1)	Int. Cap.
	(1)	(2)
Skill	0.039***	−0.010
	(0.007)	(0.011)
Hire	−0.004	−0.122***
	(0.006)	(0.011)
IDiff	0.789***	0.449***
	(0.021)	(0.034)
iBM	−0.0004	0.125***
	(0.003)	(0.022)
Int. Cap.	0.066***	
	(0.011)	
Prof. / Cap.	−0.098***	−0.041*
	(0.018)	(0.021)
	(0.009)	(0.007)
Observations	52,438	57,211
R^2	0.708	0.298
Adjusted R^2	0.708	0.297
Residual Std. Error	0.548 (df = 52394)	0.867 (df = 57168)
Note:		*p<0.1; **p<0.05; ***p<0.01

This table displays results from panel regressions relating intangible investment relative to physical investment in year $t+1$ to skilled labor demand in year t and intangible capital to total book equity to skilled labor demand. We include time and industry fixed effects and cluster at the firm level.

We see that a one-standard deviation increase in skilled postings is associated with a 0.04 standard deviation increase in IDiff next year. On the other hand, as the second column shows, skilled labor demand and installed intangible capital are essentially unrelated. This is in stark contrast the existing assumptions in the literature. The magnitude of the effect on IDiff is non-negligible. It is in line with investment prediction regression coefficients in Kogan and Papanikolaou (2014). Note that the general hiring rate is unrelated to intangible investment.

Now we want to see if proxies for intangible investment risk forecast demand for skilled labor. In the GE model, the productivity Z_t captured exogenous frontier productivity. In general, this productivity could contain idiosyncratic and industry-level components as well. We use three different measures of innovations in Z_t.

First, we use a stock based measure. We sort firms based on their intangible investment rates each July and hold value-weighted portfolios of the firms in the top tercile and short firms in the bottom tercile. Call this R_t^I.

Second, we use a measure directly related to the GE model. Recall that firm sales in the model are:

$$Sale_t = X_t \left[K_t^{\alpha} + \frac{O_t}{Z_t} \right]$$

In general, supposes that we have sales which are generated from:

$$Sale_t = X_t f(K_t) + \frac{X_t}{Z_t} g(O_t)$$

where f and g are differentiable function. We take second order Taylor expansions of each, which leads to the following estimating equation:

$$Sale_{ft} = \beta_{1t} K_{ft} + \beta_{2t} K_{ft}^2 + \beta_{3t} O_{ft} + \beta_{3t} O_{ft}^2 + u_{ft}$$

We estimate this equation cross-sectionally each period. Note that the ratio of β_{1t} to β_{3t} is proportional to Z_t. We use innovations in this ratio as the model-implied ΔZ_t.

Our final measure uses patent data from Kogan et al. (2017). Their paper computes the economic value of patents filed based on stock market reactions. We create a firm level measure by summing up the value of patent filings within each firm-year. We compute the log difference between a firm's mean industry innovation (divided by total assets) and the firm's own innovation (divided by total assets), where innovation is defined by total value of patents filed. That is:

$$IndPatEx_{ft} = \log\left(IndPatVal_{jt}\right) - \log\left(IndPatVal_{ft}\right)$$

As a measure of a firm's exposure to the displacement shock we use the firm's beta with respect to R_t^I.[47] For the patent measure, we do not use an exposure measure as it already takes into effect the firm's relative position.

We estimate models of the form:

$$Skill_{f,t+1} = \alpha_t + \alpha_j + \beta_1 \left(Ex_{ft} \times Shock_{ft}\right) + \boldsymbol{X}_{ft} \boldsymbol{\beta} + \varepsilon_{ft}$$

where Ex_{ft} is our measure of exposure and $Shock_{ft}$ is our shock measure. In the matrix $\boldsymbol{X}_{ft}$ we include the intangible capital to total capital ratio, the iB/M ratio, firm profits to total capital ratio, the contemporaneous and future hiring rate, and the contemporanous IDiff.

Table 8 displays the results. Overall, we see that our measures of displacement risk are associated with decreases in skilled labor demand in the future. When we use the firm's beta on R_t^I as an exposure measure and R_t^I as a shock measure, we find that a one standard

[47] These are computed on a 36 month rolling basis.

Table 8: Skilled Labor Demand and Displacement Risk

	Dependent variable:		
	Skill(t+1)		
	(1)	(2)	(3)
Int. Fac. Beta	0.040***	0.036***	
	(0.007)	(0.006)	
Int. Fac. Beta x R_t^I	0.015**		
	(0.006)		
Int. Fac. Beta x ΔZ_t		−0.035***	
		(0.012)	
IndPatEx			−0.091***
			(0.007)
Skill	0.227***	0.225***	0.245***
	(0.029)	(0.029)	(0.033)
Hire	−0.094***	−0.093***	−0.116***
	(0.018)	(0.018)	(0.025)
IDiff	0.055***	0.056***	0.054***
	(0.008)	(0.008)	(0.013)
iB/M	−0.073***	−0.073***	−0.084***
	(0.012)	(0.012)	(0.031)
Int. Cap.	−0.050***	−0.050***	−0.070***
	(0.006)	(0.006)	(0.009)
Profits	0.069***	0.070***	0.044***
	(0.008)	(0.008)	(0.011)
Observations	45,581	45,581	22,373
R^2	0.069	0.069	0.106
Adjusted R^2	0.068	0.068	0.104
Residual Std. Error	0.780 (df = 45538)	0.780 (df = 45538)	0.813 (df = 22331)
Note:			*p<0.1; **p<0.05; ***p<0.01

