Process Intangibles and Agency Conflicts*

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Abstract

Intangible capital can be used to create new goods and services (product intangibles) or to improve the efficiency of the firm (process intangibles). We report and study a new empirical fact: Executive and skilled labor pay is increasing in firm process intensity (the fraction of intangibles corresponding to process intangibles). We rationalize this fact in a dynamic principal-agent model, with the optimal contract uncovering process intensity's direct and indirect effect on compensation. The direct effect is a level effect: Higher process intensity increases the returns to shirking. The indirect effect is a slope effect: Higher complementarity between process intangibles and physical capital investment increases the agent's hold-up power over the firm for any level of process intensity. We verify these effects in the data. Importantly, we show that these effects are present in executive compensation and in the wages of highly skilled innovative employees, which we can measure using proprietary granular vacancy posting data from a labor-market data firm. In our baseline specification, a one standard deviation increase in process intensity is associated with an 8% increase in executive pay and a 3% increase in skilled labor wages relative to industry peers.

Keywords: Process Intangibles, Intangible capital, Dynamic contracting, Compensation.

JEL Classification: D21, E22, G31, G32, L22, O31, O34.

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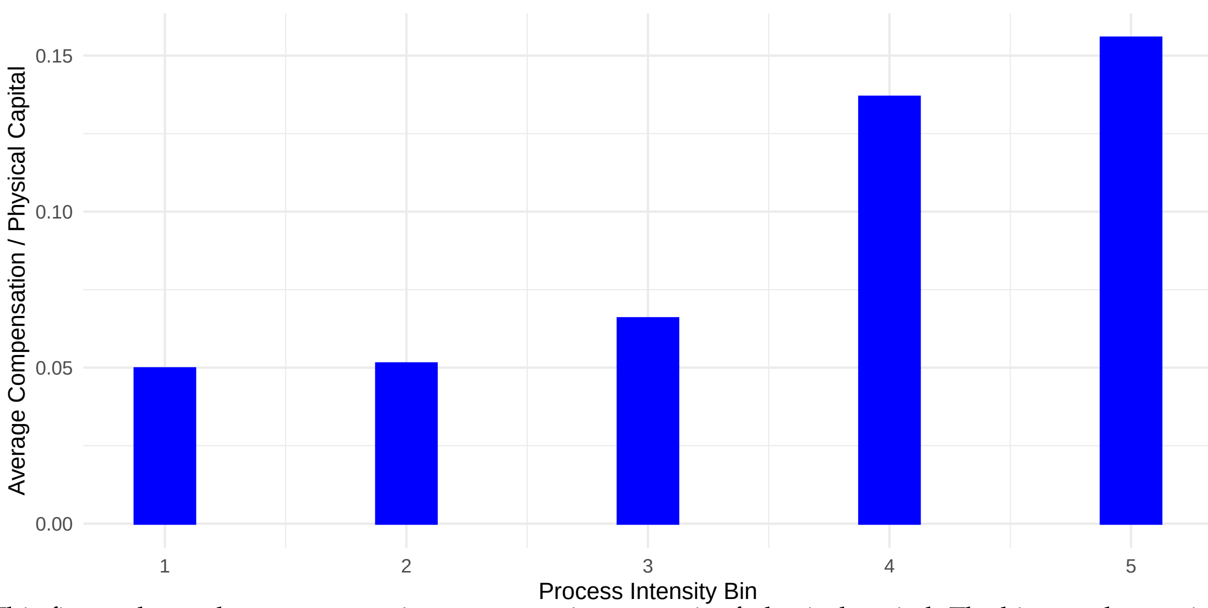
1 Introduction

Intangible and innovative capital can play multiple roles within the firm. For example, intangible capital can be used with other inputs to create new output. We call these intangibles "product intangibles". On the other hand, some intangibles are used to make the firm more efficient, by, for example, reducing costs or better organizing resources. We refer to these intangibles as "process intangibles."[1] Do these different uses of intangibles affect the compensation of executives and skilled employees? The data show that the answer is yes: Higher process intensity (process intangibles relative to total intangibles) is associated with higher pay.

Figure 1: Average Executive Compensation by Process Intensity Bin



This figure shows the mean executive compensation per unit of physical capital. The bins on the x-axis are created by sorting firms based on their process intensity each year. The bins are equally spaced. The y-axis is created by taking total executive compensation in the year and dividing it by the physical capital stock.

Figure 1 plots average executive compensation as a function of the firm process intensity.[2] As the level of process intensity increases, the average executive compensa-

[1]The OECD's Oslo Manual defines product innovation as *the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses* and meanwhile defines process and organization innovation as *implementation of a new or significantly improved production or a new organizational method in the firm's business practices, workplace organization or external relations* (OECD (2005)).

[2]See Section 5 for exact details on construction.

tion does, too.[3] In this paper, we rationalize this new empirical fact using a dynamic principal-agent model in which process intangibles are exposed to agency frictions and verify the model's predictions in the data.

Our model is motivated by a novel empirical stylized fact: physical investment and process intangibles are complements. This complementarity creates an agency problem. The agent's shirking effort in process innovation can reduce the efficacy of physical investment and reduce the firm's value. This fact motivates us to model the physical capital accumulation by a CES aggregation function between physical investment and process intangibles.

In our model, if the agent exerts effort, process intangibles are used to increase the efficiency of physical capital investment (i.e., the firm gets more "bang for the buck" per dollar of physical investment). If the agent shirks, they enjoy private benefits proportional to the difference in physical capital growth with and without process intangibles.[4]

We solve for the optimal contract that induces the agent to provide effort and find that there are two channels through which process intensity and compensation are linked. We call these the direct and indirect effects. We can measure these effects by closing the model with a Fokker-Plank equation. The upshot of this is that we can calculate the mean level of compensation over an entire distribution of firms as we vary certain firm parameters. The direct effect can be considered a level effect: Holding other variables and parameters fixed, as the process intensity of the firm increases, so does the promised utility to the agent. This effect arises because the agent's benefit from shirking increases as process intensity increases, ceteris paribus. Therefore, the owners of the firm must promise the agent more utility to induce them to provide effort.

The indirect effect is akin to a slope effect: The process intensity-compensation association becomes stronger as the complementarity between process intangibles and physical investment becomes larger. This effect is a hold-up problem. As process intangibles become more important to the physical capital growth process, the agent can extract more rents from the firm. This is most easily in the extreme cases. When physical investment and process intangibles are perfect substitutes, any rent extraction by the agent can be perfectly offset by an equivalent increase in physical capital investment. The

[3]This graph is unconditional on the level of intangibles. We show that this results holds conditionally on intangibles and other covariates as well, see Section 2.

[4]We could also motivate our modelling choice following arguments by Jensen and Meckling (1976). Intangibles are generally harder for outsiders (owners) to monitor (Lev (2000)), and this monitoring issue is exacerbated by the internal-to-the-firm nature of process intangibles.

level of physical capital growth is affected, but the marginal product of investment is not. In the other extreme case, process intangibles and physical investment are perfect complements. In this case, the agent must be induced to provide effort; otherwise, all physical investment is wasted: The agent can block the firm from growing until he is compensated enough. In reality, most firms are somewhere between these two extremes.

We measure process intensity in the data using information contained in patent claims (Bena and Simintzi (2019)). They scrape the text of filed patents, looking for phrases like a process for... or a product for... to determine the type of patent. In that paper, they measure process intensity similarly to ours. There are other methods of measuring product versus process intensity.[5] We focus on the Bena and Simintzi (2019) data and method because it is straightforward, publicly-available, and has already been used successfully in the previous paper.

We measure our main outcome variable, compensation, in two different ways. First, we use executive compensation, both total and deferred, from Compustat. This is the standard data used in the literature to test dynamic principal-agent models (Ward (2022)). The argument for using this data is that executives are the most powerful people in a firm and are best positioned to extract rents. However, it is not clear that executive effort actually matters for process intangibles to be effective.[6] Our second measure overcomes that issue. We gather wage data on vacancy postings from Burning Glass Technologies (BGT).[7] BGT is a firm whose competitive advantage is its unique vacancy posting data. The main benefit of this data is that BGT provides a large and standardized set of skills associated with each vacancy posting. Therefore, we can look at the posted wages for workers with skills specific to innovation, process improvement, and research and development (R&D).

Empirically, we verify the direct and indirect effects identified in the model, conditional on several covariates and fixed effects. We find that a one standard deviation increase in the process intensity of the firm is associated with an 8.4% increase in total compensation, a 7.6% increase in deferred compensation, and a 1.7% increase in the fraction of compensation deferred for executives. These are all measured relative to firm physical capital, which is consistent with the normalization in the theoretical model. The

[5]We cite these papers below.

[6]For example, when Nissan had a break-through in its car production methods (Link), its CEO was embroiled in a serious legal scandal. Exerting effort over process innovations was surely the last thing on his mind.

[7]BGT has since merged with Lightcast, and the merged entity uses the Lightcast name.

wage data from BGT is not a total flow, so it must be normalized differently. We normalize with respect to the wage of job postings requiring similar skills at other firms within the same industry-year (i.e., the leave-one-out industry-date mean). A one standard deviation increase in process intensity is associated with a 3.1% increase in this relative skilled wage. We first measure the complementarity of physical capital investment and process intensity to test the indirect effect. We do this by examining how the marginal product of physical investment on actual physical capital growth varies with the level of process intensity. We then sort firms based on our measure of complementarity.[8] High complementarity firms have uniformly stronger associations between process intensity and compensation. A one standard deviation increase in process intensity is associated with a 16.5% increase in total compensation in the high complementarity firms, compared with a 6.7% increase in the low complementarity firms. For deferred compensation and the BGT relative skilled wage, these numbers are 17.7% versus 7% and 4.9% versus 2.4%, respectively.

These empirical results are robust to several different specifications. First, we repeat our main regressions at the executive level instead of the firm level. Results are qualitatively similar, even when we restrict our sample to executives who changed firms at least once. Second, we exploit the granularity of the BGT data even further and split our high skilled workers into those with product-focused innovative skills and those with process-focused innovative skills. We find our effects are present in the second group, but not the first. Third, we test another channel connecting process intensity and compensation that is specific to the model. In the model, agency friction becomes stronger as uncertainty about capital growth increases. This implies that we should see another indirect effect in the data: Higher uncertainty in capital growth should lead to a stronger process intensity-compensation connection. We show that this is also empirically true.

We make three main contributions. First, we present a new finding that heterogeneity in the uses of intangibles is associated with heterogeneity in pay. In particular, higher process intensity is associated with higher pay. Second, we develop a dynamic principal-agent model with heterogeneity in intangibles that can rationalize the empirical phenomenon. Importantly, the model shows that there is a direct and indirect effect of process intensity on compensation: The level effect comes from variation in the shirking benefit, and the slope effect comes from variation in the complementarity between pro-

[8]Due to data limitations, we estimate complementarity at the four-digit NAICS level and assign all firms in that industry to have the same complementarity.

cess intangibles and physical capital investment. Third, we show that both the direct and indirect effects exist in the data, not only for executives but also for the skilled works whose effort determines the efficacy of process intangibles.

This paper sits at the intersection of three different literature. First, we contribute to the literature on dynamic agency theory (Biais et al. (2007), DeMarzo and Sannikov (2006), DeMarzo and Fishman (2007*a*), DeMarzo and Fishman (2007*b*), DeMarzo et al. (2012), Sannikov (2008), Morellec, Nikolov and Schürhoff (2018), Nikolov and Whited (2014), Tong and Ying (2018), Back, Kakhbod and Xing (2022)). Our model extends this framework to include heterogeneous forms of intangible capital. This adds new testable predictions (the core of our paper) and new state variables, adding computational complexity. Most relevantly, Ward (2022) studies the role of agency frictions on intangibles, but does not distinguish between different types of intangibles. We consider the papers complement, as we essentially take Ward (2022)'s result as a starting point (there are agency frictions on intangibles) and take the next natural steps. To the best of our knowledge, there are no other papers relating intangibles and agency frictions.[9]

Second, we contribute to the literature connecting intangible capital and finance (Crouzet and Eberly (2018), Eisfeldt and Papanikolaou (2013), Ewens, Peters and Wang (2019), Kung and Schmid (2015), Lev and Radhakrishnan (2005), Peters and Taylor (2017), Ward (2020)). None of these papers formally model the agency conflict nor do they attempt to measure heterogeneous intangible capital.[10] We use the methods of Ewens, Peters and Wang (2019) and Peters and Taylor (2017) to create our firm-level measure of intangible capital and investment. We fit within the subset of this literature that looks at the relationship between pay and innovation/intangibles (Bhandari and McGrattan (2021), Kline et al. (2019), Kogan et al. (2020), Lerner and Wulf (2007), Lustig, Syverson and Van Nieuwerburgh (2011), Song et al. (2019)). These papers also do not look at agency conflicts or the heterogeneous nature of intangibles.

Third, we contribute to the small literature on process versus product innovation and finance. Our measure of process innovation intensity comes from Bena and Simintzi (2019). Ganglmair, Robinson and Seeligson (2022) provide a survey of the empirical evidence on process claims over time and provide their measure of process intensity.[11] None of these papers are concerned with compensation or agency. To the best of our

[9] Grabner (2014) studies the empirical relationship between "creativity-dependent" firms and incentive pay.

[10] In fact, we combine patent data and intangible capital measures to get our heterogeneous measures.

[11] Angenendt (2018) also estimates process intensity.

knowledge, we are the first to explicitly tie a formal model of the firm (with or without agency) to the empirical data on process versus product innovation.[12]

2 Stylized Facts

This section presents three key empirical stylized facts that motivate our model in the next section. The model will then provide further implications for us to test. These facts also serve as a summary of our main results. We rely on simple double sorts or regressions in this section and defer the more detailed empirical work to Section 6. We leave formal data description and variable construction to Section 5.[13]

The facts we present are the following: First, firms with higher process intensity provide higher compensation for their executives. Second, the association between process intensity and compensation increases in the amount of physical capital investment. Third, firms with higher process intensity have lower contemporaneous sales. All three facts are conditional on the level of the intangible capital stock.

Figure 2 displays the first stylized fact. To construct this figure, we independently sorted firms into three bins based on their process intensity and three bins based on their intangible capital to physical capital ratios.[14] We see two effects here. First, the average level of executive compensation is increasing as the intangible capital bin increases (intangible capital level increases). This is implied by Ward (2022). Second, within each intangible capital bin (conditioning on the intangible capital level), executive compensation increases with the level of process intensity. This novel fact suggests that not only does the level of intangibles matter, but that the type of intangibles matter, too. This empirical fact has not been documented in the data, nor has it been explained by the existing models.

