Investing in Human Capital Incubation*

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Abstract

This paper examines the role of firms' intangible capital investments in fostering the growth of employee human capital and the subsequent spillover effects on other firms. Using U.S. Census Bureau employee-employer matched data, we provide the first direct evidence that firms' investments in intangibles significantly enhance the human capital of their employees, designating these firms as "human capital incubators." We develop a model in which workers' preferences for skill development influence their career decisions, thereby shaping the labor supply to firms. Firms recognize this by investing in intangibles not only to boost output but also to attract talent. We validate the model by demonstrating that human capital incubation is positively correlated with firm productivity, profitability, and market power, as well as with greater inflows of younger workers. Our model estimation reveals that incubator firms capture 37% of the value generated from their investments in employees' human capital, while the remaining 63% of this value spills over to other firms that hire their workers. Additionally, 29% of the production value of intangible investment is embodied directly in the skills of employees.

Keywords: human capital, wage growth, AKM model, intangible investment, labor market power, labor flow, knowledge spillover

JEL Classification: E22, G31, J24, J31, J42, L22

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1. Introduction

Theories of intangible capital emphasize the interplay between intangible capital and the workforce, whereby intangible investments can raise the productivity of key employees (Eisfeldt and Papanikolaou, 2013; Sun and Xiaolan, 2019; Crouzet, Eberly, Eisfeldt, and Papanikolaou, 2022a). Despite strong theoretical agreement that a significant component of intangible capital may be embodied in the skills of firm's workforce, direct empirical evidence linking employers' intangible investment to worker-level human capital growth is scant. In this paper, we bridge this gap by empirically showing that firms' intangible capital investment is indeed strongly associated with increased growth in the skill level of their employees. We refer to such investment as "human capital incubation", and the firms engaging in this investment as "human capital incubators."

Survey evidence consistently shows that employees place great importance on the opportunities employers provide to develop their skills, and often make career choices based on such considerations.[1] As such, workers should value opportunities to work for these *human capital incubators*. Building on this insight and our empirical results, we develop a model that examines the interaction between firms and workers, highlighting how workers' preference for human capital growth shapes their career decisions, firms' recruitment and retention outcomes, and ultimately, firms' incentives to invest in intangible assets.

We start by providing new empirical evidence that firms' intangible investments drive workers human capital growth using the U.S. Census Bureau's employee-employer matched data from the Longitudinal Employer-Household Dynamics (LEHD). We link the employer-employee data to information on investment in intangibles reported by publicly-traded Compustat firms. To measure worker skill and its growth, we follow a long literature in labor economics, starting with Abowd, Kramarz, and Margolis (1999), by decom-

[1] For example, the 2021 Gallup American Upskilling Survey found that, "Most workers (57%) are very or extremely interested in participating in training to upgrade their skills or to learn new skills that could help them advance their career". Further, "Nearly three-in-four workers (71%) who have participated in upskilling agree or strongly agree that it has enhanced their satisfaction with work."

posing log earnings into firm- and worker-specific components, where the worker-specific component can be interpreted as unobserved worker ability stemming from portable human capital. We follow Lachowska, Mas, Saggio, and Woodbury (2023) by estimating these components in a time-varying manner over short-T moving window panels. While Lachowska et al. (2023) focus on time-variation in the firm effects, we instead shift the focus onto time-variation in the worker-specific component of earnings—a within-worker measure of human capital growth.

Motivated by theories of the human element of intangible capital, we average worker-level human capital growth at the firm-level, and analyze the relationship of average human capital growth employers' intangible investments. Since the literature on intangibles emphasizes their complementarity with skilled workers, we focus on employees who are above the age of 25 and predicted to have a bachelor's degree or above in the LEHD. Consistent with the notion that intangible investment makes skilled workers more productive, we uncover a robust, highly-significant positive relationship between intangible investment per worker and human capital growth.

In terms of magnitudes, ordinary least squares estimates imply that a standard deviation increase in intangible investment per worker is associated with a 1.2 to 2.5% increase in human capital measured over the next 2 years. Instrumental variables estimates using tax incentives for R&D from (Bloom, Schankerman, and Van Reenen, 2013; Lucking, Bloom, and Van Reenen, 2019) support a causal interpretation of this relationship, and imply a roughly 2.5% marginal effect. Moreover, since intangible investment is both right-skewed and persistently different across firms, these estimates imply that a small set of high-investing firms contribute greatly to the overall distribution of worker skill in the economy.

Firms' investments that enhance workers' skill levels lead to higher productivity and wage growth for those workers. In turn, this benefits the focal firm by granting it greater market power, given its unique role in fostering workers' human-capital growth. At the same time, it can generate a positive externality for workers and other firms in the labor market, since human capital accumulation is both nonrival and nonexcludable. We next study the implications of these firm–worker and cross-firm interactions in a structural model, which we use to quantify the value firms gain from their own investments into human capital incubation, as well as the positive externalities such investments generate to other firms. In the model, firms face productivity shocks and hire inexperienced and experienced workers to produce. Intangibles not only serve as a productive input, but also help promote human-capital growth and "incubate" inexperienced workers, as we document in our empirical evidence. Workers make their career decisions by considering two factors: the first is current wage income, and the second is the expected path of their future wage, which is influenced by the growth of their human capital. This, in turn, suggests that workers are more willing to supply labor to firms with higher intangible investment and greater ability to incubate them, allowing these firms to attract workers more easily and charge a larger wage markdown. Put differently, firms invest in their labor-market power via intangible investment.

We estimate the model to match the averages of firms' intangible investment, profitability, and hiring decisions. In particular, to pin down how firms' intangible capital influences workers' human-capital accumulation, we perform an indirect inference exercise that matches the regression coefficient of workers' human-capital growth on firms' intangible investment. Using the estimated model, we conduct a counterfactual analysis in which we shut off this mechanism and assume that workers make static, discrete choices in their labor-supply decisions. Our results suggest that, relative to the counterfactual model, firms in the baseline model can charge a higher wage markdown because they compensate workers through faster human-capital growth, which translates into higher wages over time. A firm's ability to incubate workers benefits not only the workers but also the firms that subsequently hire them, since these firms also possess market power and can extract rents from the human capital workers have accumulated. This latter component represents an "externality" of firms' human-capital incubation. Our estimation results indicate that for human-capital incubators—defined as firms in the top tercile of the distribution of worker human-capital growth—the markdown they extract accounts for 37% of the total value they create through human-capital incubation, while the remainder represents knowledge spillovers to other firms competing in the labor market.

Our model also yields several other predictions. First, as intangibles serve a dual role—functioning as a productive investment input and fostering human-capital growth—our model suggests that firms with higher productivity, and thus a stronger incentive to invest in intangibles for production purposes, would also have a greater ability to grow their workers' human capital. Firms with stronger incubation ability also tend to experience higher profitability, valuations, and market power. Second, our model naturally produces a centrality pattern in firms' hiring networks: firms with higher incubation ability tend to have a comparative advantage in hiring novice workers with limited experience, training them, and, as these workers gain experience, they move to other firms, creating a knowledge-spillover effect. Although we do not directly target these qualitative features of the model in our estimation, we verify that they are all supported in the data.

1.1. Related Literature

Our paper primarily contributes to three strands of literature. First, it is closely related to the literature on intangible capital (see Crouzet, Eberly, Eisfeldt, and Papanikolaou (2022b) and Corrado, Haskel, Jona-Lasinio, and Iommi (2022) for recent reviews.[2] One area has emphasized the relationship between intangible capital, market concentration/market power, and investment (Crouzet and Eberly, 2019, 2023; De Ridder, 2024); we contribute here by documenting a link between intangible investment and market power over skilled workers via the impact of intangible investment on human capital growth. Our work is also motivated by prior work that emphasizes theoretical predictions that key employees

[2] See also Kogan and Papanikolaou (2019) for a review of the role of intangibles in asset pricing specifically.

are both an important input to and benefit from intangible investments (Eisfeldt and Papanikolaou, 2013; Sun and Xiaolan, 2019; Crouzet et al., 2022a; Gozen and Ozkara, 2024). We contribute to this literature by providing the first direct estimates demonstrating that firms' intangible investments are associated with within-worker labor productivity increases. In addition, through the structural model, we quantify the importance of intangible investment not only in production, but also in labor markets, where individuals prefer working for a firm that can increase their human capital. This model allows us to document the total value that firms appropriate from their intangible investments, as well as the positive externalities intangible investment generates for other firms by improving the distribution of worker skill.

