Beyond Training: Worker Agency, Informal Learning, and Competition

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Abstract

We study how labor market competition shapes workplace skill development. Using large-scale linked survey and administrative data from Norway, complemented by vignette experiments with workers and managers, we show that human capital accumulation is greater in competitive markets. This pattern is driven primarily by workers' own learning efforts rather than firm-provided training. Competition strengthens worker incentives by improving outside options, tightening the link between productivity and pay, and fostering informal learning. Most skill accumulation occurs through learning-by-doing, self-study, and peer interaction, and is concentrated in higher-order, transferable skills. Firms in competitive markets also invest more in training, consistent with higher returns to skill investment despite greater poaching risk. Together, the findings challenge the view that competition suppresses training and instead highlight its role as a catalyst for human-capital accumulation.

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1 Introduction

Wages rise far into adulthood, long after formal education ends. This well-documented pattern highlights the labor market not only as a place where skills are used, but as a key setting in which they are formed (Mincer, 1974). From Smith's (1776) reflections on skill acquisition to Becker's (1962) seminal theory, this idea has anchored decades of research—positioning on-the-job learning as both a driver of productivity and a foundation for economic opportunity, social mobility, and spatial inequality.

Nonetheless, in contrast to the voluminous literature on the returns to education, we know far less about how skills develop in the workplace. The literature on adult learning remains largely theoretical, focusing primarily on formal, firm-led training and the incentives firms face when investing in worker skills. A central view holds that when firms fear poaching, they underinvest in general skills — those valued across employers — since they may not capture the full return. Consequently, competition among firms is often viewed as causing underinvestment in training and, as a result, market failure (Pigou, 1912; Becker, 1962; Acemoglu and Pischke, 1999a,b).

Yet a broader literature suggests skill formation in the workplace is more complex. First, human capital investment is fundamentally an individual decision, shaped by incentives and worker agency (Ben-Porath, 1967). Second, wage growth is closely tied to informal, experience-based learning — which may account for a large share of life-cycle earnings growth (Mincer, 1974; Lucas, 1988). Third, competition between firms plays a central role in driving innovation (Schumpeter, 1934). And fourth, higher-order skills — such as problem-solving and adaptability — are difficult to acquire through formal training (Deming and Silliman, 2024). These insights lay the seeds of a more integrated framework for understanding human capital formation—one that considers the joint role of workers and firms, and how their decisions are shaped by market conditions.

Building on these ideas, we propose a simple framework for understanding skill formation in the labor market, emphasizing how competitive conditions shape the decisions of both firms and workers. Using new data that combine large-scale surveys, administrative records, and survey experiments, we move beyond firm-centered models that focus on formal training. Instead, we show that workers are the primary agents of skill development, accumulating skills informally through self-study, learning-by-doing, and peer interactions. This process depends less on firms' direct investments and more on worker incentives—shaped by outside opportunities and prospects for advancement within and beyond the firm.

To operationalize these insights, we field a nationally representative survey of tens of thousands of workers in the Norwegian labor market. The survey takes 20 minutes to complete and consists of three parts: (i) skills, tasks, and the structure of daily work; (ii) learning at work; and (iii) workplace environment and organization. We capture a wide range of dimensions — task content, time use, skill requirements, learning processes, internal mobility, workplace incentives, and the role of education. A key design feature is that it explicitly distinguishes between formal firm-led training and informal worker-led learning and records both the intensity and context of skill development. Our primary benchmark outcome is deliberately simple: whether workers perceive themselves to have become better at their job over the past year.

All survey responses are linked to detailed longitudinal administrative data from Statistics Norway (2000–2023). These data provide individual-level records on wages, employment histories, occupations, education, demographics, and workplace transitions. Crucially, we also link workers to the firms that employ them, giving us access to firm-level accounts, organizational structure, industry affiliation, and workforce composition. This linkage allows us to connect what workers report about learning, task structure, and workplace behavior to both labor market outcomes and firm-level conditions, including measures of firm investments in training. To gain insight into the behavioral foundations behind our core set of results in the linked survey-administrative data, we field separate vignette experiments with thousands of workers and managers.

Our central finding is that productivity grows substantially faster in competitive labor markets. This occurs because competition tightens the link between productivity and pay, giving workers stronger incentives to develop their own skills. The primary channel is informal, worker-led learning—accumulated through learning-by-doing, peer learning, and self-study—rather than formal, firm-financed training. The gains are concentrated in higher-order, general skills that are portable across firms, reflecting that competition raises the returns to transferable, high-order skills relatively more. While informal learning eclipses firm training in importance, we also find that firms expand training in more competitive markets because competitive pressure—often mirrored in product markets—raises the need for continual skill upgrading to stay productive and retain talent.