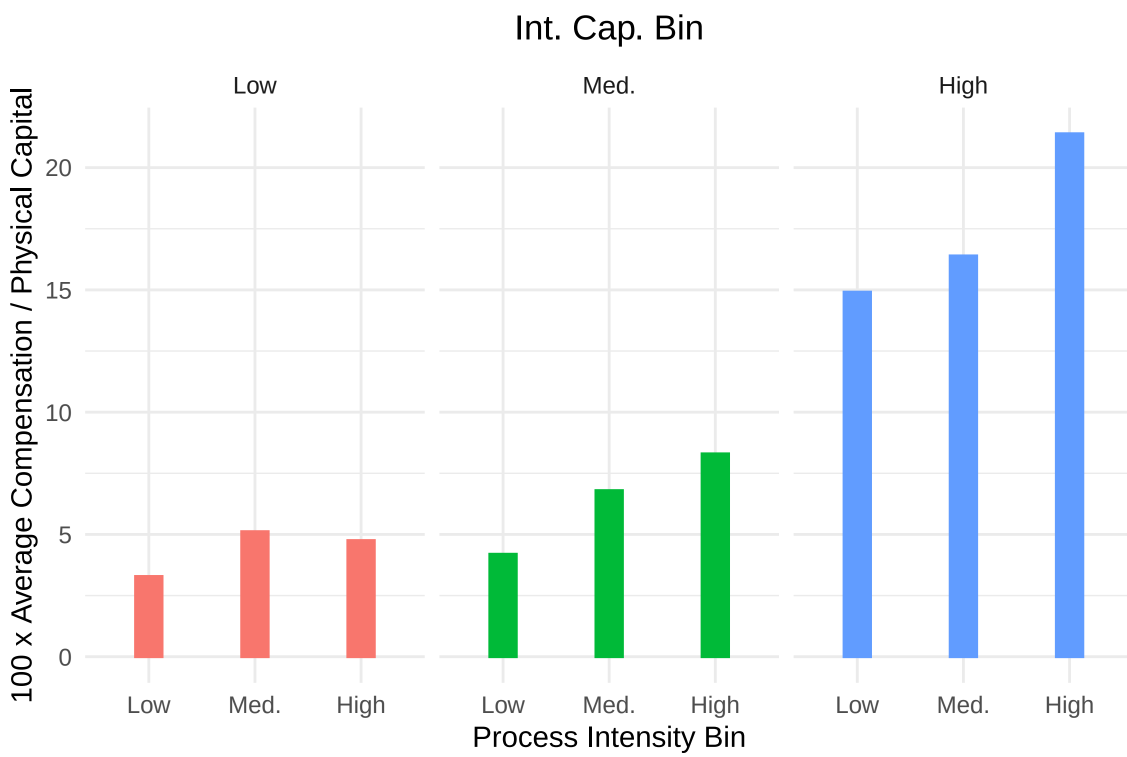
Figure 3 displays our second stylized fact. This figure shows the sensitivity of executive compensation to a one-standard deviation increase in process intensity by physical

[12] Mohnen and Hall (2013) provide an overview of the empirical evidence linking firm outcomes to process and product innovation.

[13] This section focuses on total executive compensation, one of our three compensation and salary measures. We leave the other two, deferred compensation and skilled labor salaries, to the main Results section.

[14] The bins are rebalanced every year. Sorting based on intangible capital is done conditional on industry, as Eisfeldt, Kim and Papanikolaou (2020) suggest. Process intensity is already normalized by the industry average process intensity.

Figure 2: Executive Compensation by Intangible Capital and Process Intensity Bin



This figure shows the mean executive compensation per unit of physical capital. The bins on the x-axis are created by sorting firms based on their process intensity each year. Each sub-graph and color is created by annually sorting firms based on their intangible capital to physical capital stocks. Bins are rebalanced each year for both variables, and the intangible capital bin assignments are conditional on industry. The measure of process intensity is scaled by the industry average process intensity. The compensation variable as been multiplied by 100 to remove small decimal numbers.

capital investment bin.[15] 95% confidence intervals are also displayed.

The key takeaway here is that the sensitivity is increasing as physical investment increases. This captures our idea of the hold-up problem inherent in process intangibles. Firms undertaking more physical investment are more "dependent" on the efforts of the agents to fully realize the benefits of the investment. The agent can thus extract rents from the firm. This effect is increasing with physical investment. This positive relationship is predicated on the assumption that physical investment and process intangibles are complements. This assumption is verified in the Appendix D.[16] Consider the extreme case where physical investment and process intangibles are perfect substitutes. Then, there is no interaction between process intangibles and physical investment in executive compensation.

The third stylized fact is that sales are decreasing with process intensity, conditional on the level of intangible capital. To show this fact, we estimate:

$$Sales_{ft} = y_t + y_j + \beta_1 ProcIn_{ft} + \beta_2 IK_{ft} + \beta_3 iB/M_{ft} + \beta_4 Size_{ft} + \varepsilon_{ft} \tag{2.1}$$

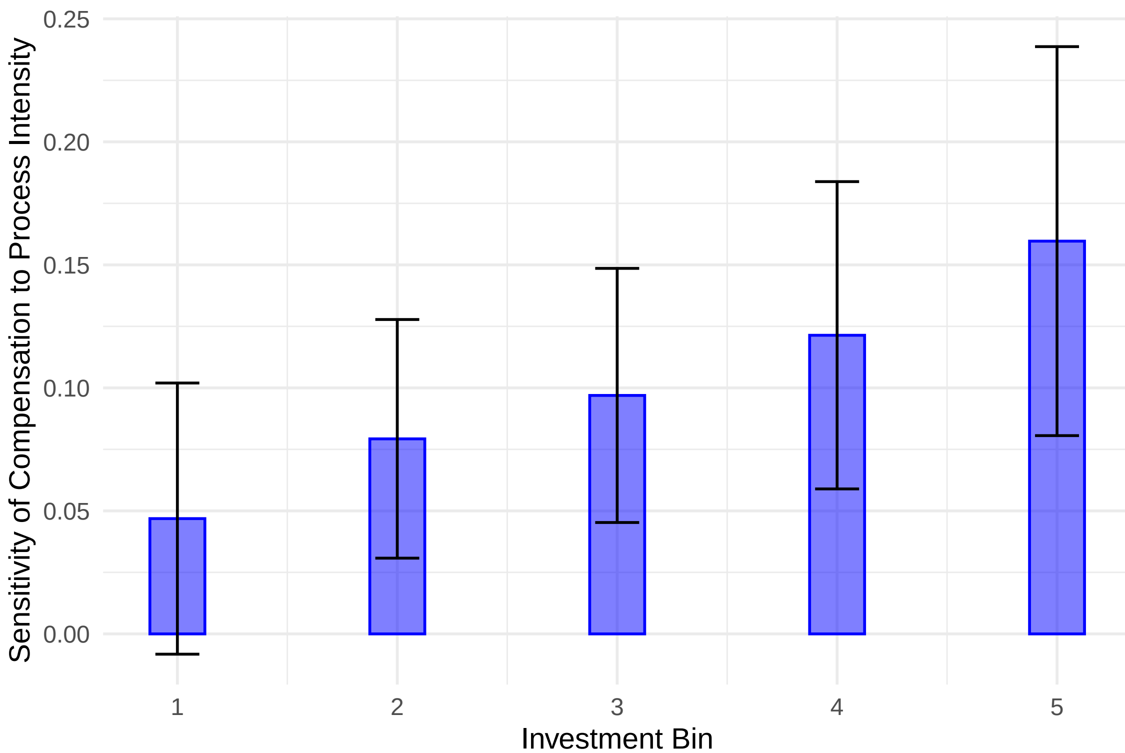
where sales are divided by physical capital, $ProcIn$ is our main process intensity measure as explained in Section 5, iB/M is the book-to-market ratio with intangibles added to the book value, and Size is market capitalization. The two fixed effects, y_t and y_j, control for date and industry effects, respectively. Standard errors are clustered at the firm level. All variables are logged, except for process intensity (since 0 is meaningfully frequent), which is expressed in standard deviation units.

Table 1 displays the results. The top row shows the estimates for the effects of process intensity on sales. The effects are negative and significant across specifications. A one standard deviation increase in process intensity is associated with about a 10% decrease in sales. Column (1) displays the sparsest specification using only intangible capital and process intensity without any controls or fixed effects. Column (2) adds controls. Column (3) adds fixed effects, without controls, and Column (4) includes all controls and fixed effects.

[15] The sensitivity is measured as the simple regression coefficient on process intensity when log compensation is regressed on process intensity, intangible capital, and firm size. Physical capital investment bins are created analogously to the process intensity bins above.

[16] Moreover, we also document there that the complementarity between physical investment and process intangibles is much stronger than the complementarity between physical investment and product intangibles.

Figure 3: Sensitivity of Executive Compensation to Process Intensity by Physical Investment Bin



This figure shows the sensitivity of log executive compensation (over physical capital) to a one-standard deviation increase in process intensity by physical investment bin. The sensitivity is measured as the simple regression coefficient on process intensity when log compensation is regressed on process intensity, intangible capital, and firm size. The investment bins are based on the physical investment to physical capital ratio of firms. They are rebalanced every year. 95% confidence intervals are displayed.

Table 1 Here

We next turn to the model, which will capture these stylized facts and provide further implications for the connection between compensation and process intensity.

3 Model setting

3.1 Capital, investment, and agency

The firm produces output using both physical and intangible capital, whose stock values are K and O, respectively. The firm determines its investment, I, in the physical capital and its investment, S, in the intangible capital. Both I and S are assumed to be non-negative, so that investment is irreversible. Physical and intangible investments are subject to convex adjustment costs $C_K(I)$ and $C_O(S)$, respectively. The instantaneous cash flow produced by the firm is

$$Y = \mu K^{\alpha}(\theta O)^{1-\alpha} - I - S - C_K(I) - C_O(S), \tag{3.1}$$

after netting investments and adjustment costs. The production requires a combination of physical capital and a fraction, θ, of intangibles that are used towards product innovation. They are aggregated by a Cobb-Douglas production function $\mu K^{\alpha}(\theta O)^{1-\alpha}$ with the productivity rate μ. Following Eisfeldt and Papanikolaou (2013), we assume the adjustment costs for physical and intangible investment as

$$C_K(I) = \frac{Q_K}{c_K}\left(\frac{I}{K}\right)^{c_K} K \quad \text{and} \quad C_O(I) = \frac{Q_O}{c_O}\left(\frac{S}{O}\right)^{c_O} O, \tag{3.2}$$

respectively, with constants c_K, c_O, Q_K, and Q_O.

The intangible capital O evolves according to

$$\mathrm{d}O_t = (S_t - \delta_O O_t)\mathrm{d}t, \tag{3.3}$$

where δ_O is the deprecation rate of the intangible capital. The evolution of K follows

$$\mathrm{d}K_t = (D(e_t, I_t, O_t) - \delta_K K_t)\ \mathrm{d}t + \sigma K_t \mathrm{d}Z^e, \tag{3.4}$$

where δ_K is the deprecation rate of the physical capital and Z^e is a Brownian motion describing shocks to the physical capital. Accumulation of physical capital depends on both investment I and a fraction, $1-\theta$, of intangibles. The production function D takes a CES form

$$D(e, I, O) = \frac{A}{a^{1/\rho}} \left[a\, I^{\rho} + e(1-a)(1-\theta)^{\rho} O^{\rho} \right]^{1/\rho}. \tag{3.5}$$

The presence of intangibles in the production function D models the process innovation, which makes physical investment more efficient: a larger value of $(1-\theta)O$ increases the physical capital K more for the given physical investment I. See Lin (2012) for a more detailed discussion on this production function on physical capital. The CES parameter ρ measures the complementarity between the physical investment and the intangibles in the physical capital accumulation. The lower ρ is, the more complementarity between the two components. The factor $a^{-1/\rho}$ in front of the CES function is a normalization factor so that the production function D takes the same value for different CES parameter ρ when the intangible capital O is zero.

In the production function D, the agent's effort e is either 0 or 1. When $e = 1$, the agent exerts full effort and works efficiently; when $e = 0$, the agent shirks his effort and enjoys a flow of private benefits $\lambda\Lambda$. The parameter λ is a positive constant and Λ measures the increment of the firm's physical capital accumulation due to the agent's effort, conditional on the physical capital investment and the intangible:[17]

$$\Lambda(I, O) = D(1, I, O) - D(0, I, O). \tag{3.6}$$

When the agent exerts full effort, i.e., $e = 1$, the physical capital increases by $D(1, I, O)$. However, when the agent shirks, i.e., $e = 0$, the physical capital only increases by $D(0, I, O) = AI$, which is independent of intangibles. Therefore, Λ measures how much stake the agent controls in the process innovation.

For positive ρ, four properties of Λ are important for our results: (i) $\Lambda(I, O)$ increases with O, indicating a more important role agent's effort plays in the physical capital accumulation, hence a higher shirking benefit, when a firm possesses more intangibles; (ii) $\Lambda(I, O)$ increases in $1-\theta$, implying that more process innovation increases the agency friction; (iii) When $0 < \rho < 1$, $\frac{\partial \Lambda}{\partial (1-\theta)}$ increases in I. This indicates a hold up problem for the physical investment and the problem is more severe when the firm invests more.

[17] He (2009) also makes the benefit function dependent on the investment rate.

(iv) When $\rho_1 < \rho_2$,

$$\frac{\partial \Lambda_{\rho_1}}{\partial(1-\theta)} > \frac{\partial \Lambda_{\rho_2}}{\partial(1-\theta)} > 0,\text{[18]} \tag{3.7}$$

for fixed I and O. Therefore, the agency friction is more severe when ρ is smaller and process intensity is higher.

The dependence of D on the agent's effort models the agency friction on the process innovation. We assume that the firm's owner (principal) only observes the dynamics of O and K, but cannot observe the agent's effort e due to the random shocks in Z^e. This introduces agency friction in process innovation.[19]

Our model setting mirrors the stylized facts documented in the previous section. Among the intangible capital O, θO is used in the product innovation to generate output, $(1-\theta)O$ is utilized in the process innovation to improve the efficacy of physical investment. Therefore, we call $1-\theta$ firm's *process intensity*. As $1-\theta$ increases, the Cobb-Douglas production function $\mu K^{\alpha}(\theta O)^{1-\alpha}$ decreases, which maps to the third stylized fact that sales decrease in process intensity. Complementarity between physical investment and process intangibles in the second stylized fact motivates the CES aggregation between physical investment and process intangibles in (3.5). Agent's effort e in the CES function represents the hold up problem: shirking reduces the efficacy of physical investment. The property (iii) of the shirking benefit Λ also echos the empirical pattern in Figure 3.

Next, we present a contracting problem between the owner of our model firm (principal) and an executive or a skilled employee (agent) who has expertise in process innovation.

3.2 Contracting problem

The principal offers a contract with a cumulative compensation of C to the agent. The agent does not subsidize the firm by accepting negative compensation. Therefore, C is a non-decreasing process. For a given compensation plan C, the agent's continuation

[18] For the first inequality, we normalize Λ by $a^{1/\rho}$ so that the normalized $\Lambda(I, 0)$ has the same value for different ρ.