Adjacent work in finance focuses on the measurement and value of intangibles, especially organizational capital (Eisfeldt and Papanikolaou, 2013, 2014); customer capital (Gourio and Rudanko, 2014; Dou, Ji, Reibstein, and Wu, 2021; Baker, Baugh, and Sammon, 2023; He, Mostrom, and Sufi, 2024), separating organizational from knowledge capital (Peters and Taylor, 2017; Ewens, Peters, and Wang, 2025); and valuing the contribution of intangible capital types to firm value (Belo, Gala, Salomao, and Vitorino, 2022). We do not attempt to innovate on the measurement of intangible capital, taking existing methods from prior work (especially Peters and Taylor (2017)), though we do document that the human capital growth relationship holds separately and simultaneously for both organizational and knowledge/R&D capital. Our model also implies that a substantial portion of the value of intangible capital (29%) stems from its direct impact on the skills of the workers themselves, with the remainder of the value coming from the installed intangible capital stock.

Additional related work in corporate finance examines the relationship between corporate investment and skilled labor mobility (Jeffers, 2023; Ma, Wang, and Wu, 2023; Chen, Zhang, and Zhang, 2025; Sanati, 2025), and how contracts and financial incentives are constructed to facilitate intangible asset creation (Chen, Li, Thakor, and Ward, 2023; Chen, Kakhbod, Kazemi, and Xing, 2025; Ladika, Döttling, and Perotti, 2025). Relative to this we work, we offer a direct lens into how intangible investment is associated with worker-level human capital growth, and in turn how it influences the flow of workers into human capital incubating firms.

Second, this paper contributes to the literature on firms' contribution to workers' human capital. Firms play an important role in workers' human capital development and future earnings trajectories as emphasized by (Bagger, Fontaine, Postel-Vinay, and Robin, 2014; Gregory, 2020; Acabbi, Alati, and Mazzone, 2022; Gao, Wang, and Wu, 2024; Arellano-Bover and Saltiel, 2026). While these papers acknowledge that firms may play a pervasive role in human capital trajectories, they do not characterize the endogenous determinants of human capital growth. We contribute to this literature by documenting that firms' investment decisions play a first-order role in human capital creation. Several previous papers identify channels on how firm's affect employees human capital, such as firms' training (Almeida and Carneiro, 2009; Bapna, Langer, Mehra, Gopal, and Gupta, 2013; Riley, Michael, and Mahoney, 2017; Ma, Nakab, and Vidart, 2024, 2025), and coworkers (Nix, 2020; Jarosch, Oberfield, and Rossi-Hansberg, 2021; Ma, Nakab, and Vidart, 2022; Herkenhoff, Lise, Menzio, and Phillips, 2024). We contribute here by empirically documenting a new channel whereby firms' investments, especially intangible investments, can increase workers' human capital, and we provide a model for understanding the mechanism and quantifying the magnitudes.

Finally, our work connects to work in labor economics which decomposes earnings into worker and firm-specific components, which began with the seminal work of Abowd, Kramarz, and Margolis (1999). Recent influential papers using the Abowd, Kramarz, and Margolis (1999) methodology include (Card, Heining, and Kline, 2013; Card, Cardoso, Heining, and Kline, 2018; Sorkin, 2018; Song, Price, Guvenen, Bloom, and von Wachter, 2018; Di Addario, Kline, Saggio, and Sølvsten, 2023). Other work extends the Abowd, Kramarz, and Margolis (1999) framework by either allowing for worker-firm interactions

(Bonhomme, Lamadon, and Manresa, 2019) or allowing for more flexible time-variation in the firm components (Engbom, Moser, and Sauermann, 2023; Lachowska et al., 2023). We shift the focus to time series changes in the worker-specific component of earnings, providing a a framework to measure human capital growth of a worker.[3]

The rest of the paper proceeds as follows. Section 2 explains the data and describes the measures. Section 3 presents results showing that intangible investments increase employees' human capital. Section 4 introduces our model, and Section 5 explores the model implications for rents and externalities generated by human capital incubation. Section 6 concludes.

2. Data and Measurement

In this section, Section 2.1 describes data sources, Section 2.2 explains how we measure human capital, and Section 2.3 summaries the data.

2.1. Data Sources

We primarily use restricted-use microdata from the US Census Bureau for firms' employees and employment information, and Compustat for firms' financial fundamentals and market information. The Longitudinal Employer-Household Dynamics (LEHD) is an employer-employee matched dataset that records workers' wage information and their employment history.[4] Therefore, we observe the distribution of wages within a firm and the inflow and outflow of labor forces of a firm. In addition, we also have access to the demographic information (age, gender, race/ethnicity, and education level) of workers.

[3]Our approach also borrows methodology introduced in Bonhomme, Lamadon, and Manresa (2019) to mitigate known biases in the Abowd, Kramarz, and Margolis (1999) framework stemming from limited observed mobility of workers across firms (Andrews, Gill, Schank, and Upward, 2008; Bonhomme, Holzheu, Lamadon, Manresa, Mogstad, and Setzler, 2023).

[4]See Abowd, Stephens, Vilhuber, Andersson, McKinney, Roemer, and Woodcock (2009) and Vilhuber et al. (2018) for details regarding the LEHD.

We have earnings information from 29 states.[5] Since we do not have access to every state in the United States, we use the Longitudinal Business Database (LBD), which provides payments and employment information of private, non-farm business establishments in the US, to supplement the information on firms' payments to workers.[6] The two datasets can be linked using the crosswalk between the State Employer Identification Number (SEIN) and the federal Employer Identification Number (EIN).

We collect annual data on firm fundamentals from the Compustat North America database. We construct intangible (organizational and knowledge investment), following Peters and Taylor (2017) and Ewens, Peters, and Wang (2025), with physical investment. In addition, we measure labor productivity and markup similar to Donangelo, Gourio, Kehrig, and Palacios (2019) and De Loecker, Eeckhout, and Unger (2020), respectively, as well as profitability and Peters and Taylor (2017) Total Q. We also observe a firm's total assets, employment, cash and short-term investments, total debt in current liabilities, long-term debt, and dividends. All variables are converted to 2017 real dollars using the GDP implicit price deflator and are winsorized cross-sectionally at the 1% level. We link the Compustat information to Census datasets using the Compustat-SSEL Bridge.

2.2. Measuring Human Capital Growth

We focus on employees aged between 25 and 54 with a bachelor's degree to measure the effects of firms' investments on the human capital growth of their employees.[7] We apply the minimum earnings criterion, which equals the Social Security Administration (SSA) cutoff for receiving a full year of credits toward SSA retirement benefits. We assign the worker's primary firm as the firm that pays the highest wage in the year (Seegmiller, 2021).

[5]AZ, CA, CO, CT, DE, IN, KS, MA, MD, ME, MT, ND, NE, NJ, NM, NV, OH, OK, OR, PA, SC, SD, TN, TX, UT, VA, WA, WI, WY. See Appendix Figure A1 for the start year by state.

[6]See Chow, Fort, Goetz, Goldschlag, Lawrence, Perlman, Stinson, and White (2021) for details regarding the LBD.

[7]Education is not directly observable for all individuals in the LEHD, so we make use of LEHD education imputations for individuals aged 25+ in the LEHD individual characteristics files.

We first residualize the log of real wage by running the following regression specification

$$log(W_{it}) = Age_{it} + Gender_i + Race_i + Ethnicity_i + \gamma_t + w_{it}.$$

where W_{it} be the total real wages an individual i received from all firms in year t. Thus, we include five fixed effects (age, gender, race, ethnicity, and year) to calculate the residuals of log total real wages w_{it}.

Then, we decompose residual earnings into worker and firm heterogeneity, along the lines of Abowd, Kramarz, and Margolis (1999) (AKM henceforth), with two departures. First, following Lachowska et al. (2023), we estimate time-varying firm effects by by estimating the decomposition using moving window 2-year panels. However, unlike Lachowska et al. (2023), our primary focus will be on analyzing time-series changes in the *worker* component of earnings, rather than the firm component. Next, we follow Bonhomme, Lamadon, and Manresa (2019) by clustering firms into classes based off their earnings distribution. This mitigates challenges related to limited mobility bias, which pushes down covariances between estimated worker and firm effects and inflates the firm component contribution to earnings inequality (Andrews et al., 2008).[8] For panel time period T (consisting of the years t and $t-1$), we run the following regression specification:

$$w_{it} = X_{iT} + X_{g(c)t} + \epsilon_{it} \tag{1}$$

where X_{iT} is the individual fixed effects for year group T and $X_{g(c)t}$ is firm group ($g(c)$)-AKM components of firm c in year t. For the firm groups, we keep firms with more than 50 LEHD employees within the year group, and we cluster firms into 100 groups using K-means clustering using the ten deciles from the empirical CDF of firms' residual earnings distribution (w_{it}) (Bonhomme, Lamadon, and Manresa, 2019).[9]

[8]Bonhomme et al. (2023) document that this bias becomes small as the number of movers across firms increases. Because we work with large publicly-traded firms, there are more movers to begin with, which further mitigates this potential bias.