We present five key findings in support of this result. First, we show that workers are aware of the competitive conditions they face. A central assumption in labor economics is that workers respond to incentives shaped by market structure—but this requires that they perceive those conditions in the first place. Whether they do has rarely been tested. For instance, Jäger et al. (2024) find only a weak correlation between workers' subjective assessments of potential wages and actual wages at nearby firms in German data, suggesting limited awareness of local opportunities. To examine this question, we construct an Outside-Opportunity Index (OOI) by aggregating responses to twelve survey items capturing perceived outside options across occupation–commuting zone cells. The OOI is strongly and negatively correlated with the Herfindahl–Hirschman Index (HHI, correlation of –0.46), one of the most widely used structural measures of labor market concentration. This alignment indicates that workers perceptions of their opportunities accurately reflect the structure of their labor markets. While the OOI and HHI capture distinct aspects of competition—one perceptual, the other structural—their correspondence suggests that workers internalize the competitive conditions shaping their incentives. To our knowledge, this is the first belief-based evidence linking workers' perceptions of competition to the HHI.

Second, we show that learning occurs disproportionately in competitive markets. Workers in these markets report greater skill development and experience faster wage growth. This relationship is strongly positive: moving from below-mean to above-mean market competitiveness increases workers' belief that they have improved at their job by roughly 25 percent of a standard deviation. Interestingly, this association is robust to the inclusion of fixed effects for commuting zone, occupation, worker age, education, and firm characteristics. The association is robust to using either the OOI or the HHI as the measure of market structure.

Third, we examine how workers learn. Respondents report acquiring skills through a wide range of channels, including mentoring, peer interaction, self-study, formal firm training, and employer-sponsored education. Our survey categories capture virtually all reported learning channels, with fewer than 2 percent of responses falling into the residual 'other' category. Most learning occurs informally, and formal training is only weakly correlated with informal learning. Crucially, only informal learning is strongly associated with self-assessed skill development (0.4, compared to just 0.1 for formal training). Informal learning and formal training both increase with labor market competition, but the relationship is substantially stronger for informal learning. Consistent with the view that firms and workers respond to distinct incentives, investments in formal training are most sensitive to product market competition, while informal learning responds most strongly to labor market competition. Since these markets are often correlated, the key insight is not that firms lose the incentive to train in competitive environments—but that these are precisely the environments in which they cannot afford not to.

Fourth, formal training and informal learning map onto the development of distinct types of skills. Informal learning disproportionately drives the acquisition of higher-order skills—communication, leadership, decision-making, and teamwork—while formal training is more closely tied to basic or task-specific skills. Although both types of skills increase with competition, the largest gains occur in higher-order skills, which are also most strongly correlated with wage growth and self-reported job improvement. This pattern aligns with the incentive mechanism proposed above: as competition tightens the link between productivity and pay, workers invest more in transferable, high-return skills—and they do so primarily through informal learning.

Fifth, we examine whether firms in competitive markets underinvest in transferable skills, which is a core prediction of models of firm-led training and market structure. We construct data-driven measures of transferability by weighting each skill according to how easily workers believe it applies across occupations, firms, and industries, minimizing researcher discretion. Across each of these levels of transferability, higher-order skills are perceived to apply to a broad range of roles. We find that labor market competition is positively associated with skill development, and the slope is, if anything, steeper for the most transferable skills. This pattern contradicts the canonical view that competition deters investment in portable skills. While some of the association reflects occupational composition, we are unable to change the sign of this association with the addition of a large set of controls.

To complement our main evidence, we conduct two independent vignette experiments that randomize workers and managers to different levels of market competition and elicit their perceived behavioral responses. We deliberately describe the competitive environment without specifying whether it reflects labor- or product market concentration. In reality, these dimensions are highly correlated, and the design aims to mirror workers' and managers' integrated perceptions of competitive pressure. Workers assigned to competitive conditions anticipate substantially greater human capital accumulation: they report that stronger opportunities for advancement increase motivation to engage in both formal and informal learning, and raise willingness to invest in higher-order skills that are otherwise more costly to develop. Managers exposed to the same conditions assign greater strategic importance to training—both in basic and transferable skills—not only to boost productivity but also to recruit, retain, and remain viable in high-pressure markets. In short, both sides view skill investment as a strategic response to competition: workers because incentives strengthen, and firms because survival demands it.