[19] We can also consider the case where the dynamics of O is subject to random shocks, for example, $\mathrm{d}O_t = (S_t - \delta_O O_t)\mathrm{d}t + \sigma_O O_t \mathrm{d}W_t$ for another Brownian motion W independent of Z^e. However, contracting on O does not provide an incentive to the agent in our model and makes the agent's continuation utility more volatile. We will show later that the principal's value function is concave in the agent's continuation utility. Therefore, the principal is implicitly risk averse in the agent's continuation utility, hence does not load on the intangibles in the optimal contract.

utility U is

$$U_t = \max_{e \in \{0,1\}} \mathbb{E}_t^e \Big[\int_t^\tau e^{-\gamma(s-t)} \big[dC_s + (1-e_s)\lambda\Lambda_s ds \big] \Big]. \tag{3.8}$$

The expectation is taken with respect to a probability $\mathbb{P}^e$, which is induced by the agent's effort e. The Brownian motion Z^e in (3.4) is under the measure $\mathbb{P}^e$. The agent is assumed to be risk neutral, discounting future compensation and potential private shirking benefit using a subjective discounting rate of γ. The firm is terminated at an endogenously determined stopping time τ, after which the agent collects the outside value, which is normalized to be zero.

The principal of the firm chooses a contract to maximize the expected future cash flow net compensation discounted by the interest rate r. Principal chooses among the contracts which incentivize the agent's full effort $e = 1$. Therefore, the principal's optimization problem at time zero is

$$\max_{I,S,C} \mathbb{E}^{e^*} \Big[\int_0^\tau e^{-rs} \left[Y_s ds - dC_s \right] + e^{-r\tau} \big(\ell_K K_\tau + \ell_O O_\tau \big) \Big], \tag{3.9}$$

subject to agent's incentive compatibility constraint that the agent chooses the full effort optimally, i.e., $e^* = 1$ and agent's participation constraint $U_0 \geq 0$. In (3.9), the firm's termination time is

$$\tau = \inf\{t \geq 0 : U_t = 0\},$$

when the agent's continuation value from the contract reaches his outside value. The firm is terminated at τ to protect the agent's limited liability with respect to his outside value. At the termination time, the firm's physical and intangible capital are both liquidated. The recovery rate for physical capital is ℓ_K and the recovery rate for intangibles is ℓ_O. Termination is inefficient for the firm. The principal designs the optimal contract to manage the agent's continuation utility U in order to provide the incentive to work and meanwhile mitigate inefficient firm termination.

To avoid the principal deferring the compensation forever, We assume that

$$r < \gamma,$$

so the principal is more patient than the agent. The same technical condition is required by DeMarzo and Sannikov (2006).

4 Optimal contract and implications

4.1 Optimal contract

In order to incentivize the agent's full effort, the principal exposes the agent's continuation utility to variations in K. Introducing a pay-performance sensitivity φ to dK yields the benefit of working $\varphi\Lambda$ for the agent. Comparing to the cost of working (losing the shirking benefits) $\lambda\Lambda$, the principal needs to choose $\varphi \geq \lambda$ to incentivize the agent's full effort. The following result summarizes the agent's optimal effort choice and dynamics of the continuation utility.

Lemma 4.1 *For a given cumulative compensation C, there exists a process φ such that the agent's continuation utility follows*

$$dU_t = \gamma U_t dt + \varphi_t K_t \sigma dZ_t^{e^*} - dC_t, \tag{4.1}$$

where the agent's optimal effort is

$$e_t^* = \begin{cases} 1, & \varphi_t \geq \lambda, \\ 0, & \textit{otherwise}. \end{cases} \tag{4.2}$$

Therefore, in order to incentivize full effort, agent's incentive compatibility constraint is

$$\varphi \geq \lambda. \tag{4.3}$$

We now turn to the principal's problem (3.9). Introduce the principal's value function as

$$V(K_t, U_t, O_t) = \max_{I,S,C} \mathbb{E}_t^{e^*} \Big[\int_t^{\tau} e^{-r(s-t)} \big[Y_s \mathrm{d}s - \mathrm{d}C_s \big] + e^{-r(\tau-t)} \big(\ell_K K_\tau + \ell_O O_\tau \big) \Big]. \tag{4.4}$$

The homogeneity in K allows us to introduce a function v via

$$V(K, U, O) = K\, v(u, o), \tag{4.5}$$

where

$$u = U/K \quad \text{and} \quad o = O/K$$

are the continuation utility to physical capital ratio and the intangible to physical capital ratio, respectively. Physical capital accumulation takes the form

$$D(e,I,O) = K\,d(e,i,o), \quad \text{where} \quad d(e,i,o) = \frac{A}{a^{1/\rho}}\left[a i^{\rho} + e(1-a)(1-\theta)^{\rho} o^{\rho}\right]^{1/\rho}. \tag{4.6}$$

When $e = 1$, we denote $d(1,i,o)$ by $d(i,o)$ to simplify notation. Using u and o as two state variables for the principal's problem, the optimal contract, and the optimal investment strategies are characterized by the following result.

Proposition 4.1 *The function v, the optimal contract, and the optimal investment are described as follows:*

(i) The function v satisfies the HJB equation

$$\begin{aligned} 0 = \max\Big\{ & -(r+\delta_K)v + \max_{i\geq 0, s\geq 0, \varphi\geq\lambda} \Big\{ \big(v - o\,\partial_o v - u\,\partial_u v\big) d(i,o) \\ & + \big(s - (\delta_O - \delta_K)o\big)\partial_o v + (\gamma + \delta_K) u\,\partial_u v \\ & + \frac{1}{2} o^2 \sigma^2 \partial^2_{oo} v + \frac{1}{2}(\varphi - u)^2 \sigma^2 \partial^2_{uu} v - o(\varphi - u)\sigma^2 \partial^2_{ou} v \\ & + \mu(\theta o)^{1-\alpha} - i - s - C_K(i) - C_O(s/o)o \Big\}, -\partial_u v - 1 \Big\}. \end{aligned} \tag{4.7}$$

(ii) Define $\overline{u}(o) = \inf\{u : \partial_u v(u,o) = -1\}$. The optimal compensation is a reflection type. Whenever $u_t < \overline{u}(o_t)$, no compensation is paid, i.e., $dC^*_t = 0$. Only when $u_t = \overline{u}(o_t)$, compensation is paid to keep the state process (u,o) below $\overline{u}$.

(iii) When

$$\partial^2_{uu} v < 0 \quad \text{and} \quad \lambda > u + \frac{o\partial^2_{ou} v}{\partial^2_{uu} v}, \tag{4.8}$$

the optimal contract sensitivity φ^* is λ.

(iv) When $v - o\,\partial_o v - u\,\partial_u v > 0$, the optimal physical investment and physical capital ratio, i^*, satisfies the first order condition

$$\big(v - o\,\partial_o v - u\,\partial_u v\big)\partial_i d(i^*, o) = 1 + Q_K (i^*)^{c_K - 1}; \tag{4.9}$$

otherwise, $i^* = 0$. If $\partial_o v > 1$, the optimal intangible investment and physical capital ratio, s^*, is

$$s^* = o\Big(\frac{\partial_o v - 1}{Q_o}\Big)^{\frac{1}{c_O - 1}}; \tag{4.10}$$

otherwise $s^* = 0$.

To understand the HJB equation (4.7), we first use (3.3), (3.4), and (4.1) to derive the dynamics of $u = U/K$ and $o = O/K$:

$$\mathrm{d}o_t = \big[s_t - (\delta_O - \delta_K)o_t - o_t\, d(i_t, o_t) + o_t\, \sigma^2\big]\mathrm{d}t - o_t\, \sigma \mathrm{d}Z_t, \tag{4.11}$$

$$\mathrm{d}u_t = \big[(\gamma + \delta_K)u_t - u_t\, d(i, o) + \sigma^2(u_t - \varphi_t)\big]\mathrm{d}t + \sigma(\varphi_t - u_t)\mathrm{d}Z_t - \frac{1}{K}\mathrm{d}C_t, \tag{4.12}$$

where $d(i, o) = A[ai^\rho + (1-a)(1-\theta)^\rho o^\rho]^{1/\rho}$, $i = I/K$, $o = O/K$, and the superscript 1 is suppressed on Z^1 to simplify notation. Equation (4.7) divides the state space into two regions: (i) continuation region where

$$\underbrace{r\, vK}_{\text{Expected change}} = \underbrace{\mathbb{E}\big[\mathrm{d}(Kv)\big]}_{\text{Expected change in } V} + \underbrace{Y}_{\text{Net cash flow}}$$
$$= K\, \mathcal{L}_{u,o} v + v\, \mathbb{E}[\mathrm{d}K] + \mathbb{E}[\mathrm{d}K\, \mathrm{d}v] + Y,$$

where $\mathcal{L}_{u,o}$ is the infinitesimal generator of (u, o) in (4.11) and (4.12); (ii) compensation region, where the marginal benefit of compensation $-\partial_u v$ equals the unit marginal cost. The right-hand side of (4.7) compares two groups of terms corresponding to continuation and compensation, respectively. Only one group equals zero for each point in the state space. The boundary between the continuation and the compensation region is $\overline{u}$. The optimal compensation satisfies $dC_t^* = 0$ when $u_t < \overline{u}(o_t)$ and $dC_t^* > 0$ when $u_t = \overline{u}(o_t)$. This compensation maintains the state process to be lower than the compensation boundary and reflects the state process whenever the compensation boundary is reached.

The optimal pay-performance sensitivity is determined by the constrained optimization problem

$$\max_{\varphi \geq \lambda} \Big\{ \frac{1}{2}(\varphi - u)^2 \sigma^2 \partial^2_{uu} v - o(\varphi - u)\sigma^2 \partial^2_{ou} v \Big\},$$

where the pay-performance sensitivity φ is subject to the incentive compatibility constraint $\varphi \geq \lambda$. When the conditions (4.8) are satisfied, the incentive compatibility constraint is binding, i.e., $\varphi^* = \lambda$. Conditions (4.8) will be verified numerically in our experiments later.

The optimal investments are determined jointly by their first-order conditions and the non-negativity constraint. When $i^* > 0$, it satisfies the first order condition (4.9), where the right-hand side is the marginal cost of physical investment. The left-hand side of

(4.9) consists of two components. First, the marginal impact of physical investment on the growth rate of the physical capital is $\partial_i d(i^*, o)$. Therefore, the marginal benefit on the value function, due to the change of physical capital accumulation, is $v\, \partial_i d(i^*, o)$. Second, the growth in physical capital reduces the intangible and physical capital ratio, at the rate of $o\, \partial_i d(i^*, o)$, and also reduces the continuation utility and physical capital ratio, at the rate of $u\, \partial_i d(i^*, o)$. Both reductions introduce the marginal cost $(o\, \partial_o v + u\, \partial_u v)\partial_i d(i^*, o)$. The optimal investment in the physical capital balances the net marginal benefit on the left-hand side of (4.9) and the marginal cost on the right-hand side. The optimal investment in the intangible capital satisfies the following first-order condition, when $\partial_o v > 0$,

$$\partial_o v = 1 + Q_O \left(s^*/o\right)^{c_O - 1},$$

where the marginal cost on the right-hand side matches the marginal benefit $\partial_o v$ on the left. This first-order condition yields the optimal choice of s^* in (4.10).

The HJB equation (4.7) is combined with several boundary conditions, which we specify next. When U reaches 0, both physical and intangible assets are liquidated. Therefore, the boundary condition at $u = 0$ is

$$v(0, o) = \ell_K + \ell_O o. \tag{4.13}$$

The endogenous compensation boundary $\overline{u}$ is determined jointly with the solution of (4.7). When $o = 0$, (4.11) shows that the drift of do is non-negative and the volatility vanishes. Therefore, the boundary condition at $o = 0$ is not needed in an upwind numeric scheme. Finally, we impose a technical Neumann boundary condition at a sufficiently large level $\overline{o}$

$$\partial_o v(u, \overline{o}) = 0.$$[20]

4.2 Stationary distribution

After the optimal contract and investment strategies are characterized for an individual firm in the previous section, we examine in this section the stationary distribution of the state variables.[21] This helps us to better match model predictions with empirical observations.

[20]Our numeric experiments show that the function v in a fixed bounded domain is not sensitive to the choice of $\overline{o}$ when $\overline{o}$ is sufficiently large.

[21]Hopenhayn (1992).

Because the volatility of u in (4.12) is non-degenerate at $u = 0$, firm liquidation happens with positive probability under the optimal contract. In order to maintain a stationary mass of firms, we introduce firm entry. The stationary density g of the state variable (u, o) satisfies the stationary Fokker-Planck-Kolmogorov equation:

$$\mathcal{L}^*_{u,o}\, g(u, o) + m\, \psi(u, o) = 0, \tag{4.14}$$

where $\mathcal{L}^*_{u,o}$ is the adjoint operator of the infinitesimal generator $\mathcal{L}_{u,o}$, $\psi(u, o)$ represents an entry density integrating to one, and m is an entry rate. To ensure that the stationary density g integrates into one, the entry rate m is chosen to match the existing mass:

$$m = -\int_0^\infty \int_0^{\overline{u}(o)} \mathcal{L}^* g(u, o)\, \mathrm{d}u\, \mathrm{d}o.$$

Coefficients in the infinitesimal generator $\mathcal{L}_{u,o}$ depend on the optimal investment strategies and the agent's optimal effort under the optimal contract. Therefore, the stationary density g describes the behavior of the equilibrium state variables.