[9]We restrict the sample to the largest connected set of employee-groups of employer-year (Engbom, Moser, and Sauermann, 2023). Since we group firms into classes which have many workers, the restriction does not change the sample in practice.

Note that the AKM model rests on the assumption that earnings are additively separable into worker and firm heterogeneity, and that mobility across firms is uncorrelated with the wage residuals. Prior work exploring the validity of these assumptions has found that the AKM model represents a good approximation of the earnings process in advanced economies.[10] Since AKM worker fixed effects capture the earnings component driven by unobserved worker ability that is portable across all firms (Card, Heining, and Kline, 2013; Card, Cardoso, and Kline, 2015; Song et al., 2018), we proxy for the individual's human capital growth at year t by taking

$$\text{H.C. Growth}_{i,T\to T+2} \equiv X_{i,T+2} - X_{i,T},$$

which is the change in the worker component of earnings across adjacent, non-overlapping 2-year panels. Since our analysis takes place at the firm-year level, we compute the firm-level average of $\text{H.C. Growth}_{i,T\to T+2}$ of all workers in our sample at firm f:

$$\text{H.C. Growth}_{f,T\to T+2} = \frac{1}{N_f}\sum_{i\in f}\text{H.C. Growth}_{i,T\to T+2} \tag{2}$$

Equation (2) constitutes our measure of firm-level human capital growth.

2.3. Summary Statistics

The final LEHD-Compustat merged data set spans from 1990 to 2020. The first panel of Table 1 reports the summary statistics for the financial characteristics of firms. Panel A presents the firm's human capital incubation measure along with average pay per worker. There is meaningful dispersion in human capital growth, at about 10% per year; the mean of the human capital incubation measure is about 2.6%; this mean should be interpreted with some caution, as the fixed effects for each non-overlapping adjact panels

[10]Bonhomme, Lamadon, and Manresa (2019) relaxes the additive separability assumption to allow for worker-firm match effects, finding that while systematic worker/firm-type match effects are detectable, they explain a very small portion of earnings variation relative to worker effects, so that earnings are approximately log-additive in practice. Card, Heining, and Kline (2013) and Song et al. (2018) provide evidence in support of the conditional random mobility assumption.

are identified relative to an unobserved intercept that may not be strictly comparable.[11] Since we measure human capital growth by comparing worker effects in adjact non-overlapping 2-year windows, these growth rates can be interpreted as per 2-years, and dividing by 2 converts to annualized magnitudes.

Panel B shows financial characteristics, including investment, labor productivity, profitability, log markups, and valuation measures. Our main investment-related variable is the intangible investment per worker, which is the sum of organizational and knowledge investment per worker. We construct organizational and knowledge investment following Peters and Taylor (2017). Firms in our sample spend about $40,000 dollars in intangible investments per worker on average, although this is highly right-skewed, with the median being half of the mean. See also the table notes for definitions of these variables.

Panel C shows the labor market characteristics. We define young workers as employees aged 25-34. Also, we measure inflow (hiring) and outflow (separation) of workers over two years, since our human capital growth measures calculate changes over the two future years relative to the two adjacent previous years.[12] For the differences in inflow and outflow shares of young and old workers in the economy, we first calculate a firm's share of young (old) inflow (outflow) in the economy as the young (old) inflow (outflow) to a firm relative to total young (old) inflow (outflow) in the economy. Then, we take the differences between a firm's share of young inflow (outflow) and old (outflow). These measures are conceptually related to the degree centrality measure.

[11]The inclusion of year fixed effects in all specifications nets out this "missing intercept", making this a non-issue for our empirical results, which are identified off cross-sectional differences in investment and human capital growth.

[12]In our data, the net worker flow has a right-skewed distribution. The sizable inflow from corporate mergers and acquisitions affects the distribution. In addition, due to the age restrictions on the employee sample, we do not include retirements, and for modeling purposes, we do not include involuntary outflow (i.e., transitioning from employment to nonemployment).

3. Intangible Investment and Human Capital Growth

In this section, we present evidence that a firm's intangible investments increases its employees' human capital growth. We first estimate the relationship between employees' human capital growth and firm investments using the following regression specification:

$$\text{H.C. Growth}_{f,T\to T+2} = \beta \text{ Investment}_{f,t} + \gamma_t + \eta_{\text{ind}(f)} + X_{f,t} + \epsilon_{f,t} \tag{3}$$

where $y_{f,t}$ is the outcome variable, which is a firm c's human capital growth in year t, Industry$_{f,t}$ is a firm's investment, γ_t is year-fixed effects, $\eta_{NAICS(f)}$ is industry-fixed effects[13], and $X_{f,t}$ is firm-year level controls. Standard errors are clustered at the firm level.

Table 2 reports the coefficient estimates for β in the specification (3). Column (1) presents estimates with year-fixed effects. Column (2) includes year and industry fixed effects. Column (3) includes year and industry firm fixed effects, along with firm-year-level controls. We control for firm size (log of total assets and employment) and variables plausibly related to financial constraints (log of firm age, an indicator of whether the firm pays dividends, cash and short-term investments, and total long-term debt divided by total assets). Column (4) includes year-by-industry fixed effects and firm-year level controls; this is our preferred specification. We standardize intangible investment per employee so that the coefficients can be interpreted as the effect of a one-standard-deviation increase in intangible investment per employee on employees' human capital growth.

The results show that an increase in intangible investments is associated with a significant correlation with employee's human capital growth. Estimates from our preferred most saturated specifation in column (4) show that one standard deviation increase of intangible investment per employee increases the average employee's human capital growth measure by 1.2%, and also about 12% of a standard deviation of firm-level human capital

[13]Our base industry definition is NAICS-4 digit.

growth. While less saturated specifications tend to have larger coefficients, the positive relationship is always highly significant, with t-statistics clustered at the firm level always above 10 no matter the specification.

While this strong association between the average human capital growth of a firm's employees and their intangible investment is compelling, it's still possible that some unobserved characteristic is affecting both firms' investment and the growth in workers' human capital. To support our interpretation that this is a causal relationship, we exploit tax treatment of R&D to generate plausibly exogenous variation in firms' propensity to engage in intangible investment. Specifically, Bloom, Schankerman, and Van Reenen (2013) show that firms have heterogeneous exposure to both state-level and federal R&D tax policies, and this generates variation in the propensity for firms to spend on R&D, and hence boost intangible investment. Additionally, Bloom, Schankerman, and Van Reenen (2013) show that this variation can affect firm investment in two ways: first, by directly promoting R&D spending through the firm's own exposure to tax credits; and second, through cross-firm spillovers stemming from knowledge flows driven increased R&D spending among technologically-connected firms, or from product market spillovers. We use the updated version of the data provided by Lucking, Bloom, and Van Reenen (2019) on Nick Bloom's website.

Table 3 presents the results from the instrumental variable estimation. Because the instruments are only available for a subset of firms the sample is smaller. We focus on our preferred specification with firm controls and industry-year fixed effects. In Panel A, we instrument for intangible investment using both the set of spillover (technological and product market) and direct (firm-level federal and state) tax IVs on intangible investments per worker, so that there are four instruments in total. The instruments jointly explain intangible investment, with a first-stage F-stat of about 25. A standard deviation increase in instrumented intangible investment per worker is now associated with 2.5% increase in human capital growth, about double the coefficient when compared to the same specification in the last column of Table 2, and similar to the OLS specifications with industry fixed effects but without firm-level controls. In Panels B and C, we use separate spillover and tax IVs, respectively. Either sets of IVs individually predicts a similar marginal effect on firm human capital growth, and also with a similar first stage strength. Overall, this suggests a robust causal relationship between firms' intangible investments and human capital growth, which is if anything understated by our OLS estimates.

We next examine how different subcomponents of firm intangible investments relate to workers' human capital growth, and Table A1 illustrates the results. Defining organizational capital and knowledge capital investments as in Peters and Taylor (2017), we find that, per standard deviation increase, organizational capital investments have a slightly stronger relationship than knowledge capital investments. For comparison, we also examine the impact of physical capital investment per worker, finding a strongly positive relationship, but with smaller coefficient. This is potentially consistent with the productivity of physical capital also being partly embodied in workers' skill. The final column shows that each separate investment component retains the same significantly positive relationship when included together with the other components. The results show that each type of investment may have different channels to influence employees' human capital.