This table displays the results from estimating panel regressions of skilled labor demand in year $t+1$ on proxies for displacement risk and displacement risk exposure in year t. Our measures of displacement risk shocks are the return to a long-short portfolio sorted on intangible investment, R_t^I, a general equilibrium model-implied shock, ΔZ_t, and the leave-one-out industry patent values. Our measure of exposure to displacement risk is the firm's beta with respect to R_t^I. We include year and industry fixed-effects and cluster at the firm level.

deviation increase in displacement risk is associated with a 0.015 standard deviation increase in skilled labor demand in the next period. When we use ΔZ_t as our shock measure, we find a one standard deviation increase in ΔZ_t is associated with a 0.035 standard deviation decrease in skilled labor demand. Both of these values are for firms whose exposure is about one standard deviation above the mean exposure. Finally, when a firm's industry peers are about 1% more productive in terms of innovative value, that firm's skilled labor demand decreases by 0.091 standard deviations. Overall, we see that firm's post fewer skilled labor vacancies when they have large exposures to displacement/frontier shocks and these shocks hit them adversely.

Our final results concern high-skill wages and intangible investment. Note that, according to the GE model, intangible investment and high skill wages are positively correlated. When demand for skilled workers increases, perhaps due to their marginal products increasing, the Nash bargained wage also increases.

We begin by creating a wage index using Occupation and Employment Statistics (OES) data combined with the Belo et al. (2017) skill measure. For each industry, we measure the median annual wage from OES. From the the St. Louis Fed, we download the consumer price index (CPI) and create the following high-skill-index:

$$HighSIndex_t = \sum_{j=1}^{N} Skill_{jt} \times RealWage_{jt} \times \mathbf{1}[j \text{ is high skill industry}] \tag{21}$$

where we define an index as high skill if it falls above the year t median of the Belo et al. (2017) index. $Skill$ is our measure of skill used above, and the real wage is computed using the OES data and CPI. This index is simply a weighted average of real wages where the weights are based on skill. That is, we bias our index to high skill wages. We also strengthen this bias by using the median cut-off. We create a low skill version as follows:

$$LowSIndex_t = \sum_{j=1}^{N} Skill_{jt}^{-1} \times RealWage_{jt} \times \mathbf{1}[j \text{ is low skill industry}]$$

We use the the inverse of skill now because we want to bias towards to low skill wages. Finally, our Wage Index is:

$$WageIndex_t = \frac{HighSIndex_t}{LowSIndex_t}$$

Finally, we compute standardized innovations to this index.

First, we show that this wage index is negatively correlated with proxies for the displacement shock. We use a number of proxies. We consider $-R_t^I$, ΔZ_t, innovations to aggregate patent values (divided by total assets), and returns on a physical investment portfolio (R_t^P). Table 9 displays the results. We see that, indeed, the high skill wage index is negatively correlated with displacement risk, as predicted by the model.

In our final regressions, we look at two different relations. First, we estimate:

$$\frac{Profits_{ft}}{TotalAssets_{ft}} = \alpha_t + \alpha_j + \beta_1 \beta_{ft}^{R_t^I} + \beta_2 \left(\beta_{ft}^{R_t^I} \times WageIndex_t \right) + \boldsymbol{X}_{ft}\boldsymbol{\beta} + \varepsilon_{ft}$$

Table 9: Correlation between High Wage Index and Measures of Displacement Risk

Shock proxy:	$-R_t^I$	Δz_t	Innovations to Aggregate Patent values	R_t^P
Correlation w/ Wage Index:	-0.153	-0.144	-0.350	-0.1222

This table displays correlations between our High Skill Wage Index and proxies for displacement risk. See the body of the paper for details on how we construct the index. The proxies are, in order, the negative of the return to a long-short portfolio sorted on intangible investment, the model-implied displacement shock, innovations the aggregate value of patents filed to total assets, and returns to a long-short portfolio sorted on physical investment. The sample is 1997-2018.

where the remaining covariates are skilled labor demand, total hiring, the iB/M ratio, and the intangible capital intensity. The idea here is that firms undertaking more intangible investment should have a larger stock of skilled labor. That means, when the high skilled wage is higher, these firms should be spending more money out of earnings on labor costs.