4.3 Quantitative model implications

We examine the quantitative implications of our model in this section. We calibrate several model parameters to the data. For the agent shirking benefit parameter λ, it follows (4.1) that the sensitivity of changes in U with respect to changes in K is λ when the incentive compatibility constraint is satisfied. We proxy U using the total compensation from Execucomp and regress changes in the total compensation on changes in the physical capital to obtain λ. For the volatility parameter σ, we estimate it using the standard deviation of annual changes in the log physical capital stock. Finally, γ is calibrated so that the mean of u is matched to the data. We assume the recovery rate of intangibles after termination is zero, i.e., $\ell_O = 0$, because a firm's internal organizational innovation is hard to be replicated after liquidation. For firm entry, we assume that the principal has all bargaining power so that a new firm starts at $u^e(o)$ which maximizes the principal's value $v(\cdot, o)$ for a given o. The entry density $\psi(u, o)$ is assumed to have the decomposition $\psi(u, o) = \zeta(o)\xi(u|o)$, where ζ is the density of a log normal distribution with parameters μ_ψ and σ_ψ, and ξ has a unit mass at $u^e(o)$. All other model parameters are summarized in Table 2. They are all consistent with the parameter choice in the

Figure 4: Principal's Value Function

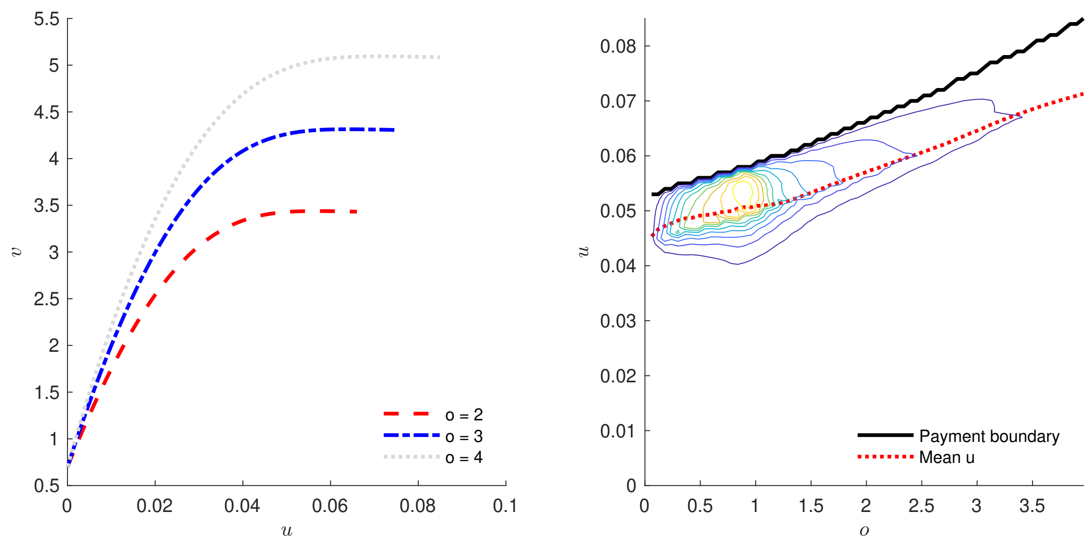


Figure 5: Principal's value function, compensation boundary, conditional mean of continuation utility, and stationary density. Parameters are listed in Table 2.

literature.[22]

Table 2 Here

We now present the model implications of our calibrated model. The left panel of Figure 4 shows the principal's value function v for different values of o. Given o, the function $v(u, o)$ is concave in u implying that the principal is endogenously risk-averse towards variations in u. This endogenous risk aversion is generated by the threat of inefficient liquidation. Given u, the function $v(u, o)$ is increasing in o, because intangibles improve the efficiency of physical capital investment, hence increase the principal's value. The right panel of Figure 4 presents the compensation boundary $\overline{u}$, the mean of

[22]For simplicity and computational ease, we set $\ell_K = 0.7$, $\ell_O = 0$, $\mu_\psi = 0$, and $\sigma_\psi = 1$.

[22] $\frac{A}{a^{1/\rho}}$ agrees with Lin (2012).

[22]The parameters Q_K and Q_O are in monthly unit. To annualize them, we use the following argument from the first best case. Let b be the marginal benefit of investment i. Then the first-best optimization in i is $\max_{i\geq 0}\left\{b\,i - i - \frac{Q_K}{c_K} i^{c_K}\right\}$. Therefore, the optimal monthly investment is $i^* = \left(\frac{b-1}{Q_K}\right)^{\frac{1}{c_K-1}}$. Scaling monthly Q_K to $Q_K/12^{c_K-1}$, we obtain the annualized optimal investment $12i = \left(\frac{b-1}{Q_K/12^{c_K-1}}\right)^{\frac{1}{c_K-1}}$.

Figure 6: Compensation boundary and Conditional Mean: Varying θ

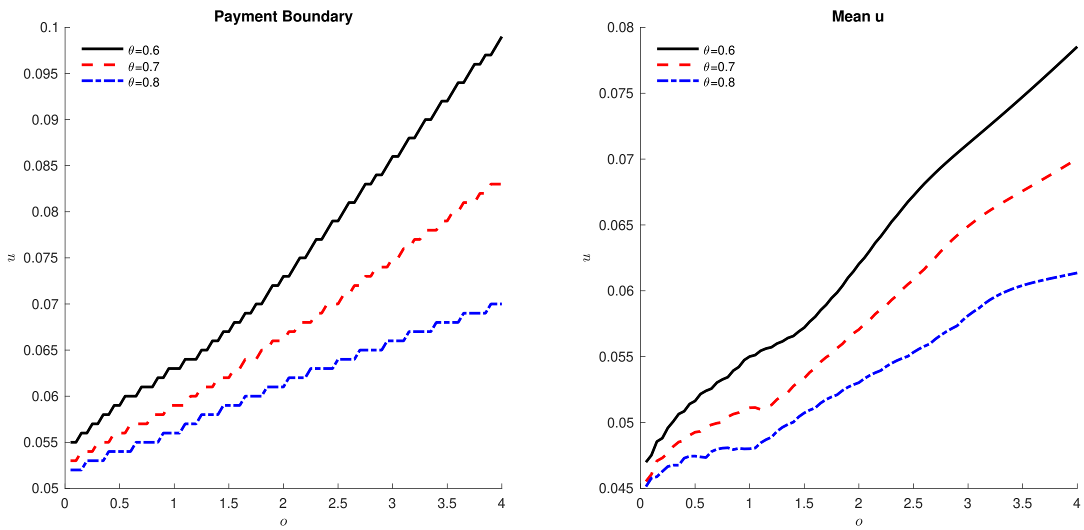


Figure 7: Compensation boundary and conditional mean of continuation utility for different values of θ. Other parameters are listed in Table 2.

the continuation utility conditioning on o, and the stationary density. The compensation boundary $\overline{u}$ increases with o. This is due to two effects. First, the production function d of the physical capital investment increases with o. A higher intangible-physical capital ratio improves the efficiency of physical capital investment via process innovation. However, it also elevates the importance of the agent's effort in the physical capital accumulation. Therefore, agency friction worsens with more intangibles. In order to mitigate inefficient liquidation, the principal increases the compensation boundary $\overline{u}$ to build up the agent's continuation by deferring more compensations into the future. The level curves of stationary density show that the state variables (u, o) concentrate in a region close to the compensation boundary. This is because the drift of u in (4.12) is positive in most parts of the state space, pushing u to increase, meanwhile the reflecting type of compensation ensures $u \leq \overline{u}$. Conditioning on o, the mean of u under the stationary distribution is represented by the red dotted line in the right panel. It increases with o, following the same pattern of the compensation boundary and indicating a positive relationship between the average deferred compensation and the intangible capital.

The impact of θ on the compensation is presented in Figure 6. When θ increases,

Figure 8: Compensation Boundary and Conditional Mean: Varying ρ

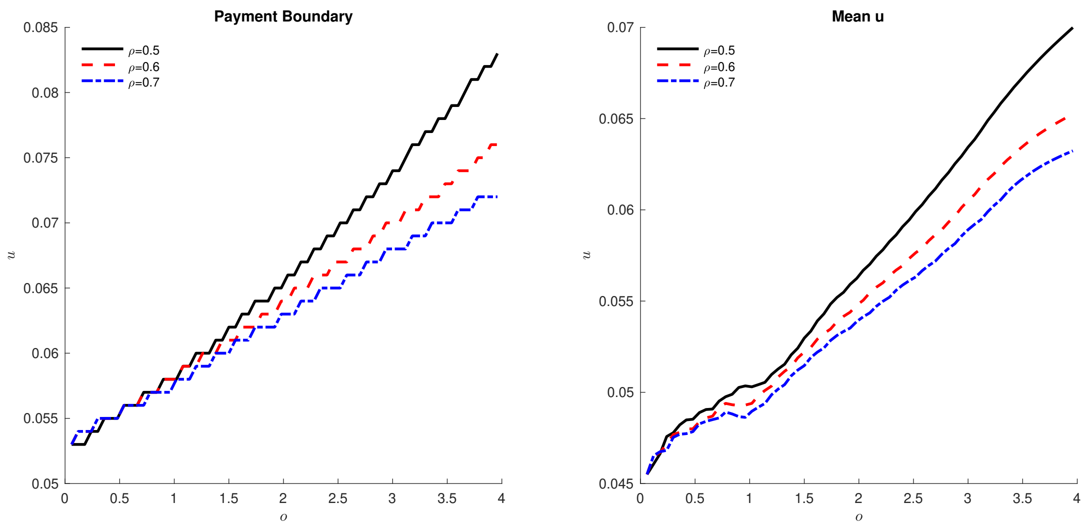


Figure 9: Compensation boundary and conditional mean of continuation utility for different values of ρ. Other parameters are listed in Table 2.

more proportion of the intangible capital is used in the product innovation, and less proportion is used in the process innovation. Given i and o, the physical capital accumulation function d decreases in θ when the agent exerts full effort. As a result, the physical capital accumulation depends less on the agent's effort and the agency friction is less severe when θ increases. The left panel of Figure 6 shows that the compensation boundary decreases with θ, implying that the principal defers less compensation into the future when less proportion of the intangible capital is used for process innovation. The conditional mean of u in the right panel of Figure 6 shows the same pattern.

The impact of ρ is presented in Figure 8. When ρ increases, the complementarity between the physical capital investment and the intangible capital used in the process innovation weakens. It becomes easier to substitute process innovation using physical capital investment, hence the agent's effort becomes less important in the physical capital accumulation and the agency friction subsides. Therefore, as ρ increases, Figure 8 shows that both the compensation boundary and the conditional mean of u decrease in ρ, hence the optimal contract depends less on the deferred compensation.

These model predictions on the intensity of process innovation and the complementarity between the physical capital investment and the intangible capital will be tested in our empirical analysis next.

5 Data

This section describes our data sources and how we construct our final data set. We also provide a set of stylized facts. These facts will constitute the main empirical phenomena that we are trying to understand.

5.1 CRSP and Compustat

We begin by describing our data preparation procedure for CRSP/Compustat. These data sets give information on the firm balance sheet and income statement variables. The key variables we will construct from CRSP/Compustat are investment rates (intangible and physical) and capital stocks. We will also construct a number of variables commonly used in the finance literature as controls in our regressions.

We employ a number of standard filters on our data. First, we only retain firms traded on AMEX, NASDAQ, or NYSE stock exchanges. Second, following Fama and French (2015), we drop the first two years a firm appears in the data.[23] Third, we drop firms in the Transportation, Finance, and Public industries. Fourth, we drop micro-cap firms as defined by Fama and French (2015).[24]

We describe the construction of our intangible capital stock and investment variables in the next subsection. We will describe the other CRSP/Compustat variables as we use them, since they are more standard.

5.2 Definition of Intangible Capital

Internally generated intangible capital stocks and their associated investment rates are not reported on firm balance sheets, so we must construct these variables ourselves. To do so, we follow Peters and Taylor (2017). First, if any of the following Compustat variables are NAs, we set the values to 0: xrd (R&D), xsga (Selling, General, and Admin-

[23]We drop entirely firms that do not have beyond two full years of data.

[24]Micro-caps are defined as firms whose market capitalization is less than the market capitalization of the 20th percentile NYSE firm's size.

istrative), rdip (R&D in progress), cogs (Costs of Goods Sold). Second, we construct a variable called SGA.

SGA is defined as follows. If R&D is greater than Selling, General, and Administrative expenses and R&D is less than Costs of Goods Sold, then we set SGA equal to Selling, General, and Administrative expenses. Otherwise, we set SGA equal to Selling, General, and Administrative expenses minus the sum of R&D and R&D in progress.[25]

The third and final part of the Peters and Taylor (2017) method uses the perpetual inventory method to construct the "Knowledge Capital" (K_{Know}) and "Organization Capital" (K_{Org}) stocks.

$$K_{Know,ft} = (1 - \delta_{Know})K_{Know,f,t-1} + \frac{R\&D_{ft}}{CPI_t} \tag{5.1}$$

$$K_{Org,ft} = (1 - \delta_{Org})K_{Org,f,t-1} + (0.3)\frac{SGA_{ft}}{CPI_t} \tag{5.2}$$

where CPI_t is the consumer price index.[26] We follow Ewens, Peters and Wang (2019) when we select δ_{Know} and δ_{Org}. Ewens, Peters and Wang (2019) show that there is heterogeneity in these parameters across industries.[27] We use their estimates from their pooled estimation, leading to $\delta_{Know} = 0.28$ and $\delta_{Org} = 0.3$.

We define intangible capital as the sum of Knowledge Capital and Organization Capital, $K_{Int} = K_{Know} + K_{Org}$.[28] It follows from our definition of intangible capital that we construct intangible investment as $R\&D_{ft} + SGA_{ft}$.

5.3 Execucomp

We use Execucomp to calculate the compensation to top executives at a firm.[29] Our main measure of compensation from Execucomp is total compensation (data item: TDC1). This total compensation measure includes salary, bonus, long-term incentive plans, option awards, and stock awards.

In order to capture a more direct measure of continuation utility (the variable U in

[25]Our results are similar using the Eisfeldt, Kim and Papanikolaou (2020) method of construction. Results are available upon request.

[26]The CPI is gathered from the Bureau of Economic Analysis.

[27]For example, their estimates of δ_{Know} range from 0.18 to 0.31.

[28]If either K_{Know} or K_{Org} is less than 0, we set K_{Int} to zero.

[29]Execucomp usually includes the compensation for the top five executives at the firm. Sometimes the compensation for the top nine is included.

the model), we also look at deferred compensation. FASB Statement NO. 123 (revised 2004), "... requires a public entity to measure the cost of employee services received in exchange for an award of equity instruments based on the grant-date fair value of the award."[30] We use this fair value of equity based compensation (e.g., stocks and options) as a measure of future promise utility. We also use the fraction of deferred compensation in the total compensation as another measure of promised utility.

5.4 Burning Glass Technologies

We are interested in, not only, the payments to top executives, but also the payments to specialists/skilled labor. Though executives are unlikely to be directly involved in innovation activities, they are arguably the best positioned to extract rents from the firm. Indeed, most papers studying agency conflicts such as the one we study use data from Execucomp to test their predictions. On the other hand, it is plausible that the skilled labor directly involved with innovation has the most information about the technology in question. Therefore, these workers are also well positioned to extract knowledge based rents.[31]

Burning Glass Technologies (BGT) is a labor market data firm that collects vacancy and resume data from the Internet using machine learning techniques. The data set we use is collected by an "electronic spider" that scrapes job posting sites like Indeed.com and Monster.com for information about the vacancies posted there.

BGT collects the unstructured data on the websites and arranges them in a database with standardized variables. This allows cross-firm and intertemporal comparisons. Most importantly for us, BGT standardizes the set of skills firms looking for. For example, one firm may want to hire someone "proficient at Microsoft Word." Another firm might simply state that "the job will require a good deal of writing, so facility with word processors like Microsoft Word is a must". BGT would assign "Microsoft Word" as a skill for both firms. For each job posting, BGT assigns a number for employee skills.[32] These skills are drawn from a list created by BGT, which means that the subjective nature of this data is somewhat reduced.

[30] Link to statement.