Finally, we validate the relationship between intangible investment and human capital growth with measures of perceived career advancement opportunities. Instead of using our human capital incubation measure, we use Glassdoor's career opportunities rating, which employees assign on a scale of 1 to 5. Table A2 shows that intangible investments are positively associated with employees' ratings of career opportunities. This provides independent validation that not only is intangible investment associated with growth in worker human capital, but also that workers are likely to be aware of such an association. Our model, presented in the next section, explores the quantitative implications of an economy where workers supply labor to firms who have heterogeneous ability to grow their human capital.

3.1. Alternative Interpretations

Before proceeding with the model, we briefly discuss threats to our interpretation of the above empirical results. One concern could be that intangible investments are associated with backloaded wage contracts that are used to incentivize effort of skilled employees who are involved in the production of intangible capital (Chen et al., 2023, 2025). Thus, increases in earnings in response to intangible investments represent workers realizing these promised benefits. However, any such rents promised to the worker should be specific to the worker-firm match, whereas the AKM worker intercept is the component worker-specific earnings ability that is portable across *all* firms.[14] Instead, the residual component of earnings ϵ_{it} in equation (1) would tend to pick up such time-varying contractual worker-firm earnings effects if they are present (Song et al., 2018). This highlights part of the reason why we focus on changes in the worker-specific intercept in (1) rather than total earnings.

Any increase in the portable component of a worker's earnings that is related to their productivity—whether it's driven by new knowledge about a technology, increased understanding of production processes, industry domain knowledge, trade secrets, and so on—is consistent with our mechanism. If intangible investment simply made workers better at extracting rents from employers, such changes in earnings intercepts may not only capture marginal productivity changes; however, such a change would have to make workers uniformly better at extracting rents from *all* firms. This would also have to be purely about workers getting better at redistributing existing output to themselves, and this seems a highly unlikely result of firms' intangible investments. More likely is that intangible investments may endow workers with new knowledge that may be scarce because they are highly-specialized or expert, for which firms are willing to pay a premium to access. Since firms are simply paying a worker for some scarce valuable productive

[14]Many papers make this point about the interpretation of worker effects in the AKM setup: Card et al. (2018); Card, Heining, and Kline (2013); Card, Cardoso, and Kline (2015); Song et al. (2018); Kline (2024), to name just a few.

input that the worker now possesses, this still falls within the channels that we have in mind.

Given that a non-trivial component of spending categorized as "intangible investment" constitutes payments to specialized employees who are involved in the knowledge creation process (Eisfeldt, Falato, and Xiaolan, 2023), it is also possible that worker fixed effects increase because the workers who were involved in generating successful intangible capital investments are identified ex post. Under this interpretation, some of the change may not be from increasing the skill of the given workers, but instead in revealing workers' underlying skill-level to the firms. To the extent that this facilitates a more efficient allocation of workers to firms, this channel also improves aggregate productivity. In such a world productive workers would still be willing to forgo some current earnings the opportunity to reveal their productivity, meaning the model mechanism we highlight would play out in a very similar way. Furthermore, the endogenous sorting of workers into intangible-investing firms would tend to reveal worker types ex ante, as unproductive workers with private information about their ability would also want to avoid being revealed when investments they are involved in fail to pan out. Thus it's not clear why such a pooling equilibrium across worker types would exist in the first place. Finally, our estimates are for the firms' *entire* college-educated workforce, rather than, say a very small and specialized set of R&D workers. All of this is to say, while this channel may exist, it is both closely related to the channel that we highlight, and is also quite unlikely to be the dominant force driving our estimates to begin with.

Another concern could be that the AKM model does not allow for systematic interactions between worker and firm types, and intangible investment may affect the interaction. However, econometric estimates of such complementarities, while measurable in principle, have been found to explain a very small fraction of the variation in earnings compared to the common worker-specific component that is equally portable across all firms. Thus the log additivity of earnings in worker and firm heterogeneity imposed by the (slightly-modified) AKM framework we use turns out to be a very good approximation of the earnings distribution in practice. Evidence supporting the approximate log additivity of earnings has been documented by Bonhomme, Lamadon, and Manresa (2019) in Sweden; Card, Heining, and Kline (2013) in Germany; and Lamadon, Mogstad, and Setzler (2022) and Song et al. (2018) in the United States.

4. Model

We model two types of workers, “inexperienced” and "experienced". We assume all “inexperienced” workers have a human capital level of h^N, while experienced workers have a human capital level of $h^H > h^N$.

We model J firms in the industry. For an inexperienced work i employed at firm $j \in [1, 2, ...J]$, the probability for his human capital increase from h^N to h^H in a given period is governed $f(g_{j,t})$, where $g_{j,t}$ denotes firm j's propensity to grow its workers' human capital, and $f(\cdot)$ is an increasing function with a range in between 0 and 1. Some firms are better at growing workers' human capital and thus would be perceived to have higher $g_{j,t}$.

4.1. Workers' Career Path

Every period, a fraction ι of new, inexperienced, workers enters the economy. All entrant workers, together with the incumbent inexperienced and experienced workers will choose a company to supply their labor, which offers a per-period return:

$$u_{i,j,t} = \theta w_{j,t}(h_{i,t}) + a_{j,t} + \epsilon_{i,j,t}, \tag{4}$$

where $w_{j,t}(h_{i,t})$ is the log wage offered by firm j in period t to worker i with human capital level of $h_{i,t}$, θ measures the sensitivity of workers' utility to their wage income, and $a_{j,t}$ captures a common shock to workers' employment preference at time t regarding firm j, which can depend on, for example, unobserved amenities offered by company j.

We use $U(h_{i,t})$ to denote a worker's continuation value, before realizing this period's preference shock and making his optimal labor supply decisions

$$U(h_{i,t}) = \max_{j\in J} \mathbb{E}\left\{\mathring{U}\left[h_{i,t}, w_{j,t}(h_{i,t}), g_{j,t}\right] + \epsilon_{i,j,t}\right\}, \tag{5}$$

where $\mathring{U}!\left[h_{i,t}, w_{j,t}(h_{i,t}), g_{j,t}\right]$ denotes the mean utility of worker i from choosing to work for firm j in period t, holding the realization of the preference shock at its median level. The term $w_{j,t}(h_{i,t})$ is the wage that firm j offers to a worker with human capital $h_{i,t}$, which is chosen by the firm and discussed in detail in the next section. The parameter $g_{j,t}$ captures firm j's ability to "incubate" inexperienced workers, and we model it as the probability that the firm upgrades such a worker to an experienced one, growing his human capital from h^N to h^H. We can express the mean utility of workers in the following recursive form:

$$\begin{aligned} &\mathring{U}\left[h_{i,t}, w_{j,t}(h_{i,t}), g_{j,t}\right] \\ &= \begin{cases} w_{j,t}(h^N) + a_{j,t} + \frac{1}{1+r}\left[(1-g_{j,t})U(h^N) + g_{j,t}U(h^H)\right], & \text{if } h_{i,t} = h^N \\ w_{j,t}(h^H) + a_{j,t} + \frac{1}{1+r}\left[(1-\iota)U(h^H) + \iota\underline{U}\right], & \text{if } h_{i,t} = h^H \end{cases} \end{aligned} \tag{6}$$

where ι is the probability that an experienced worker exits the market, and $\underline{U}$ is the continuation value for an exiting worker.[15]

At the beginning of each period, firms post their wages, and each individual worker i makes his labor supply decisions to maximize his utility from working, which can be characterized by:

$$\begin{aligned} &\mathbb{I}_{i,j,t} = \\ &\begin{cases} 1, & \mathring{U}\left[h_{i,t}, w_{j,t}(h_{i,t}), g_{j,t}\right] + \epsilon_{i,j,t} > \mathring{U}\left[h_{i,t}, w_{k,t}(h_{i,t}), g_{k,t}\right] + \epsilon_{i,k,t}, \forall k \in J \\ 0, & \text{otherwise.} \end{cases} \end{aligned} \tag{7}$$

[15]The rate of exiting equals the fraction of new entrants each period. We normalize the value of the exiting workers, $\underline{U}$, to zero.

where $\{\epsilon_{i,j,t}\}$ represents a shock to the workers' utility from working for firm j, which we assume to follow a Type I Extreme Value distribution. Within this assumption, we can calculate the probability that a worker with human capital level $h_{i,t}$ ends up choosing to work for firm j before the realization of the preference shocks, which can be expressed as:

$$\Pr_{j,t}(h_{i,t}) = \frac{\exp\left\{\mathring{U}\left[h_{i,t}, w_{j,t}(h_{i,t}), g_{j,t}\right]\right\}}{\exp\left\{\mathring{U}\left[h_{i,t}, w_{j,t}(h_{i,t}), g_{j,t}\right]\right\} + \sum_{k\in J\setminus j}\exp\left\{\mathring{U}\left[h_{i,t}, w_{k,t}(h_{i,t}), g_{k,t}\right]\right\}} \tag{8}$$

Equation 16 suggests that firms face upward-sloping labor supply curves. A firm can recruit more workers if it posts higher wages in the current period or if it is better at helping workers to grow their human capital (reflected by a high $g_{j,t}$), which allows workers to attain higher wages in future periods. In other words, higher wages and higher $g_{j,t}$ acts as substitutes in workers' labor-supply decisions. By investing in a higher g, firms can strengthen their future labor-market power because the substitutability implies that they will then need to raise wages by a smaller amount to recruit the same amount of workers.