Second, we estimate:

$$IndPatEx_{f,t+1} = \alpha_t + \alpha_j + \beta_1 \frac{SkilledWage_{ft}}{WageIndex_t} + \boldsymbol{X}_{ft}\boldsymbol{\beta} + \varepsilon_{ft}$$

The variable $SkilledWage_{ft}$ comes from Burning Glass. We use the subset of postings that have wage information (about 5%) and compute the relative high skill wage to low skill wage for the firm in a given year. The idea in this regressions is that firms with higher marginal products of intangible capital should have higher wages. This is implied by the Nash bargain wage. In the GE model, there is a representative firm, but in general, this marginal productivity could be heterogenous. We proxy for this unobserved marginal value by the realized relative patent "productivity," a measure of intangible assets.

Table 10 displays the results. The first column shows that firms that covary more with the intangible investment portfolio have lower profits when the relative wage of high skilled workers is large compared to low skilled workers. These firms are plowing back earnings into wage payments, which are the costs of intangible investment. The second column relates innovation to posted wages. Firms that post high-skill wages that are relatively higher than the aggregate high skill wage index are more innovative in the future. Note that this is not a causal claim. We are taking the Nash bargained wage to the data. In the model it depends on the marginal value of intangible capital, and the realized value of relative firm innovative productivity is our proxy for this marginal variable.

8 Conclusion

Intangible investment is associated with positive expected returns. We have studied the implications of this fact for asset pricing, and we have justified this positive association in general equilibrium.

We find that the effect of intangible investment on stock returns is larger than the effect of physical investment. We have also shown that intangible capital is less risky than physical capital. These are empirical facts that have important implications for the value premium

Table 10: Profits, SKilled Wages, and Innovation

	Dependent variable:	
	Profits(t+1)	Rel. Innovation.
	(1)	(2)
Int. Fac. Beta	-0.113^{***}	
	(0.012)	
Int. Fac. Beta x WageIndex	-0.032^{***}	
	(0.007)	
Skill Wage / WageIndex		0.128^{**}
		(0.054)
Skill	0.011	0.199
	(0.015)	(0.193)
Hire	0.049^{***}	-0.100
	(0.013)	(0.143)
IDiff	-0.520^{***}	0.253^{***}
	(0.037)	(0.046)
iB/M	-0.106^{***}	-0.405^{***}
	(0.016)	(0.068)
Int. Cap.	0.023	-0.014
	(0.019)	(0.028)
Observations	33,930	3,027
R^2	0.332	0.160
Adjusted R^2	0.331	0.155
Residual Std. Error	0.708 (df = 33896)	0.631 (df = 3008)
Note:		*p<0.1; **p<0.05; ***p<0.01

This table displays the results from estimating panel regressions of profits in year $t+1$ (first column) and relative patent values in year $t+1$ (second column) on aggregate and firm-specific high-skill wages. The wage index is described in the body of the paper. The skilled wage at the firm level is based on BGT high-skill job postings that have wage data. The relative patent values are measured as the firm-level patent value compared to the industry average patent value.

and the decline of the HML portfolio. Failing to account for intangible investment can explain why the HML (and iHML) portfolios underperformed in the late 1990s and since 2010. A new value factor, IDiffHML, does not suffer this decline. It is a proper subset of the iHML. For example, within the subset of high book-to-market firms (properly account for installed intangible capital), we keep the firms that do relatively more intangible investment versus physical investment. We do the opposite for the short leg of the factor.

In the second part of the paper, we show why intangible investment is associated with positive expected returns. We rely on the connection between skilled labor and intangible investment. The model has high skilled workers and shareholders. Due to labor market frictions, the firm must post vacancies for skilled labor. Because intangible investment is at least partly portable and embodied in human capital, skilled labor's outside option is increasing in the stock of intangible capital in the economy. Intangible capital is exposed to displacement risk: it is fragile. Following a displacement shock, some of the firm's intangible capital is rendered useless, and the rent sharing between shareholder and skilled labor moves in favor of the skilled labor. Labor market frictions and their outside option allow them to extract more rents from the firm. Because shareholders care about their relative consumption compared to the aggregate, this adverse sharing shift makes shareholders' marginal utility increase, and leads to the firm demanding less skilled labor.

We validated the models assumptions using high quality skilled labor demand data from Burning Glass Technologies. We mapped firm-level demand for high skilled workers to their intangible investment rates and showed the relation is, indeed, between investment and skilled labor, not the installed intangible capital stock. The model mechanism is based on displacement/frontier risk affecting high intangibles firms more strongly than other firms. We use three different measures of displacement shocks and find that skilled labor demand in the next period drops for firms with large exposures to these shocks when the firm is highly exposed. We ended by relating the posted skilled wage to the marginal product of intangible capital, as prescribed by the Nash bargained wage in the general equilibrium model. Indeed, firms posting high skill wages which are higher than the aggregate high skilled wage index have more valuable innovations in the future.

This paper opens the door for more studies comparing and contrasting intangible investment and physical investment. For example, we have focused on first moments of returns, but anecdotally, intangible investment is associated with high-risk, high-reward bets, especially relative to physical investment. The exploration of intangible investment and high moment risk is an interesting next step.[48]

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