[31] For example, if computer programmers are trying to solve a complex and highly specialized problem, it is feasible that even their direct managers cannot tell the difference between slow progress and shirking.

[32] 7% of jobs have no assigned skills or skills are assigned to a non-existent job posting. We drop these cases from the data set.

There are three lists of skills, and the difference between these lists is the level of granularity. For example, the least granular list has 29 different levels, such as Administration, Design, Business, and Health Care. We use the middle list (in terms of granularity) that has 677 levels. Examples of skills here include Litigation, Water Testing and Treatment, and Technical Support.

We classify certain skills as being innovation intensive (II) versus not. We call a job posting an innovation intensive job (II job) posting if it has one of these skills assigned to it.[33] Our selection of skills for this categorization is subjective. We ask ourselves "What skills are associated with the creation of new ideas and products?" Note that this related to, but different than, "high skill." For example, medical doctors are highly skilled and educated, but we do not consider them to typically be involved in the creation of new products or processes. Consequently, medical doctors are not "innovation" job holders.

Around 5% of all BGT job postings have an associated salary. These are the salaries the employer is offering for the position. For each firm-year, we compute the average II job salary. Similarly, we compute the average II job salary within an industry year.

There are two drawbacks to the BGT data. First, BGT data only go back to 2010. As we will see, this reduces our sample size to less than 2000 observations for regressions using BGT data. Second, as alluded to above, even though the II workers in BGT are the ones actually undertaking the innovative work, it is not clear how much power these workers have to extract rents from shirking. This second drawback is not so problematic, since we have Execucomp data, as well. Our results are consistent with either the executives or the II workers, or both, being subject to agency conflicts.

5.5 Process Claims Data

Our data for process claims comes from the data set compiled by Bena and Simintzi (2019).[34] The authors collect data from the U.S. Patent and Trademark Office (USPTO) up to 2021. They parse the structured-text of each patent to identify the claims section of the patent. Patent claims delineate the scope of the patent in the eyes of the law. To that end, they are important and precisely written. For example, the outcomes of patent

[33] We require only one skill to be II because it is not true that more non-II skills reduce the innovativeness of the job, so to speak. For example, one company may want someone who understands artificial intelligence, while another company wants this same role to also manage people and write reports. The second company's posting would have a smaller fraction of skills classified as II, but that role just described is no less innovative.

[34] We refer the reader to that paper's Internet Appendix for further details not discussed here.

infringement lawsuits frequently depend on these claims. Within the claims section of the patent, the authors then classify each claim as being either process or product oriented.

Though definitions are subjective, the existing literature (Bena and Simintzi (2019), Ganglmair, Robinson and Seeligson (2022)) generally defines process innovations as those that improve firm productivity/production methods or reduce costs, meanwhile product innovations introduce new products.

Within each-firm year, we compute the total number of process claims across all patents and divide that sum by the total number of claims, processes, and products. This measure aggregates information from all the patents filed by the firm that year. This measure is similar to that used by Bena and Simintzi (2019). Note that in the model process intensity, $1 - \theta$, is a parameter. Our measure of process intensity in the data is allowed to vary by firm-year. However, most of the variation in process intensity can be captured by a firm-level fixed effect.[35] Thus, our measures do a good job of sorting firms into different, relatively invariant, groups, which is in line with our theory.

By using patent data to construct the process intensity of the firm, we are assuming that this patent-level measure is a good proxy for the overall-firm level measure. We use the patent data because no firm-level measure of process intensity exists. If, for example, firm-level process intensity, p^f, is:

$$p^f = \beta p^p + e$$

where $\beta > 1$, p^p is the patent level measure, and e is noise, then we have classic errors-in-variables on the right-hand side. This will not lead to problems in inference, since we are interested in cross-firm comparisons.

Throughout, we drop firms with no claims of any kind (i.e., no patents). This is implicit in our measures of process intensity that are defined as the number of process claims over total claims.

5.6 Summary Statistics

Table 3 displays summary statistics. We allocate firms to different portfolios based on their process intensity measure, $1 - \theta$, and the averages of select variables are computed

[35] 50% of the variation in process intensity is captured by firm-fixed effects. Adding a full set of controls, including industry fixed effects, increases the R^2 of the regression by only 8%.

for each portfolio. The firms are assigned to a portfolio each year.

The first column lists the portfolio, where a higher portfolio number indicates a larger average process intensity. The second column lists what we call the "iB/M" ratio.[36] The iB/M ratio is constructed similarly to the classic book-to-market ratio.[37] Instead of simply taking the ratio of book equity to market capitalization, we add the intangible capital stock to book equity before computing the ratio. The standard measures of book equity fail to account for internally generated intangibles, which are becoming an increasingly important part of the firm's capital stock.[38] The iB/M ratio is almost monotonically decreasing in the firm's process intensity. Though we do not explore the iB/M ratio in the model, this result is in line with the production-based asset pricing literature. According to Lin (2012), as the process intensity increases, the marginal product of physical investment increases. This increase in marginal product increases what Kogan and Papanikolaou (2014) call the "present value of growth opportunities." Kogan and Papanikolaou (2014) show that, everything else equal, a larger present value of growth opportunities leads to a lower book-to-market ratio.[39] Thus, this empirical result is consistent with our interpretation of process intensity.

Table 3 Here

The next three columns show the intangible investment rate, physical investment rate, and intangible capital stock, all scaled by physical capital. None of these variables have a monotonic relationship with our process intensity portfolio ranking, but the difference between the averages in the fifth and first portfolios are all large and positive.

The final three columns show our compensation and salary measures.[40]

6 Empirical Results

This section displays our main empirical results. First, we look at Execucomp data and show that higher process intensity is associated with higher total compensation, deferred compensation, and deferred compensation as a fraction of the total compensation.

[36] This terminology follows Park (2019) and Kazemi (2022).

[37] We construct firm book equity following the standard method outlined in, e.g., Bali, Engle and Murray (2016).

[38] See Peters and Taylor (2017), Kazemi (2022), Belo et al. (2022).

[39] Kazemi (2022) shows the same result for the iB/M ratio.

[40] Compensation is scaled by physical capital, and the II salary is scaled by the industry average.

Second, we show that higher process intensity is associated with higher II job salaries relative to industry peers.

We end with a robustness subsection. In that subsection, we provide three further tests. First, we exploit the granularity of the BGT data and show that II job salaries with a process focus are more affected by firm-level process intensity than II job salaries with a product focus. Second, we re-estimate our Execucomp tests, this time restricting our sample to executives who worked in at least two firms. This alleviates concerns about higher pay being a firm characteristic. Third, we study the relationship between uncertainty, compensation, and process intensity. If the compensation and process intensity connection is due to agency frictions, as we propose in this paper, we should see the association between process intensity and compensation strengthen when there are larger agency frictions. We find that this is the case.

We test the relationship between physical capital and process intensity. This relationship hinges on the model parameter, ρ. In the model, physical capital growth follows:

$$\frac{\mathrm{d}K_t}{K_t} = \left(-\delta_K + A\left[a\, i_t^{\rho} + (1-a)\left((1-\theta)o_t\right)^{\rho}\right]^{\frac{1}{\rho}}\right)\mathrm{d}t + \sigma \mathrm{d}Z_t.$$

Thus, the parameter ρ reflects the substitution elasticity. A priori, ρ could imply that physical investment and process intangibles are substitutes or complements in the physical capital production process. We have assumed they are complements in the model. Here we test that assumption. If physical investment and process intangibles are substitutes, then conditional on the stock of intangibles, a higher process intensity should reduce physical capital investment. The reverse is true if they are complements.

We estimate the following panel regression:

$$PhysInv_{ft} = y_t + y_j + \beta_1 ProcIn_{ft} + \beta_2 IK_{ft} + \beta_3 iB/M_{ft} + \beta_4 Size_{ft} + \beta_5 Sales_{ft} + \varepsilon_{ft} \quad (6.1)$$

where $PhysInv_{ft}$ is physical capital investment (Compustat: capex) divided by the physical capital stock.

Table 4 displays the results. Looking at the top row, we see that the sign of the process intensity coefficient is positive across specifications. Taking the final three columns together, we conclude that, on average, physical investment and process intangibles are complementary in the creation of physical capital. That is, $\rho > 0$. The effect is statistically and economically significant: a one standard deviation increase in process intensity is associated with around a 3% increase in physical capital investment.

Table 4 Here

This result and the results of Table 1 are (almost) mirror images of each other. We can imagine freezing the amount of intangible capital and physical capital in the firm and simply varying the process intensity of the firm. According to the model, when process intensity is lowered, current sales should go up, and on the flip side, as we increase process intensity, more of the firm's intangible capital stock is devoted to physical capital production. While this second effect depends on the parameter ρ, under our specification, we have shown that increases in process intensity are associated with increases in physical capital investment. Thus, we see a clear pendulum: as we vary the process intensity of the firm, we are shifting resources from current sales to "future sales" in the form of investment.

6.1 Process Intensity, Compensation, and Salaries

6.1.1 The Direct Effect

We have shown that process intensity is associated with lower contemporaneous sales and higher physical capital investment. These results do not depend on our proposed agency frictions. We now turn to compensation and salaries. The following regression estimates are our main empirical results. We show that higher process intensity is associated with higher total and deferred compensation, as well as higher salaries for II job employees relative to their industry peers. These results correspond to what we called the direct effect of agency frictions on the process intensity-compensation association.

We estimate specifications of the form:

$$\text{Compensation Measure}_{ft} = y_t + y_j + \beta_1 ProcIn_{ft} + \beta_2 IK_{ft} + \beta_3 Size_{ft} + \beta_4 iB/M_{ft} + \beta_5 Sales_{ft} + \varepsilon_{ft} \tag{6.2}$$

where the variables are the same as before. One difference here is in the final listed control. For example, when use deferred compensation as our dependent variable, we will control for total compensation. Similarly, when the relative II job salary is the dependent variable, we will control for total compensation. The dependent variables are either total compensation divided by physical capital, deferred compensation (stocks and option awards) divided by total compensation, or the posted II job salary relative to industry peers in the same year.

Table 5 displays the results when the dependent variables are either total or deferred compensation, both from Execucomp. Looking at row one, we see that the increases in process intensity are associated with increases in both types of executive compensation. A one standard deviation increase in process intensity is associated with a 7% increase in total executive compensation, for a given quantity of intangibles. The effects on deferred compensation are similar. A one standard deviation increase in process intensity is associated with an 8% increase in deferred compensation. The sign on intangible capital (row 2) is positive throughout. This is consistent with the model: We can either think of fixing the intangible capital level and increasing process intensity to increase agency frictions, or we can fix the process intensity but increase the amount of intangibles subject to this emphasis on process innovation to increase agency frictions. Firm size is associated with decreases in total compensation and deferred compensation. It may be the case that executives controlling bigger firms accept lower pay due to the non-compensation benefits of "empire building." Higher iB/M ratios are also associated with lower compensation. Book-to-market ratios can be used as measures of performance. For example, a low iB/M ratio implies market values the firm much more than its balance sheet shows. This higher "bang for the buck" could be associated with better management and, therefore, higher pay for executives. Higher sales are associated with higher total compensation and deferred compensation.

Table 5 Here

The previous results show that both forms (total and deferred) of compensation are increasing in process intensity, but they do not tell us how the composition of payment changes. According to the model, the payment boundary and average promised utility increase in process intensity (Figure 6). The empirical analog of this result is that deferred compensation should become a larger fraction of total compensation as process intensity increases. We re-estimate equation (6.2) using the ratio of deferred to total compensation as our dependent variable.

Table 6 displays the results. The top row shows us that process intensity increases are associated with a larger fraction of compensation deferred. The same is true of intangible capital (row two). At first blush, it may seem that the two coefficients (on process intensity and intangible capital) should be equal, since it is the quantity $(1-\theta)o$

that affects agency frictions and investment. However, o is a state variable, so increasing o can affect other firm decision variables, which can then affect the coefficient estimates. The key is that both coefficients have the same sign. The effect sizes for process intensity are smaller than in the specifications that look solely at total or deferred compensation. A one standard deviation increase in process intensity is associated with a 1-2% increase in the fraction of total compensation deferred. The fact that this effect is smaller than the previous ones tells us that process intensity is affecting both the current and future components of compensation.

Table 6 Here

Up to this point, we have examined executive pay, but executives are unlikely to be directly involved in the innovation or investment process. At the same time, executives probably have the most scope for extracting rents from their firms. II job employees, though less powerful than c-suite executives, are directly involved in implementing and developing new processes. It is their efforts that determine success or failure. Because internal process innovations and improvements are inherently opaque (especially to outsiders), it is difficult to assess the efficacy of the hours worked by II employees even if their managers can see that the quantity of working hours is high.In the next two tables, we will show that II employee wages and salaries are also increasing in process intensity, lending credence to hypothesis that non-executives can extract rents, too. To the best of our knowledge, we are one of the first papers to test the consequences of dynamic agency theory in compensation of non-executives.

Table 7 shows our estimation results when we use the relative II job salary as the dependent variable in equation (6.2). As explained in the Data section, these are posted salaries, not total wage bills. Therefore, we cannot scale by firm size or capital. Instead, we scale by the leave-one-out industry-year mean of the II job salary. The coefficients can be interpreted as "how much more, relative to similar peers, does a firm pay for a given set of skills?" The first row shows that a one standard deviation increase in process intensity is associated with a 3% increase in relative II job salary. The coefficient on process intensity is similar across specifications. Note that our sample size is much smaller, given that Burning Glass Data only starts in 2010 and not all vacancy postings have wage data.

Table 7 Here

6.1.2 The Indirect Effect

This section verifies what we have called the indirect effect of agency frictions on the process intensity-compensation association. We focus on $1/\rho$, which measures the complementarity between physical investment and process intangibles (see equation 3.6). In the model section, we calibrated ρ based on Lin (2012), but now we will estimate a proxy in the data.

Firms with lower values of ρ will have stronger complementarity between physical investment and process intensity. That is, the marginal effect of physical capital investment on physical capital growth should be increasing in process intensity. Due to data limitations, we cannot estimate ρ for each firm. Instead, we estimate ρ for each industry.[41] We then assume that all firms in that industry have the same ρ.

We estimate:

$$\begin{aligned}\frac{\text{Three Year Capital}_{ft}}{K_{ft}} &= \alpha_j + \beta_{1j}\text{Physical Investment}_{ft} + \beta_{2j}\text{Process Intensity} \\ &+ \beta_{3j}\text{Intangible Capital} + \beta_{4j}Size \\ &+ \beta_{5j}\text{Physical Investment} \times \text{Process Intensity} \\ &+ \beta_{6j}iB/M_{ft} + \beta_{7j}Sales_{ft} + \varepsilon_{ft} \qquad (6.3)\end{aligned}$$

The dependent variable is the sum of real physical capital over years t through $t+2$ divided by real physical capital in year t.