4.2. Firm Production

Firms use capital and labor as their inputs to produce outputs. We use $K_{j,t}$ to denote the amount of capital owned by the firm in period t. $N_{j,t}$ and $H_{j,t}$ represent the number of inexperienced and experienced workers hired with skill levels of 1 and $\bar{h}$, respectively. Therefore, the total skill-adjusted labor can be calculated as $h^N N_{j,t} + h^H H_{j,t}$ and the firm's per-period output is described as follows:

$$\pi_{j,t} = z_{j,t} K_{j,t}^{\alpha} (h^N N_{j,t} + h^H H_{j,t})^{\beta}, \tag{9}$$

where $z_{j,t}$ is a firm-level productivity shock, following an AR(1) process:

$$z_{j,t+1} = \rho z_{j,t} + \epsilon_{z,t+1}, \quad \text{where } \epsilon_{z,t+1} \sim N(0, \sigma_z^2) \tag{10}$$

Capital depreciates at rate δ, and the firm can make new investments, $I_{j,t}$, subject to a capital adjustment cost

$$\Phi_K = \phi^K \cdot \frac{I_{j,t}^2}{K_{j,t}}, \quad \text{where } K_{j,t+1} = K_{j,t} \times (1 - \delta_K) + I_{j,t} \tag{11}$$

In our model, investments play a "dual role"; on the one hand, they enter indirectly into the firm's productive function; on the other hand, they enhance the firm's ability to incubate their inexperienced workers, so that they will have a higher probability to "upgrade" their human capital:

$$\begin{aligned} g_{j,t+1} &= (1-\delta_g)\, g_{j,t} \;+ \left[1 - (1-\delta_g) g_{j,t}\right] \left[1 - \exp\left(-\chi \frac{I_{j,t}}{N_{j,t} + H_{j,t}}\right)\right] \\ &= 1 - \left[1 - (1-\delta_g) g_{j,t}\right] \exp\left(-\chi \frac{I_{j,t}}{N_{j,t} + H_{j,t}}\right). \end{aligned} \tag{12}$$

Firms post wages for workers, conditional on their skill levels. We use $w^N = w(h^N)$ and $w^H = w(h^H)$ to denote wages paid to inexperienced and experienced workers, respectively. $g_{j,t}$, discussed above, depends on the firm's past intangible investment decisions, and thus serves as a signal observable to all participants in the labor market. As shown in equation 8, both a firm's wages and its $g_{j,t}$ enter into workers' utility function and thus will influence their labor supply decisions. Given the distribution of wages and the firms' $\{g_{k \neq j,t}\}$ in the economy, the number of inexperienced and experienced workers hired by j can be expressed as:

$$N_{j,t} = \Pr_{j,t}(h^N) N_t, \tag{13}$$

$$H_{j,t} = \Pr_{j,t}(h^H) H_t, \tag{14}$$

where N_t and H_t denote the total number of inexperienced and experienced workers in the economy. In every period, the firm pays an additional labor cost:

$$\Phi_w = \phi^w \cdot (N_{j,t} + H_{j,t}), \tag{15}$$

which captures the ongoing training expenses required to keep workers aligned with the firm's latest technologies, as well as broader administrative and overhead costs associated with maintaining the workforce.

To simplify notation, we drop the firm subscript and adopt a non-prime and prime notation, with the latter denoting variables in the next period. We can write the firm's Bellman Equation as:

$$\begin{aligned} V(z, g, K) = \max_{\{\underline{w}, \bar{w}, K\}} & \pi - N \cdot w^N - H \cdot w^H - [K' - (1-\delta)K] - \Phi^K - \Phi^N - \Phi^H \\ & + \frac{1}{1+r}\mathbb{E}V(z', g', K') \end{aligned} \tag{16}$$

4.3. Equilibrium

A stationary Perfect Bayesian Equilibrium consists of (i) the firm's value function V, (ii) the workers' utility function U; (iii) firm policy functions ; (iv) workers' labor supply decisions; and (v) a bounded sequence of firm and worker measures $\{\Gamma_t\}_{t=1}^{\infty}$, such that for all $t \geq 0$:

1. Firms' value and policy functions are solutions to the firm's optimization problem.
2. Workers' labor supply and utility are solutions to their utility maximization problem.
3. The labor market clears.
4. The probability law governing the evolution of the industry, P^{Γ}, is consistent with firms' and workers' optimal choices.
5. The distribution of firms and workers are stationary, $\Gamma_t = \Gamma_{t+1}$.

4.4. Mechanism

In Figure 1, we illustrate the solution to the model, highlighting how firms' production decisions interact with their role in growing workers' human capital. The red curves depict workers' indifference curves, which slope downward because workers substitute current-period wages for firms' ability to raise their human-capital growth rate g', which helps them to increase their wages in future periods.

The blue curves represent firms' iso-cost curves that trade off wage payments and intangible investments. While wage payments are equally costly for all firms, the net cost of g'—defined as the out-of-pocket expenditure required to make the intangible investment necessary to raise g to g' in the next period, minus the productivity gain generated by this additional intangible capital—is given by:

$$\left[\frac{\partial g' - (1 - \delta_g) g}{\partial I}\right] \cdot \left[1 + 2\phi^K \cdot \frac{I}{K} - \frac{1}{1+r} \frac{\partial \mathbb{E} V(z', g', K')}{\partial K'}\right] \tag{17}$$

For firms with low g, achieving any given level of next-period incubation ability g' requires substantial intangible investment. As a result, these firms rely more heavily on current wage payments rather than using human-capital growth as part of the compensation bundle. In contrast, firms with higher g can maintain or raise their incubation capacity with relatively modest investment. These firms, therefore, substitute away from wage payments and compensate workers partly through higher expected human-capital growth.

Similarly, firms with higher productivity z naturally invest more in intangibles for production purposes. This increases the marginal value of their intangible capital and, after subtracting this production-side benefit, lowers the *net* cost of g'. Consequently, high-z firms also find it optimal to rely less on current wages and more on the promise of future human-capital growth to attract and retain workers.

Taken together, these patterns—illustrated in Figure 1—highlight the dual role of intangible investment in our model: it directly enhances current production efficiency while simultaneously shaping firms' ability to incubate workers' human capital. More importantly, these two functions interact. A firm's production environment influences how it optimally positions itself in the labor market—whether by offering higher periodical wages or by relying more heavily on human-capital growth as a compensating mechanism for workers.

4.5. Estimation

In this section, we present the model estimation approach and discuss the intuition behind the estimation process.

We estimate the model parameters using the Simulated Method of Moments (SMM), choosing the parameter values that minimizes the distance between model-generated moments and their empirical counterparts. Prior to estimation, we fix the agents' discount rate at 5% and calibrate the separation rate to 6% to match the observed rate at which workers exit the labor force in our sample. We also normalize the human-capital level of inexperienced workers to one, so the human capital assigned to experienced workers should be interpreted relative to this benchmark.

We classify the parameters to be estimated into two groups. The first group consists of parameters pertains to firms' production technologies and are relatively standard in the production-based literature. For these parameters, we rely on empirical moments commonly used in the existing literature, ensuring that our identification strategy remains consistent with standard practices.

To identify the curvature of the production function with respect to labor, β, we use the regression coefficient of log–output on log–employment. We pin down the depreciation rate of intangible capital using firms' average intangible investment rates. Given this depreciation rate, we can also construct each firm's stock of intangible capital over the past five years by accumulating the undepreciated portion of past intangible investments. We do this both in the actual data and in our simulated model data. We then regress log-output on the log of this constructed intangible capital stock measure to identify the curvature of the production function with respect to intangible capital.

Lastly, we use the standard deviation of firms' intangible investment to identify ϕ_K, the adjustment-cost parameter governing intangible investment, and we match the autocorrelation and standard deviation of firms' log output to discipline the parameters governing the TFP process, ρ_z and σ_z.

The second group of parameters is more model-specific and governs workers' preferences and the evolution of their human capital. To identify ϕ^w, the additional per-worker cost of maintaining the workforce, we use the average wage paid by firms. The logic is that a higher ϕ^w raises firms' effective labor costs, which induces them to apply a larger wage markdown, thereby lowering equilibrium wages. To identify the human-capital level of experienced workers, we match the within-firm dispersion in wage rates. A larger gap in human capital between experienced and inexperienced workers translates into greater within-firm wage dispersion, as firms equate the marginal benefit of employing a worker to the marginal wage cost.

Next, we turn to the identification of workers' labor-supply elasticity, θ. A common challenge in estimating labor supply is the potential endogeneity of wages. When a firm offers a higher wage, this may reflect unobserved firm-level factors—captured, for instance, by a negative realization of $a_{j,t}$ in equation (2)—that reduce workers' willingness to supply labor to that firm. In response, the firm must raise its wage to attract workers, but these same unobserved factors simultaneously depress realized hiring. As a result, a naïve regression of hiring on wages would bias the estimated elasticity toward zero.

To address this endogeneity concern, one can instrument for wage changes using idiosyncratic firm-level shocks that move labor demand. Seegmiller (2021) estimates labor supply elasticities for Compustat firms using firm-level idiosyncratic annual stock returns, arguing that after conditioning on market controls, the component of idiosyncratic stock returns that are related to firm-specific earnings is nearly entirely driven by labor demand shocks, thus providing identifying variation for the slope of the supply curve.

Accordingly, we calibrate $\theta = 2.53$ using the pooled homogeneous estimate of the average firm-level labor supply elasticity from Seegmiller (2021).[16]

Lastly, we identify the parameters governing firms' ability to incubate workers—namely, χ, which captures how firms' intangible investment contributes to their incubation capacity, and ρ_g, which governs the persistence of that capacity. Both parameters are disciplined using the empirical measure constructed in Section 2.2. The parameter χ is identified from the regression coefficient β in equation (1), estimated using an instrument derived from firms' R&D tax credits. To recover ρ_g, we compute the autocorrelation of firms' human-capital incubation capacity, $g_{i,t}$, in the simulated data and match it to the autocorrelation of the empirical measure in equation (1). Importantly, in both the actual and simulated data, the observed autocorrelation reflects not only the intrinsic persistence ρ_g but also the realized autocorrelation of firms' intangible investment choices, which are endogenously determined in our model. This procedure, therefore, allows us to obtain an unbiased estimate of the persistence parameter.

Table 4 presents our parameter estimates.

4.6. Model Validation

The model generates several predictions about firms with high human-capital growth ability. First, because intangible capital plays a dual role in production and worker development, firms with higher productivity endogenously invest more in intangibles. This greater intangible investment simultaneously raises their ability to grow workers' human capital, which, in turn, enables these firms to expand their workforce more effectively, further enhancing profitability and firm valuation.

Table 5 provides empirical support for these predictions. Panel A shows that firms with higher human-capital incubation capacity exhibit superior performance metrics—

[16] Seegmiller (2021) further shows that alternative labor demand shocks stemming from firm patenting, earnings announcement return surprises, or customer stock returns yield very similar labor supply elasticity estimates for Compustat firms.

measured by labor productivity and profitability. Moreover, these firms also display higher markups and higher total Q. In the model, high-performing firms both have high incubation ability and higher market power, generating higher performance, valuations, and market power. We note that while we estimate market power empirically for Compustat firms using revenue-based markup estimates following De Loecker, Eeckhout, and Unger (2020), in the model the market power comes from the labor market side. However, as Ridder, Grassi, and Morzenti (2025) shows, such revenue-based markups capture the *total* market power of the firm when firms jointly possess labor and product market power. Additionally, recent evidence suggests that labor market power is a large and increasingly important component of Compustat firms' total market power (Seegmiller, 2021; Ren and Zhang, 2025). Thus, this finding supports the mechanism in the model that human capital incubation should be associated with a firm's market power, here stemming from their markdowns over their workers.

Our identification strategy relies on a snapshot of firms that captures their key balance-sheet characteristics alongside the composition and wage structure of their workforce. Although the estimation does not directly target worker-flow patterns, the model generates sharp predictions about them. In particular, firms with strong human-capital incubation ability optimally specialize in hiring relatively inexperienced, more junior workers. These workers benefit most from the firm's incubation capacity and are therefore willing to accept a larger wage markdown. As they accumulate experience and become more seasoned, they are more likely to be poached by firms that invest less in incubation and thus have a comparative advantage in employing more established workers.

Although these job-flow patterns are not included as targeted moments, the model implies that these should be associated with human capital growth, and so we use them as an additional validation of the model. Panel B of Table 5 reports the corresponding empirical relationships. Consistent with the model's predictions, firms with stronger human-capital incubation ability employ a larger share of young workers. We also find a positive association between incubation ability and the net inflow of workers. As the model predicts, these inflows are concentrated among young workers in particular, who stand to benefit the most from human capital growth.

Finally, firms with high human-capital growth capability tend to hire more workers in areas where they hold a comparative advantage; as these workers accumulate experience, they are increasingly poached by other firms. This pattern places high-incubation firms at the center of hiring networks. Empirically, we observe that higher incubation ability is positively related to differences in the inflow and outflow shares of young versus older workers—an analogue to a degree-centrality measure—confirming that these firms indeed occupy more central positions in hiring networks.

5. Rents and Externalities of Incubator Firms

In this section, we use the estimated model as a laboratory to quantify the value that firms can internalize by incubating workers—through higher wage markdowns—as well as the portion of workers' human-capital growth that becomes a knowledge spillover, increasing the profits of firms that subsequently hire these workers after they have been incubated.

To do so, we focus on the top tercile of firms ranked by their incubation ability, $g_{i,t}$, which we label as human capital incubating firms. For these firms, we construct three measures. The first is the "value of incubation"—for each worker in the economy, we compute their marginal productivity assuming they are experienced and that they are inexperienced. We can take the average of these productivity differential measures, and multiply it by a firm's probability of successfully incubating inexperienced workers—that is, its $g_{i,t}$—which gives the expected productivity gain that the firm realizes through incubation.

Our second measure captures firms' wage savings from incubation. For each firm, we compute a counterfactual wage in which workers do not "price in" the firm's ability to incubate. Specifically, in the simulation, we set all firms' $g_{i,t}$ to a constant value $\bar{g}$ in equation (4) and calculate the wage that these human capital incubating firms would need to offer in order to maintain their hiring unchanged. The difference between this counterfactual wage and the baseline wage thus represents these firms' wage savings from their ability to incubate. Conceptually, these savings arise because workers are willing to accept a larger markdown in exchange for faster human-capital growth.

The difference between the value of incubation and wage savings gives our measure of incubation spillover. Spillovers arise because, when a worker accumulates human capital, part of the gain is captured by the worker through higher future wages, and the remainder is captured by future employers who hire the worker—since these firms also possess labor-market power. The current firm can only increase the wage markdown to capture the portion that is captured by the workers; the remainder is an externality that benefits the firms that hire the worker after incubation.

The results, reported in Table 6, show that firms internalize a substantial fraction of the value created through worker incubation, appropriating about 37% of the value from their investments into worker skill growth. This is because firms' investment in intangible capital enhances their incubation ability and enables them to charge workers a larger markdown—highlighting a novel channel through which intangible investment strengthens firms' labor-market power. The remaining share of the value, amounting to 63%, represents a spillover to other firms, consistent with the idea that firms' investments in developing workers generate sizable knowledge externalities.

Finally, we compare these measures to the average productivity of intangible investment—computed directly from the production function (9)—which allows us to contrast the direct productivity gains from the installed intangible capital stock with the indirect gains that operate through workers' human-capital growth. We find that the total value of incubation accounts for 29% of the value generated by direct intangible investment. This result further underscores the dual role of intangible capital in both production and human-capital growth.