Notice that the coefficients have j subscripts. This is because we estimate the previous equation for each industry. β_{5j} is our measure of $1/\rho$. This coefficient measures how much process intensity increases the efficiency of physical investment. As we wrote above, we assume that all firms in industry j have the same ρ_j.[42]

With these estimates in hand, we then group firms based on $1/\rho_j$. We form two bins based on β_{5j}.[43] Firms in bin 1 have smaller estimates of β_{5j}, or, larger estimates of ρ.

Our goal is to study the interaction of the bins and process intensity. Recall (3.7). The agent can extract more benefits when ρ is smaller, and process intensity is higher. The intuition is that for small ρ firms, process intangibles are more "important" in the production of physical capital. Thus, the agents whose effort controls the efficacy of

[41] We define industry as 3 digit SIC before 2002 and 4 digit NAICS after 2002.

[42] Note that ρ_j and β_{5j} are not equivalent. The latter is a proxy of the former. Since we are interested in relative ranks across firms, this estimate is sufficient.

[43] The bins are based on the firm-level distribution of β_{5j} not the industry-level distribution.

process intangibles can exert more power over the firm.

The effect on the benefit function should be reflected in compensation. Firms with smaller ρ values should see a stronger relationship between process intensity and compensation. This follows from the definition of u_t in the model. We test this hypothesis by estimating the following:

$$\text{Compensation Measure}_{ft} = \alpha_b + \beta_{b1}\text{Process Intensity}_{ft} + \boldsymbol{X}_{ft}\boldsymbol{\beta}_b + \varepsilon_{ft} \tag{6.4}$$

The subscript b refers to the complementarity bin. Essentially, we are estimating the equation (6.2) but allowing the coefficients to vary with the bins based on $1/\rho$ (e.g., there will be a different β_1 for bin 1 and bin 2). Our control variables are the same as before, and a bin-date fixed effect. In the table, we display only the coefficients on process intensity.

Table 8 Here

Table 8 displays the results. Looking down at each column, we see that the coefficients are increasing as we move from bin 1 to bin 2, as expected. In the second row (i.e., the coefficient corresponding to high complementarity firms), the effect of process intensity on compensation is always significant. In fact, the point estimates more than double for each compensation measure as we move from bin 1 to bin 2.

This section has established our main results: Compensation and process intensity are tightly linked. This statement applies to total and deferred executive pay. It also applies to the salaries of highly skilled, innovation-based workers. Finally, these results interact with process innovation and physical capital investment complementarity predictably. The more important process intensity is to the firm's capital growth process, the more rents the agent can extract, ceteris paribus.

6.2 Robustness and Further Results

This subsection presents three robustness and placebo tests meant to rule out alternative hypotheses.

In the first test, we exploit the granularity of the Burning Glass data further and look at the difference in salaries between II jobs with a process focus and II jobs with a more product focus. For example, a chemist working at a drug company is likely working on product innovations (new drugs) versus process innovations (reducing investment costs).[44] On the other hand, an organizational specialist working on supply chain management is more likely to be working on process innovations. We exploit the richness of the Burning Glass Data to distinguish between these types of skills. We define "R&D skills" to be those focused on new scientific discoveries or similar advances.[45] Examples include Medical Research, Quantum Mechanics, Neuroscience, and Clinical Research. The other category we define is "Process skills." These could also be called organizational capital skills.[46] Examples here include Logistics, Process Improvement, Operations Analysis, and Supplier Relationship Management. With these definitions in hand, we re-estimate our II job salary regressions using each of these subcategories as the dependent variable.[47] Our hypothesis is that Process skill job salaries should be more affected by the agency frictions in our model, and, thus, their salaries should be increasing more in process intensity.[48]

Table 9 displays the results of estimating equation 6.2 restricted to either R&D skills jobs salaries or Process skills jobs salaries. The set of controls is the same as in the pooled regression. The top row shows that there is no significant relationship between process intensity and the salaries of R&D skills jobs. However, process intensity is associated with an increase in process skills jobs' salaries. Notice that the coefficient is similar in magnitude to the analogous coefficients in Table 7. Within the set of skilled, II job employees, some are more likely to be involved with process innovations relative to product innovations. We have shown that, even with such a fine distinction, there are differences in the sensitivities of salaries to process intensity. This is in line with the empirical interpretation of the model: Those employees best able to extract rents from the process innovations are the ones whose compensation should increase with process intensity.

Table 9 Here

In the second test, we ask if better executives simply self-select into process intense

[44] Of course, much of this is subjective. Is discovering a new chemical compound that leads to multiple new drugs a process or product innovation?

[45] While this is not the same as product innovation, as our previous example showed, they are more likely to be tilted in that direction.

[46] Eisfeldt and Papanikolaou (2013).

[47] When we compute the leave-one-out industry average, we do so using the subcategory.

[48] Our classification system for jobs can assign a job to both categories simultaneously. This makes sense since high skill employees are frequently asked to have an assortment of skills.

firms and hence receive higher compensation. To test this, we estimate executive-level regressions on the subset of executives who change firms in our sample. That is, we estimate:

$$\begin{aligned}\text{Compensation Measure}_{ift} = y_t + y_j + \beta_1 ProcIn_{ft} + \beta_2 IK_{ft} \\ + \beta_3 Size_{ft} + \beta_4 iB/M_{ft} + \beta_5 Sales_{ft} + \varepsilon_{ft}\end{aligned} \tag{6.5}$$

This equation looks similar to (6.2). The key difference is in the dependent variable, which is measured at the executive-firm-date (ift) level. In (6.2) we looked at firm-date level regressions.

Table 10 displays the results. The coefficient estimates on process intensity are similar to the full sample, firm-level estimates: A one standard deviation increase in process intensity is associated with a 9% increase in executive compensation.

Table 10 Here

In our third test, we look at firm-level measures of agency frictions to test if the association between process intensity and compensation is higher when frictions are stronger. According to the model, firms facing more uncertainty in the physical capital growth process should be exposed to greater agency frictions.

We compute and industry-year level of uncertainty and assign all firms within that industry-year to have the same level of uncertainty. Much like for our complementarity measure, data limitations preclude us from calculating a firm-level measure of uncertainty. Within each industry-year, we calculate the cross-sectional variance of physical capital growth at the firm level. This is our measure of σ in the model and proxies for the severity of agency frictions.

We split the firm-level distribution of uncertainty into a high and low bin each year. Then, like our complementarity regressions, we estimate the following panel regressions:

$$\text{Compensation Measure}_{ft} = \alpha_b + \beta_{b1}\text{Process Intensity}_{ft} + \boldsymbol{X}_{ft}\boldsymbol{\beta}_b + \varepsilon_{ft} \tag{6.6}$$

where now b refers to the uncertainty bin.

Table 11 displays the results. Once again, we see that firms in the high bin have significant and positive coefficients on process intensity. On top of that, the high bin coefficients are always larger than the low bin ones. For example, when moving from a low uncertainty to high uncertainty firm, the association between process intensity and total executive compensation increases by 4%.

Table 11 Here

7 Conclusion

We presented and studied a new empirical fact: Higher process intensity is associated with higher pay for executives and skilled employees. To rationalize this fact, we developed a dynamic principal-agent model in which agent effort determined the efficacy of process intangibles on the physical capital growth process. The model delivered two key channels: A direct effect and indirect effect of process intensity on compensation. The direct effect states that higher process intensity increases the benefits of shirking, so the agent must be further compensated to ensure full effort. The indirect effect states that for a given level of process intensity, higher process intangible-physical capital investment complementarity increases the hold up power the agent has over the firm. This leads to a larger effect of process intensity on compensation for all levels of process intensity.

We verified these two main effects in the data using measures of executive and skilled labor pay. Our baseline specifications showed that a one standard deviation increase in process intensity is associated with an 8% increase in executive pay and a 3% increase in skilled labor pay. When process intangible-physical investment complementarity is high (i.e., the hold up problem is serious), these numbers increase to 16% and 5%, respectively.

We have taken the level of process intensity as given. However, even if changing this ratio is costly, over the medium to long-term we expect it to be endogenous. Studying this choice is left for future work. We have also not considered the asset pricing implications of process intensity and agency. Adding a stochastic discount factor as in Kogan and Papanikolaou (2014) to the model would provide further interesting testable implications.

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A First best benchmark

To compare with the main model, we study in this section the first best benchmark, where the investment does not subject to agency friction. The firm's problem is

$$V(K,O) = \max_{I,S} \mathbb{E}\Big[\int_0^\infty e^{-rs} Y_s \mathrm{d}s \Big| K_0 = K, O_0 = O\Big], \tag{A.1}$$

subject to (3.1), (3.3), and (3.4) with $e = 1$.

The homothetic property in K allows us to introduce the following decomposition of the value function:

$$V(K,O) = Kv(o), \tag{A.2}$$

where $o = O/K$.

Proposition A.1 *The function v in (A.2) satisfies the following HJB equation*

$$\begin{aligned}(r+\delta_K)v = \max_{i,s\geq 0} \Big\{ &(v - o\partial_o v)d(i,o) + (s - (\delta_O - \delta_K)o)\partial_o v + \frac{1}{2}o^2\sigma^2\partial^2_{oo}v \\ &+ \mu(\theta o)^{1-\alpha} - i - s - \frac{Q_k}{c_K} i^{c_K} - \frac{Q_O}{c_O}\Big(\frac{s}{o}\Big)^{C_o} o\Big\},\end{aligned} \tag{A.3}$$

where $d(i,o) = A[ai^\rho + (1-a)(1-\theta)^\rho o^\rho]^{1/\rho}$. When $(v - o\partial_o v)\partial_i d(0,o) > 1$, the optimal investment in the physical capital satisfies the first order condition

$$(v - o\partial_o v)\partial_i d(i^*, o) = 1 + Q_K(i^*)^{c_K - 1}; \tag{A.4}$$

otherwise, $i^* = 0$. If $\partial_o v > 1$, then the optimal investment in the intangible capital is

$$s^* = o\Big(\frac{\partial_o v - 1}{Q_o}\Big)^{\frac{1}{c_O - 1}}; \tag{A.5}$$

otherwise $s^* = 0$.

Figure 10 provides the first best solution with the parameters in Table 2.[49] As the intangible-physical capital ratio increases, investment in the physical capital becomes more efficient, hence both the principal's value (top left panel) and the physical capital investment over physical capital stock ratio (top right panel) increase. The intangible

[49]We impose Neumann boundary condition when o is sufficiently large. The boundary condition at $o = 0$ is not needed because the drift of o is non-negative and the volatility of o vanishes at $o = 0$.

Figure 10: First Best Value Function

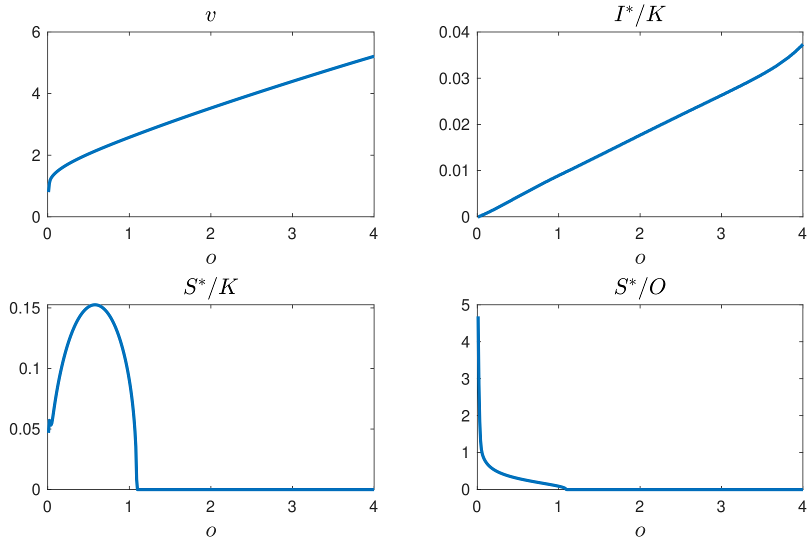

Figure 11: First best: value function v, optimal investment in the physical capital over the physical capital stock, optimal investment in the intangible over physical capital stock, and optimal investment in the intangible over intangible capital stock. The parameters are listed in Table 2.

investment over physical capital stock displays a hump shape in the bottom left panel. However the intangible investment over intangible capital stock displays a decreasing and convex pattern in the bottom right panel. When o is close to zero, even though the intangible investment is small comparing to the physical capital stock, it is large comparing to the intangible capital stock. When o is sufficiently away from zero, both S^*/K and S^*/O decrease in o due to the decreasing return to scale of the intangible capital in generating firm cash flows.

Proof of Proposition A.1

Recall the value function V in (A.1). It follows from the dynamic programming principle that $\widetilde{V}_t = e^{-rt}V(K_t, O_t) + \int_0^t e^{-rs}(dY_s - dC_s)$ is a supermartingale for an arbitrage strategy (i, s) and is a martingale under the optimal strategy. Using (A.2) and (4.11), we obtain from Itô's formula that

$$
\begin{aligned}
d\big(Kv(o)\big) =& \Big\{Kvd(i,o) - \delta_K Kv + K\partial_o v\big[s - (\delta_O - \delta_K)o - o\,d(i,o)\big] + \frac{1}{2}Ko^2\sigma^2\partial^2_{oo}v\Big\}\mathrm{d}t \\
&+ K\sigma\big(v - o\,\partial_o v\big)dZ_t.
\end{aligned}
$$

The drift of $\widetilde{V}$ (divided throughout by $e^{-rt}K$) is

$$
\begin{aligned}
&-rv + vd(i,o) - \delta_K v + \partial_o v\big[s - (\delta_O - \delta_K)o - o\,d(i,o)\big] + \frac{1}{2}o^2\sigma^2\partial^2_{oo}v \\
&+ (\theta o)^{1-\alpha} - i - s - \frac{Q_K}{c_K}i^{C_K} - \frac{Q_O}{c_O}\big(\frac{s}{o}\big)^{C_o}o
\end{aligned}
$$

Therefore the HJB equation (A.3) follows from the fact that the drift of $\widetilde{V}$ is nonpositive for any i, s and is zero for optimal i^* and s^*. The first order conditions in i^* and s^* follow from the same argument as in Proposition 4.1.

B Optimal investment

Dependence of the optimal investment in the physical and intangible capital on θ and ρ are presented in Figures 12 and 14. As θ increases, less intangible capital is used in the process innovation and the investment in the physical capital becomes less efficient. As a result, investment in both physical and intangible capital decrease. As ρ increases, complementarity between the physical capital investment and the intangible capital decreases in the physical capital accumulation, resulting decreasing in both physical and intangible capital investment.