6. Conclusion

In this paper we document a systematic and strongly-positive relationship between firms' intangible investments and the subsequent growth in the human capital of their skilled employees, consistent with a large theoretical literature that emphasizes the interplay between intangible capital and the productivity of skilled labor. Instrumental variables estimates based off direct and indirect firm exposure to R&D tax credits support a causal interpretation of this relationship. Surveys of workers' average subjective perception of firms' career growth opportunities are also positively associated with intangible investment, suggesting that workers are likely to be aware of this association.

We build a model featuring workers who supply labor to heterogeneous firms who endogenously choose their optimal investment into workers' skill growth. The model implies that productive, profitable, high-market power, and high-value firms should exhibit higher human capital growth, which we confirm in the data. Additionally, we find that young workers, who benefit the most from investments into their skills in the model, disproportionately flow into human capital incubating firms.

Quantitatively, our model implies that highly-incubating firms internalize about 37% of the value they generate from investments into human capital growth in the form of larger wage markdowns. The remaining 63% of the value generated from these investments spills over into other firms who hire newly-productive incubated workers. Finally, about 29% of the value of intangible investments is generated by its direct impact on the skills of workers themselves, with the remainder coming from the installed intangible capital stock.

These findings uncover a novel mechanism for firms' market power in the labor market, where employer generate wage markdowns because workers are willing to forgo wages today to benefit from firms' investments into their human capital growth. This further suggests that some of firms' labor market power may not be strictly anti-competitive, but instead generates spillover benefits to workers and firms. Our findings also confirm theoretical models suggesting an intrinsic link between skilled labor and intangible capital, which is in part embodied in the skills of the workers themselves.

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Tables and Figures

Table 1. Summary Statistics

	Mean	SD	Q10	Q25	Q50	Q75	Q90
Panel A: Human Capital and Wage							
Firm Human Capital Growth	0.0259	0.0970	-0.078	-0.0268	0.0206	0.0723	0.137
Average Pay	81,050	54,060	29,970	48,310	68,310	97,710	142,900
Panel B: Financial Characteristics							
Intangible Investment per worker	40.31	61.39	0.6873	7.903	19.72	47.64	100.6
Organizational Investment per worker	21.72	22.76	0	6.434	14.94	30.12	49.23
Knowledge Investment per worker	18.11	48.22	0	0	0	13.34	55.01
Physical Investment per worker	39.22	148.3	2.116	4.579	9.434	21.62	61.44
Total Investment per worker	68.19	157.2	6.495	14.09	29.88	66.57	134.1
Log Labor Productivity	4.684	0.8508	3.597	4.175	4.672	5.191	5.739
Profitability	0.0205	0.1501	-0.1149	-0.0062	0.0394	0.0844	0.1386
Log Markup	0.5598	0.4646	0.1511	0.2539	0.4268	0.7203	1.16
Total Q	1.319	2.745	0.0272	0.3309	0.7226	1.381	2.803
Panel C: Labor Market Characteristics							
Young Worker Share	0.3058	0.1283	0.1579	0.2151	0.2895	0.378	0.4783
Net Flow Rate	0.1608	0.2766	-0.0262	0.0419	0.1067	0.209	0.3904
Young Worker Share of Firm Inflows	0.4032	0.1547	0.2176	0.3077	0.4	0.5	0.6
Young Minus Old Aggregate Inflow Share	4.42E-04	0.0238	-0.01049	-0.0027	-1.87E-04	0.0023	0.0114
Young Minus Old Aggregate Outflow Share	0.0017	0.0204	-0.0070	-0.0017	2.27E-04	0.0032	0.0122

Notes. This table presents summary statistics of firm characteristics. Panel A presents the human capital incubation measure (equation (2) in main text) and the average LEHD pay per worker. Panels B and C present the firm's financial and labor market characteristics, respectively. All dollar amounts are based on 2017 real dollars, and investment variables are reported in units of thousands of dollars per worker. We construct intangible investment following Peters and Taylor (2017), which we normalize by Compustat employees. Physical investment is given by capital expoenditures. Labor productivity is given by log value added per worker, where value added is the sum of operating income before depreciation and total firm payroll calculated from the Longitudinal Business Database (LBD). Profitability is net income of prior year total assets; the log markup is estimated as the log of the ratio of sales to cost of goods sold, which is equivalent to log markups in De Loecker, Eeckhout, and Unger (2020) when industry fixed effects are included. We construct the Total Q valuation ratio as the ratio of enterprise value to total capital, following Peters and Taylor (2017). The labor market characteristics are defined as follows. The share of young workers are the fraction of LEHD employees in the firm who are between the ages of 25 and 34. The "Net Flow Rate" is given by the total number of workers who flow out of the firm over the next 2 years, minus total workers who flow into the firm, divided by total LEHD employment in the current year. The "Young worker Share of Inflows" is the total number of young workers who flow into the firm over the next 2 years, divided by total inflows into the firm over the next 2 years. The "Young Minus Old Aggregate Inflow Share" is the total number of young (25-34) workers who flow into the firm divided by total number of young workers who flow into *any* firm over the next two years, minus the total number of old (35-54) workers who flow into the firm divided by the total number of old workers who flow into *any* firm over the next two years; "Young Minus Old Aggregate Outflow Share" is defined analogously, except for workers flowing out of the firm. All numbers are rounded to satisfy the Census' disclosure guidelines.

Table 2. Relationships between Intangible Investments and Human Capital Growth

	Dependent Variable: Firm HC Growth			
	(1)	(2)	(3)	(4)
Standardized Intangible Investment per worker	0.0260***	0.0211***	0.0110***	0.0120***
	(0.0010)	(0.0011)	(0.0011)	(0.0011)
Year FE	Yes	Yes	Yes	No
Industry FE	No	Yes	Yes	No
Industry-Year FE	No	No	No	Yes
Firm Controls	No	No	Yes	Yes
Observations	62,000	62,000	62,000	62,000

Notes. This table presents the relationships between firms' intangible investments and employees' human capital growth. The outcome variable is the firm's human capital incubation measure defined in equation (2), while the explanatory variable is the standardized intangible investment per worker. The numbers are rounded to satisfy the Census' disclosure guidelines. Standard errors clustered by firm are in parentheses.

Table 3. Effects of Intangible Investments on Human Capital Growth - Instrumental Variables

	Dependent Variable: Firm HC Growth
Panel A. All IVs (F-stats: 25.03)	
Standardized Intangible Investment per worker	0.0245***
	(0.0089)
Panel B. Spillover IVs (F-stats: 26.63)	
Standardized Intangible Investment per worker	0.0243**
	(0.0114)
Panel C. Tax IVs (F-stats: 28.03)	
Standardized Intangible Investment per worker	0.0251*
	(0.0131)
Industry-Year FE	Yes
Firm Controls	Yes
Observations	13,000

Notes. This table presents the effects of firms' intangible investments on employees' human capital growth. The outcome variable is the firm's human capital incubation measure defined in equation (2). Panel A uses both spillover and direct tax instruments from Bloom, Schankerman, and Van Reenen (2013); Lucking, Bloom, and Van Reenen (2019), while Panels B and C separately use only the spillover and tax instruments, respectively. The numbers are rounded to satisfy the Census' disclosure guidelines. Standard errors clustered by firm are in parentheses.

Table 4. Parameter Estimates

Panel A. Statutory and Calibrated Parameters		
r	Discount rate	0.05
ι	Probability of a seasoned worker exiting the market	0.06
h^N	Human capital of inexperienced workers	1
Panel B. Parameters Estimated via SMM		
α	Curvature of output w.r.t intangible capital	0.365
β	Curvature of output w.r.t skill-augmented labor	0.477
δ_K	Depreciation rate of intangible capital	0.175
ϕ^K	Cost of adjusting intangible capital	1.964
ρ_z	Persistence of firm TFP shock	0.822
ϵ_z	Std of innovation to firm TFP shock	0.175
h^H	Human capital of experienced workers	3.744
ϕ^w	Marginal cost of maintaining workforce	0.151
θ	Elasticity of labor supply w.r.t current wage	2.530
$1-\delta_g$	Persistence in firms' ability to incubate	0.660
χ	Dependence of firm incubation ability on intangible investment	0.025

Notes. In this table, we report the model parameter estimates. Panel A presents the calibrated parameters. Panel B presents the parameters governing firms' operations, workers' preferences, and human capital evolution.