C Proofs for Lemma 4.1 and Proposition 4.1

Proof of Lemma 4.1

Consider a probability measure $\mathbb{P}^0$ under which

$$
dK_t = \sigma K_t dZ^0_t
$$

Figure 12: Optimal Investment: Varying θ

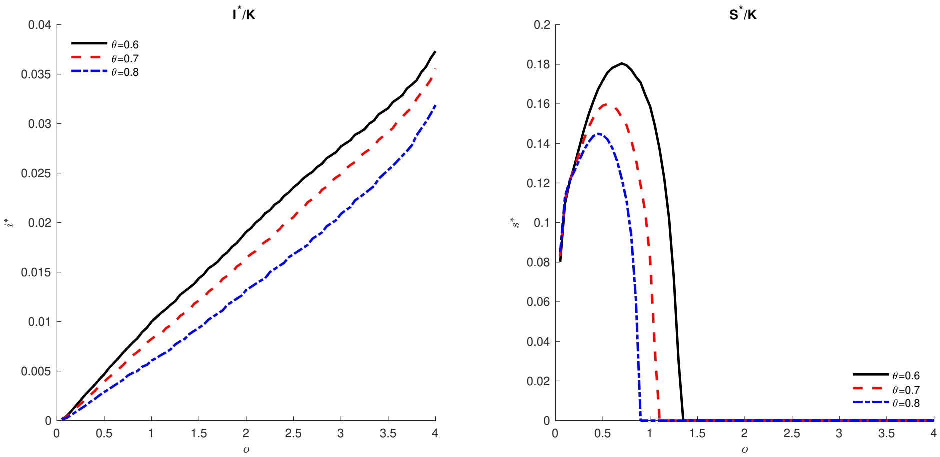

Figure 13: Optimal investment in the physical and intangible capital for different θ. Optimal investment ratios I^*/K and S^*/K are evaluated at the mean of U/K conditioning on O/K. The parameters are listed in Table 2.

Figure 14: Optimal Investment: Varying ρ

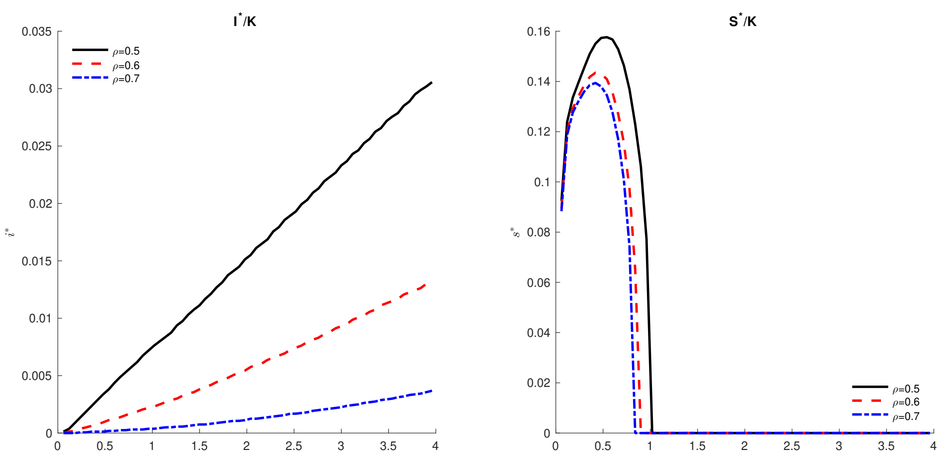

Figure 15: Optimal investment in the physical and intangible capital for different ρ. Optimal investment ratios I^*/K and S^*/K are evaluated at the mean of U/K conditioning on O/K. The parameters are listed in Table 2.

with a $\mathbb{P}^0$-Brownian motion Z^0. Introduce an equivalent probability measure $\mathbb{P}^e$ such that Z^e, defined via

$$dZ_t^e = dZ_t - \frac{D(e_t, I_t, O_t) - \delta_K K_t}{\sigma K_t},$$

is a Brownian motion under $\mathbb{P}^e$. Then K follows the dynamics (3.4).

Under $\mathbb{P}^0$, the agent's continuation value U in (3.8) has the semimartingale decomposition

$$\mathrm{d}U_t = \mathrm{d}H_t + \varphi_t \mathrm{d}K_t, \tag{C.1}$$

where φ arises from the martingale representation theorem. We will use dynamic programming to determine the finite variation process H. To this end, it follows from (3.8) and the dynamic programming that $\widetilde{U}_t = e^{-\gamma t}U_t + \int_0^t e^{-\gamma s}(\lambda\Lambda_s(1-e_s)\mathrm{d}s + \mathrm{d}C_s)$ is a super-martingale under $\mathbb{P}^e$ for arbitrary effort e and a martingale for the optimal effort e^*. We obtain from Itô's formula that

$$\begin{aligned}\mathrm{d}\widetilde{U}_t = e^{-\gamma t}\Big\{ & -\gamma U_t \mathrm{d}t + \mathrm{d}H_t + \lambda\Lambda_t(1-e_t)\mathrm{d}t + \mathrm{d}C_t \\ & + \varphi_t K_t\big(d(e_t, i_t, o_t) - \delta_K\big)\mathrm{d}t + \varphi_t K\sigma dZ_t^e\Big\},\end{aligned}$$

where $d(e,i,o) = A[ai^\rho + e(1-a)(1-\theta)^\rho o^\rho]^{1/\rho}$. The drift of $\widetilde{U}$ is nonpositive for an arbitrary effort e and is ero for the optimal effort e^*. Therefore,

$$dH_t = \big(\gamma U_t + \varphi_t\delta_K K_t\big)\mathrm{d}t - \mathrm{d}C_t - \max_{e\in\{0,1\}}\Big\{\lambda\Lambda_t(1-e) + \varphi_t K d(e, i_t, o_t)\Big\}\mathrm{d}t. \tag{C.2}$$

The optimal effort $e_t^* = 1$ if and only if

$$\varphi_t K d(1,i,o) \geq \lambda\Lambda_t + \varphi_t K d(0,i,o).$$

Recall the definition of Λ from (3.6), the previous incentive compatibility condition is equivalent to

$$\varphi_t \geq \lambda.$$

When the previous condition holds, $e^* = 1$ and we obtain from (C.1) and (C.2) that U follows (4.1).

Proof of Proposition 4.1

We drive the HJB equation (4.7) from the dynamic programming principle. To this end, it follows from the dynamic programming principle that $\widetilde{V}_t = e^{-rt}K_t v(0_t, u_t) + \int_0^t e^{-rs}(Y_s \mathrm{d}s - \mathrm{d}C_s)$ is a supermartingale under arbitrary strategy (i, s, C) and a martingale under the optimal strategy. Using Itô's formula, together with (4.11) and (4.12), we calculate

$$\begin{aligned}
\mathrm{d}\big(Kv(o,u)\big) =& \Big\{ Kv\, d(i,o) - \delta_K K v + K\partial_o v\big[s - (\delta_O - \delta_K)o - o\, d(i;o) + \sigma^2 o\big] \\
&+ K\partial_u v\big[(\gamma + \delta_K)u - u\, d(i,o) + \sigma^2(u - \varphi)\big] \\
&+ \frac{1}{2}Ko^2\sigma^2\partial^2_{oo}v + \frac{1}{2}K\sigma^2(\varphi - u)^2\partial^2_{uu}v - Ko\sigma^2(\varphi - u)\partial^2_{ou}v \\
&+ K\sigma^2\big[-o\partial_o v + (\varphi - u)\partial_u v\big]\Big\}\mathrm{d}t \\
&+ K\sigma\big[v - o\partial_o v + (\varphi - u)\partial_u v\big]\mathrm{d}Z^{e^*} - \partial_u v \mathrm{d}C_t.
\end{aligned}$$

The drift of $\widetilde{V}$, divided throughout by $e^{-\gamma t}K$, is

$$\begin{aligned}
&- rv + v\, d(i,o) - \delta_K v + \partial_o v\big[s - (\delta_O - \delta_K)o - o\, d(i,o) + \sigma^2 o\big] \\
&+ \partial_u v\big[(\gamma + \delta_K)u - u\, d(i,o) + \sigma^2(u - \varphi)\big] \\
&+ \frac{1}{2}o^2\sigma^2\partial^2_{oo}v + \frac{1}{2}(\varphi - u)^2\sigma^2\partial^2_{uu}v - o(\varphi - u)\sigma^2\partial^2_{ou}v + \sigma^2\big[-o\partial_o v + (\varphi - u)\partial_u v\big] \\
&+ \mu(\theta o)^{1-\alpha} - i - s - \frac{Q_K}{c_K}i^{c_K} + \frac{Q_O}{c_O}(i/o)^{i_O}o + (\partial_u v + 1)\Big(-\frac{1}{K}\frac{\mathrm{d}C_t}{\mathrm{d}t}\Big).
\end{aligned}$$

Therefore the dynamic programming principle implies that the HJB equation satisfied by v is

$$\begin{aligned}
(r + \delta_K)v = \max_{i,s,\varphi,C}\Big\{ &\big(v - o\,\partial_o v - u\,\partial_u v\big)d(i,o) + \big(s - (\delta_O - \delta_K)o\big)\partial_o v + (\gamma + \delta_K)u\,\partial_u v \\
&+ \frac{1}{2}o^2\sigma^2\partial^2_{oo}v + \frac{1}{2}(\varphi - u)^2\sigma^2\partial^2_{uu}v - o(\varphi - u)\sigma^2\partial^2_{ou}v \\
&+ \mu(\theta o)^{1-\alpha} - i - s - \frac{Q_K}{c_K}i^{c_K} + \frac{Q_O}{c_O}(i/o)^{i_O}o + (\partial_u v + 1)\Big(-\frac{1}{K}\frac{\mathrm{d}C_t}{\mathrm{d}t}\Big)\Big\}. \quad \text{(C.3)}
\end{aligned}$$

Because $\mathrm{d}C_t/\mathrm{d}t$ is can be infinite, if $\partial_u v + 1 < 0$, the right-hand side of the previous equation can be infinite by choosing infinite $\mathrm{d}C_t/\mathrm{d}t$. Therefore, the wellposedness of the HJB equation requires that $\partial_u v + 1 \geq 0$. As a result, the equation (C.3) is transformed to

(4.7). In order to incentivize the full effort $e^* = 1$, the incentive compatibility condition restricts $\varphi \geq \lambda$.

D Complementarity

This appendix summarizes our results on the complementarity of different types of intangibles with respect to physical investment. This is important because a claim in the model is that only process intangibles are complementary with physical investment. This assumption leads to the hold-up channel we emphasize. We check this claim in the data by estimating panel regressions with physical investment interacted with different types of intangibles.

We estimate two different regressions. First, we estimate:

$$\begin{aligned}\frac{\text{Three Year Capital}_{f,t+2}}{K_{f,t-1}} &= \alpha + \boldsymbol{\beta}'\boldsymbol{X}_{ft} + \beta_1 \text{Phys. Inv.}_{ft} \\ &+ \beta_2 \text{Proc. Int.}_{ft} + \beta_3 \text{Prod. Int.}_{ft} \\ &+ \beta_4 \text{Proc. Int.}_{ft} \times \text{Phy. Inv.}_{ft} + \beta_5 \text{Prod. Int.}_{ft} \times \text{Phy. Inv.}_{ft} + \varepsilon_{ft}.\end{aligned} \tag{D.1}$$

The dependent variable is three-year physical capital growth, $\boldsymbol{X}_{ft}$ is a vector of controls (size, iB/M ratio, and sales to capital ratio), Phys. Int. is physical capital investment (divided by physical capital), Proc. Int. is the ratio of process intangibles to physical capital, and Prod. Int. is the ratio of product intangibles to physical capital. Second, we estimate:

$$\begin{aligned}\frac{\text{Three Year Capital}_{f,t+2}}{K_{f,t-1}} &= \alpha + \boldsymbol{\beta}'\boldsymbol{X}_{ft} + \beta_1 \text{Phys. Inv.}_{ft} \\ &+ \beta_2 \text{Int. Cap.}_{ft} + \beta_3 \text{ProcIn}_{ft} \\ &+ \beta_4 \text{Int. Cap.}_{ft} \times \text{Phy. Inv.}_{ft} + \widetilde{\beta}_5 \text{ProcIn}_{ft} \times \text{Phy. Inv.}_{ft} + \varepsilon_{ft}.\end{aligned} \tag{D.2}$$

These two regressions capture the same idea: If $\beta_5 > \beta_4$ in equation (D.1), then process intangibles are more complementary with physical investment than product intangibles, and if $\widetilde{\beta}_5 > 0$ in equation (D.2) then the same thing is true. This is the source of the hold-up friction and motivation for our modeling assumptions. The first regression looks at effects of changing the level of one type of intangible while fixing the level of the other. The second regression looks at changing the composition of intangibles while fixing the total level of intangibles.

As in the body of the paper, we estimate the previous two regressions within industry, which means all the coefficients are industry dependent. We summarize the results of the estimates by looking at the mean value of the coefficients of interest across industries.

We also estimate the above two regressions using pooled panel regressions with industry and date fixed effects and clustering at the industry-date level. We estimate each panel regression on two different subsamples: The full sample and the sample restricted to firms with non-zero process intensity.

Table 12 displays the results. The first row shows the average coefficient value across industries when we estimate complementarity within industry (as in the body of the paper). The first column shows the average value of $\widetilde{\beta}_5$ in equation (D.2). The second column shows the average value of β_4 in equation (D.1). The final column shows the average value β_5 in equation (D.1). The first row is consistent with our hypothesis: $\widetilde{\beta}_5 > 0$ and $\beta_4 > \beta_5$. The second row shows the results from the pooled panel regression when using the full sample. Once again, the results are consistent with the hypothesis.[50] The final row repeats the panel regression but restricts the sample to firms with non-zero process intangibles. The anticipated effects are stronger than in the full sample results. This is encouraging, since the model is meant to capture firms that engage in both types of intangible use.

Table 12 Here

[50] $\widetilde{\beta}_5$ is statistically insignificant, however.

E Tables

Table 1: Sales and Process Intensity

	Dependent variable:			
	Sales / Physical Capital			
	(1)	(2)	(3)	(4)
Process Intensity	-0.114^{***}	-0.103^{***}	-0.109^{***}	-0.099^{***}
	(0.009)	(0.009)	(0.008)	(0.008)
Intangible Capital / Physical Capital	0.300^{***}	0.297^{***}	0.343^{***}	0.354^{***}
	(0.014)	(0.014)	(0.010)	(0.010)
iB/M Ratio			0.146^{***}	0.144^{***}
			(0.020)	(0.017)
Size			0.055^{***}	0.087^{***}
			(0.008)	(0.007)
Fixed effects	No	No	Industry + Date	Industry + Date
Observations	23,498	23,498	22,959	22,959
Note:		*p<0.1; **p<0.05; ***p<0.01		

This table shows the relationship between firm-level sales (divided by physical capital) and process intensity (in standard deviation units). The results come from estimating panel regressions (2.1). Data definitions are found in the Data section of the paper, and Compensation refers to total executive compensation from Execucomp. All variables aside from process intensity are logged. Industry fixed effects use one broad one digit SIC codes (after 2002) or one digit NAICS (before 2002), and date fixed effects correspond to years. Clustering is performed at the industry-date level, where industry is either three digit SIC or four digit NAICS (delineated by 2002, again), and date is year.

Table 2: Model Parameters

Symbol	Variable	Value	Reference
a	Weight of the physical investment in the physical capital accumulation	0.45	Lin (2012)
α	Cobb-Douglas parameter of the physical capital in cash flow	0.6	Belo et al. (2022)
A	Scale parameter in the physical capital accumulation	0.09	Lin (2012)[51]
θ	Percentage of intangibles used in the product innovation	0.7	Lin (2012)
ρ	CES parameter in the physical capital accumulation	0.5	Lin (2012)
λ	Agent shirking benefit parameter	0.07	Calibrated from data
σ	Volatility of $\log K$	0.22	Calibrated from data
δ_K	Physical capital deprecation rate	0.1	Lin (2012)
δ_O	Intangible capital deprecation rate	0.2	Lin (2012)
Q_K	Scale parameter of the physical investment adjustment cost	56.55 (monthly)[52]	Eisfeldt and Papanikolaou (2013)
c_K	Convexity parameter of the physical investment adjustment cost	1.8 (monthly)	Eisfeldt and Papanikolaou (2013)
Q_O	Scale parameter of the intangible investment adjustment cost	625 (monthly)	Eisfeldt and Papanikolaou (2013)
c_O	Convexity parameter of the physical investment adjustment cost	3.2 (monthly)	Eisfeldt and Papanikolaou (2013)
μ	Productivity rate	0.45	Ward (2022)
γ	Agent impatient parameter	0.045	Calibration from data
r	Interest rate	0.04	Ward (2022)

This table shows the parameters used in our simulations. Citations are given for the parameters based on the existing literature.

Table 3: Summary Statistics by Process Intensity

$1-\theta$ Port.	iB/M Ratio	Int. Inv.	Phy. Inv.	Int. Stock	Compensation	II Job Wage	Def. Comp.
1	0.637	0.724	0.117	2.796	49.690	0.945	12.302
2	0.672	0.514	0.131	1.997	51.442	1.025	14.835
3	0.532	0.720	0.139	3.327	65.725	1.094	21.813
4	0.520	0.943	0.149	3.834	136.783	1.143	60.768
5	0.529	1.495	0.146	6.599	155.727	1.122	44.408

This table shows means of select variables by process intensity level. Each year firms are sorted into five equally spaced portfolios (bins) based on their values of $1-\theta$. Bins are re-balanced each year. Averages of the variables displayed as column titles are computed for each bin. The iB/M ratio is the book-to-market ratio when book equity has intangible capital added in. All variables aside from the iB/M ratio and II Job Wage are relative to the firm's physical capital stock. Intangible investment is computed as described in the Data section. Physical capital investment is capital expenditures in Compustat. The intangible capital stock is as described in the Data section. Compensation is total compensation from Execucomp. II Job Wage is the average posted II job wage from BGT divided by the industry average II job wage. Deferred compensation is stock and option awards from Execucomp.

Table 4: Physical Investment and Process Intensity

	Dependent variable:			
	Physical Capital Investment			
	(1)	(2)	(3)	(4)
Process Intensity	0.002	0.027***	0.018***	0.033***
	(0.007)	(0.007)	(0.007)	(0.006)
Intangible Capital	0.140***	0.005	0.191***	0.096***
	(0.010)	(0.013)	(0.009)	(0.010)
Size		−0.161***		−0.133***
		(0.010)		(0.010)
iB/M Ratio		−0.009**		0.061***
		(0.005)		(0.004)
Sales		0.339***		0.293***
		(0.021)		(0.019)
Fixed effects	No	No	Industry + Date	Industry + Date
Observations	23,316	22,782	23,316	22,782

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows the relationship between firm-level physical capital investment (divided by physical capital) and process intensity (in standard deviation units). The results come from estimating panel regressions (6.1). Data definitions are found in the Data section of the paper, and Compensation refers to total executive compensation from Execucomp. All variables aside from process intensity are logged. Industry fixed effects use one broad one digit SIC codes (after 2002) or one digit NAICS (before 2002), and date fixed effects correspond to years. Clustering is performed at the industry-date level, where industry is either three digit SIC or four digit NAICS (delineated by 2002, again), and date is year.

Table 5: Executive Compensation and Process Intensity

	Dependent variable:			
	Total Compensation / Physical Capital		Deferred Compensation / Physical Capital	
	(1)	(2)	(3)	(4)
Process Intensity	0.026^{**}	0.076^{***}	0.064^{***}	0.084^{***}
	(0.013)	(0.009)	(0.019)	(0.016)
Intangible Capital	0.862^{***}	0.544^{***}	0.884^{***}	0.664^{***}
	(0.014)	(0.018)	(0.020)	(0.024)
Size		-0.640^{***}		-0.492^{***}
		(0.018)		(0.025)
iB/M Ratio		-0.485^{***}		-0.327^{***}
		(0.007)		(0.011)
Sales		0.413^{***}		0.328^{***}
		(0.029)		(0.034)
Fixed effects	Industry + Date	Industry + Date	Industry + Date	Industry + Date
Observations	11,963	11,764	5,512	5,405
Note:				*p<0.1; **p<0.05; ***p<0.01

This table shows the relationship between firm-level executive compensation (divided by physical capital) and process intensity (in standard deviation units). Executive compensation is either total compensation or deferred compensation. The results come from estimating panel regressions (6.2). Data definitions are found in the Data section of the paper, and Compensation refers to total executive compensation from Execucomp. All variables aside from process intensity are logged. Industry fixed effects use one broad one digit SIC codes (after 2002) or one digit NAICS (before 2002), and date fixed effects correspond to years. Clustering is performed at the industry-date level, where industry is either three digit SIC or four digit NAICS (delineated by 2002, again), and date is year.

Table 6: Fraction of Compensation Deferred and Process Intensity

	Dependent variable:	
	Deferred Compensation / Total Compensation	
	(1)	(2)
Process Intensity	0.031***	0.017**
	(0.009)	(0.008)
Intangible Capital	0.058***	0.111***
	(0.007)	(0.010)
Size		−0.012
		(0.011)
iB/M Ratio		0.140***
		(0.006)
Sales		−0.078***
		(0.015)
Fixed effects	Industry + Date	Industry + Date
Observations	5,508	5,403
Note:		*p<0.1; **p<0.05; ***p<0.01

This table shows the relationship between the firm-level fraction of executive compensation deferred and process intensity (in standard deviation units). The dependent variable is the ratio of deferred compensation in the form of stock and option grants to total executive compensation. The results come from estimating panel regressions (6.2). Data definitions are found in the Data section of the paper. All variables aside from process intensity are logged. Industry fixed effects use one broad one digit SIC codes (after 2002) or one digit NAICS (before 2002), and date fixed effects correspond to years. Clustering is performed at the industry-date level, where industry is either three digit SIC or four digit NAICS (delineated by 2002, again), and date is year.

Table 7: Innovation Intensive Salaries and Process Intensity

	Dependent variable:			
	Innovation Intensive Wage Relative to Industry Average			
	(1)	(2)	(3)	(4)
Process Intensity	0.040***	0.034**	0.038**	0.031*
	(0.015)	(0.015)	(0.016)	(0.016)
Intangible Capital	0.050***	0.077***	0.053***	0.089***
	(0.012)	(0.021)	(0.013)	(0.025)
Size		0.046***		0.046***
		(0.008)		(0.008)
iB/M Ratio		0.020		0.016
		(0.019)		(0.020)
Sales		−0.055		−0.083**
		(0.034)		(0.039)
Fixed effects	No	No	Industry + Date	Industry + Date
Observations	1,603	1,565	1,603	1,565
Note:				*p<0.1; **p<0.05; ***p<0.01

This table shows the relationship between the firm-level average innovation intensive job salary (relative to industry average) and process intensity (in standard deviation units). The dependent variable is defined as the average posted wage for innovation intensive jobs in a given firm-year from Burning Glass Technologies. The industry average used to normalize is a leave-one-out mean of the firm-year innovation intensive salaries. The results come from estimating panel regressions (6.2). Data definitions are found in the Data section of the paper. All variables aside from process intensity are logged. Industry fixed effects use one broad one digit SIC codes (after 2002) or one digit NAICS (before 2002), and date fixed effects correspond to years. Clustering is performed at the industry-date level, where industry is either three digit SIC or four digit NAICS (delineated by 2002, again), and date is year.

Table 8: Process Intensity, Compensation, and Investment Complementarity

	Dependent variable:		
	Total Compensation	Deferred Compensation	Skilled Wage Relative to Industry Average
	(1)	(2)	(3)
Bin 1 × Process Intensity	0.065^{***}	0.070^{***}	0.024
	(0.012)	(0.021)	(0.025)
Bin 2 × Process Intensity	0.167^{***}	0.177^{***}	0.049^{**}
	(0.015)	(0.027)	(0.024)
Fixed effects	Bin-Date	Bin-Date	Bin-Date
Controls?	Yes	Yes	Yes
Observations	11,355	5,224	1,297
Note:			*p<0.1; **p<0.05; ***p<0.01

This table shows the relationship between different firm-level compensation measures and process intensity (in standard deviation units) interacted with an indicator for the level of complementarity. Firms in Bin 1 have low physical capital investment and process intensity complementarity and vice versa for firms in Bin 2. In column one, the dependent variable is total executive compensation divided by physical capital. In column two it is deferred compensation divided by physical capital. In column three it is the average posted wage for innovation intensive jobs in a given firm-year from Burning Glass Technologies. The industry average used to normalize the Burning Glass salaries is a leave-one-out mean of the firm-year innovation intensive salaries. The results come from estimating panel regressions (6.4). Data definitions are found in the Data section of the paper. All variables aside from process intensity are logged. Fixed effects are at the bin-date level. Clustering is performed at the industry-date level, where industry is either three digit SIC or four digit NAICS (delineated by 2002, again), and date is year.

Table 9: Process versus R&D Jobs

	Dependent variable:	
	Process Skill Salaries	R&D Skill Salaries
	(1)	(2)
Process Intensity	0.034**	0.024
	(0.017)	(0.022)
Intangible Capital	0.080***	0.086***
	(0.025)	(0.030)
Size	0.018	−0.014
	(0.020)	(0.025)
iB/M Ratio	0.042***	0.029**
	(0.009)	(0.012)
Sales	−0.083**	−0.067
	(0.040)	(0.043)
Fixed effects	Industry + Date	Industry + Date
Observations	1,507	1,010
Note:		*p<0.1; **p<0.05; ***p<0.01

This table shows the relationship between different II job salaries and process intensity (in standard deviation units). In column one, the dependent variable is the average firm-date salary for process focused jobs divided by the leave-one-out mean of firm-date salaries. In column two it is the average firm-date salary for R&D or product focused jobs divided by the leave-one-out mean of firm-date salaries The results come from estimating panel regressions (6.2). Data definitions are found in the Data section of the paper. All variables aside from process intensity are logged. Fixed effects are at the bin-date level. Clustering is performed at the industry-date level, where industry is either three digit SIC or four digit NAICS (delineated by 2002, again), and date is year.

Table 10: Compensation of Executives Who Switch Firms

	Dependent variable:	
	Total Compensation	Deferred Compensation
	(1)	(2)
Process Intensity	0.086***	0.092***
	(0.018)	(0.021)
Intangible Capital	0.481***	0.554***
	(0.022)	(0.025)
Size	−0.524***	−0.430***
	(0.011)	(0.014)
iB/M Ratio	−0.488***	−0.503***
	(0.032)	(0.035)
Sales	0.583***	0.530***
	(0.028)	(0.035)
Fixed effects	Industry + Date	Industry + Date
Observations	5,639	5,802
Note:		*p<0.1; **p<0.05; ***p<0.01

This table shows the relationship between executive compensation (divided by the capital stock) and process intensity (in standard deviation units) amongst the set of executives who switch firms at least once in our sample. In column one, the dependent variable is the total executive compensation. In column two it is the deferred executive compensation. Data definitions are found in the Data section of the paper. All variables aside from process intensity are logged. Fixed effects are at the bin-date level. Clustering is performed at the industry-date level, where industry is either three digit SIC or four digit NAICS (delineated by 2002, again), and date is year.

Table 11: Process Intensity, Compensation, and Uncertainty

	Dependent variable:		
	Total Compensation	Deferred Compensation	Skilled Wage Relative to Industry Average
	(1)	(2)	(3)
Bin 1 × Process Intensity	0.083***	0.080***	0.004
	(0.011)	(0.024)	(0.022)
Bin 2 × Process Intensity	0.128***	0.143***	0.053**
	(0.014)	(0.022)	(0.026)
Fixed effects	Bin-Date	Bin-Date	Bin-Date
Controls?	Yes	Yes	Yes
Observations	11,633	5,334	1,316
Note:			*p<0.1; **p<0.05; ***p<0.01

This table shows the relationship between different firm-level compensation measures and process intensity (in standard deviation units) interacted with an indicator for the level of capital growth uncertainty. Firms in Bin 1 have low physical capital growth uncertainty and vice versa for firms in Bin 2. In column one, the dependent variable is total executive compensation divided by physical capital. In column two it is deferred compensation divided by physical capital. In column three it is the average posted wage for innovation intensive jobs in a given firm-year from Burning Glass Technologies. The industry average used to normalize the Burning Glass salaries is a leave-one-out mean of the firm-year innovation intensive salaries. The results come from estimating panel regressions (6.4). Data definitions are found in the Data section of the paper. All variables aside from process intensity are logged. Fixed effects are at the bin-date level. Clustering is performed at the industry-date level, where industry is either three digit SIC or four digit NAICS (delineated by 2002, again), and date is year.

Table 12: Complementarity

Specification	Ratio Regression ($\widetilde{\beta}_5$)	Levels Regressions (β_4)	Levels Regressions (β_5)
Mean Industry Coef.	0.105	1.152	0.055
Full Sample (S.E.)	0.001 (0.005)	0.012*** (0.004)	0.010** (0.004)
Pos. Proc. In. (S.E.)	0.014** (0.005)	0.016** (0.006)	0.006 (0.004)

This table shows the difference in complementarity (with physical capital investment) between process intangibles and product intangibles. Each row displays our measure of complementarity using a different specification or sample. Each column displays a coefficient related to complementarity. The first row shows the average coefficient across industries when regressions (D.1) and (D.2) are estimated within industry. The second row shows estimated coefficients from those specifications when using a pooled sample panel regression. The third row shows estimates from those specifications using only the sample of firms with non-zero process intensity, again using a panel regression. The first column is the estimate of $\widetilde{\beta}_5$ from equation (D.2). The second and third columns are estimates of β_4 and β_5 from regression (D.1). Standard errors are in parentheses (clustered at the industry-date level, where industry is 4 digit NAICS after 2002 and 3 digit SIC before 2002).