Table 5. Relationships between Firm Characteristics and Human Capital Growth

	Dependent Variable: Firm HC Growth								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Financial Characteristics									
Labor Productivity	0.0199***								
	(0.0010)								
Profitability		0.0375***							
		(0.0040)							
Markup			0.0168***						
			(0.0017)						
Total Q				0.0028***					
				(0.0003)					
Panel B: Labor Market Characteristics									
Young Worker Share					0.0572***				
					(0.0060)				
Net Flow Rate						0.0378***			
						(0.0022)			
Young Worker Share of Firm Inflows							0.0220***		
							(0.0036)		
Young Minus Old Aggregate Inflow Share								0.1468***	
								(0.0217)	
Young Minus Old Aggregate Outflow Share									0.1429***
									(0.0209)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62,000	62,000	62,000	62,000	59,000	59,000	59,000	59,000	59,000

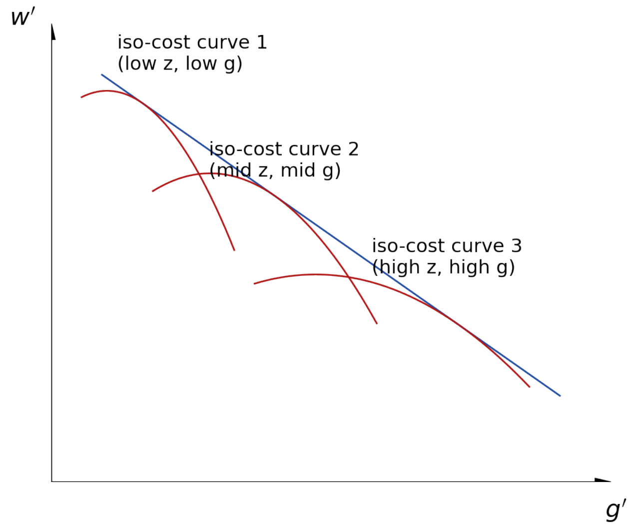
Notes. This table presents the relationships between employees' human capital growth and the characteristics. The outcome variable is the firm's human capital incubation measure defined in equation (2). Panels A and B present financial and labor market characteristics, respectively. The numbers are rounded to satisfy the Census' disclosure guidelines. See notes to Table 1 for definitions and distributions of each characteristic. Standard errors clustered by firm are in parentheses.

Table 6. Market Power, Externality, and Human Capital Incubation

	Value	Percentages of Total Value
(1) Value from incubation	1.234	100%
(2) Wage savings	0.457	37.0 %
(3) Externality	0.777	63.0 %

Note: This table reports the value that firms derive from their ability to incubate workers, focusing on firms in the top $g_{i,t}$ tercile. In row (1), we calculate the total value from incubation as the average marginal value difference between an inexperienced and an experienced worker, multiplied by the firm's $g_{i,t}$. In row (2), the wage savings reflect the wage markdown the firm can charge due to its ability to incubate. In row (3), the externality equals the difference between (1) and (2). We report both the absolute values of these variables and their values expressed as a percentage of the firm's total value from incubation.

Figure 1. Worker Preference and Firm Optimal Policy



Notes. This blue line depicts workers' indifference curve with respect to their next-period wages, w', and their firms' next-period incubation capacity, g'. Firms can raise g' by incurring costs to invest in intangible capital today, as described in Equation (16). The red curves represent firms' iso-cost schedules: for each firm, they trace the combinations of future wage payments w' and next-period incubation capacity g' that entail the same total cost today. Because firms differ in their current incubation capacity g and productivity z, their cost trade-offs between raising g' and paying higher wages are heterogeneous, giving rise to differently shaped iso-cost curves.

Appendix

Appendix Tables and Figure

Table A1. Relationships between Investments and Human Capital Growth

	Dependent Variable: Firm HC Growth				
	(1)	(2)	(3)	(4)	(5)
Standardized Organizational Investment per worker	0.008797***				0.008519***
	(0.0008013)				(0.0007959)
Standardized Knowledge Investment per worker		0.007964***			0.007354***
		(0.001223)			(0.001193)
Standardized Physical Investment per worker			0.005664***		0.004375***
			(0.001069)		(0.001039)
Standardized Total Investment per worker				0.01024***	
				(0.001190)	
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes
Observations	62,000	62,000	62,000	62,000	62,000

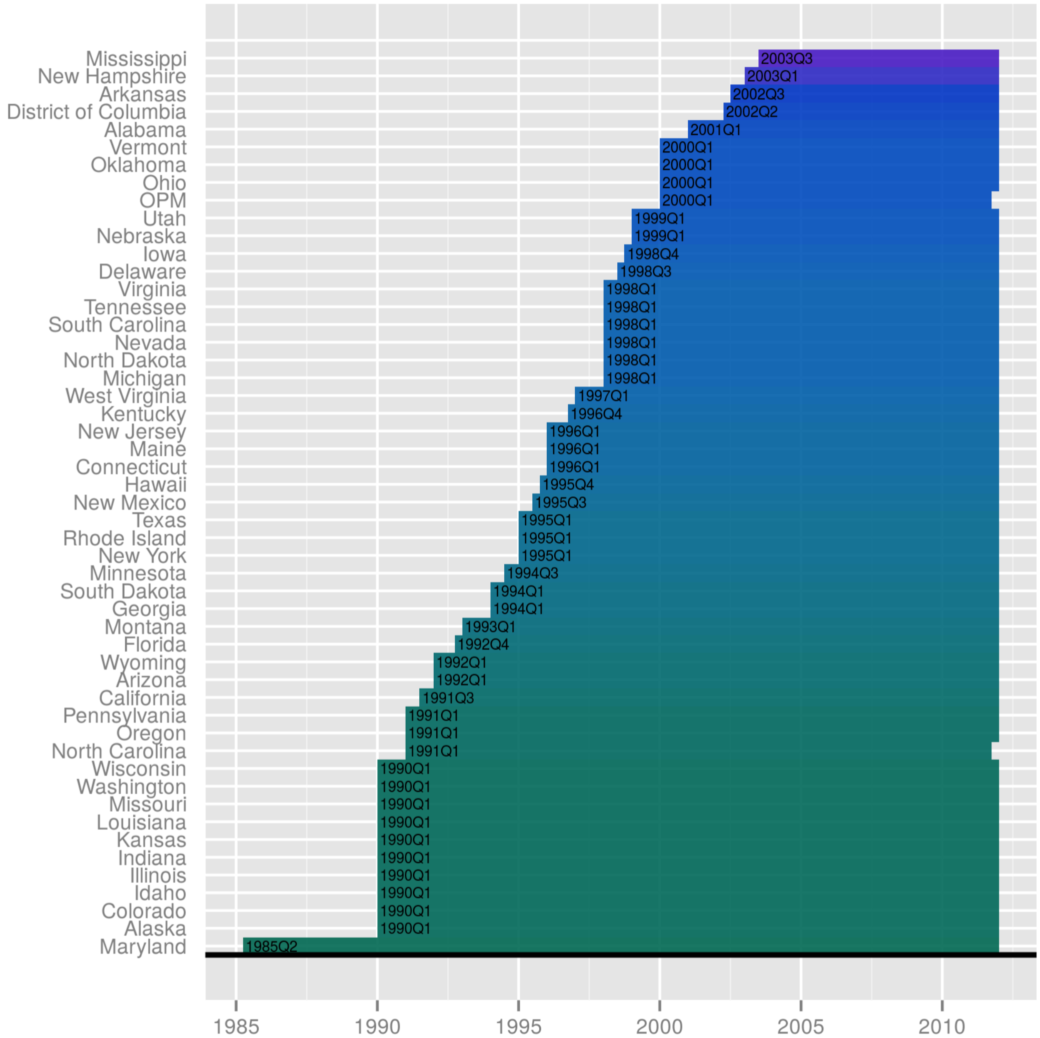
Notes. This table presents the relationships between firms' investments and employees' human capital growth. The outcome variable is the firm's human capital incubation measure defined in equation (2). The numbers are rounded to satisfy the Census' disclosure guidelines. Standard errors clustered by firm are in parentheses.

Table A2. Relationships between Investments and Career Opportunities

	Career Opportunity	
Intangible Investment per worker	0.75**	1.05***
	(0.31)	(0.36)
Tangible Investment per worker	0.49**	0.45**
	(0.20)	(0.20)
Industry-Year FE	Yes	Yes
Firm Controls	No	Yes
Observations	20,592	17,811

Notes. This table presents the relationships between firms' investments and Glassdoor's career opportunity ratings. The outcome variable is the firm's career opportunity ratings (scale from 1 to 5) from Glassdoor, where employees rate their employers' career opportunities.

Figure A1. LEHD Start Year by State



Notes. This figure reports the year-quarter that the state's LEHD data is available. Source: Census.