This paper provides evidence on how markets, firms, and workers interact to determine learning in the labor market. We contribute to the existing literature in several ways.

First, we build on a broad literature showing that skill accumulation in the labor market plays a central role in life-cycle wage growth. A robust empirical finding is that earnings rise with experience (Mincer, 1974), commonly interpreted as evidence of human capital accumulation through learning on the job (Arrow, 1962; Rosen, 1972). These returns may be substantial: Lucas (1988) suggests that human capital acquired through work may be as important as formal schooling in explaining wage trajectories. Recent research highlights the role of firms in driving both learning and wage growth (Gregory, 2020; Deming, 2023; Adda and Dustmann, 2023; Arellano-Bover and Saltiel, 2024), but offers little insight into why firms differ in their ability to generate human capital. Other strands focus on specific channels—such as employer-led training, learning-by-doing, or peer spillovers.[1] Existing research provides almost no empirical evidence on the relative importance of firm and worker investments (Loewenstein and Spletzer, 2000). Across these literatures, a central challenge remains: black-box estimates of wage growth provide limited insight into the mechanisms and settings in which learning occurs (Silliman and Virtanen, 2025). We take a step toward opening this black box by linking subjective and objective learning measures, validating them against administrative wage data, and studying how competition influences both the pace and nature of skill formation. Our results show that workers find informal learning, largely learning-by-doing, substantially more important for human capital accumulation than formal training.

Second, we build on foundational work in labor economics that treats individuals as forward-looking agents who invest in skills based on expected labor market returns (Mincer, 1958; Becker, 1962; Ben-Porath, 1967). This idea has been extended in the context of classroom settings, where motivation has been shown to be a key determinant of learning (Kremer et al., 2009; Fryer Jr, 2011; Scott-Clayton, 2011), and in the workplace, where incentive structures shape effort and productivity (Lazear, 2000; Lemieux et al., 2009; Lazear, 2018). We extend this body of work by showing that worker agency also plays a central role in human capital investment decisions, and that informal learning responds systematically to external labor market structure. Workers invest in skill development not only because of job-specific incentives but also in response to perceived outside options, highlighting the behavioral relevance of market structure in shaping human capital accumulation.

Third, we integrate the role of markets and power into our analysis of human capital formation. Seminal work by Robinson (1969), Card (2022), and Manning (2003) has emphasized the pervasive influence of employer power on wages, mobility, and labor market dynamics. Recent empirical studies have deepened this view by quantifying workers' outside options (e.g. Caldwell and Danieli, 2024; Schubert et al., 2024) and linking employer concentration to wage-setting and inequality (e.g. Azar and Marinescu, 2024; Dodini et al., 2024), job-amenities (Adams-Prassl et al., 2023), and technology adoption (Rubens, 2024). Most related to our work, several papers have suggested that competition can prevent firms from

[1] Prior work has focused on employer-led training (Brown, 1989; Bartel, 1995; Lynch and Black, 1998; Acemoglu and Pischke, 1998, 1999b,a; Black et al., 1999; Moen and Rosén, 2004; Adhvaryu et al., 2018; Caicedo et al., 2022) learning-by-doing, (Jovanovic and Nyarko, 1995; Rockoff, 2004; Haggag et al., 2017; Bollinger and Gillingham, 2019) and peer spillovers (Mas and Moretti, 2009; Herkenhoff et al., 2024; Caicedo et al., 2019; Jarosch et al., 2021). Additionally, as Bar-Isaac and Lévy (2022) suggests, firm training and informal training can be linked – if firms decisions on task allocations can offer workers distinct opportunities for learning-by-doing.

investing sufficiently in their worker's skills, for fear that they might be poached (e.g. Becker, 1962; Acemoglu and Pischke, 1998, 1999a; Dustmann and Schönberg, 2012; Adams-Prassl et al., 2022). At the same time, another strand of research shows that competition can be key for innovation (Schumpeter, 1934; Aghion et al., 2005, 2019). And, other papers note the importance of competitive markets in generating wage growth (e.g. Bagger et al., 2014). Rather than being in conflict, these perspectives highlight different mechanisms: while competition may reduce the share of returns firms can retain, it can also raise the total return to skill investment—making training worthwhile even when retention is uncertain.

In this paper, we shift the perspective from firms to workers, emphasizing worker agency as a central component of skill development. A first step is showing that workers themselves perceive and respond to local market conditions—a point we establish by validating structural measures of concentration against worker beliefs. Building on this, we demonstrate that market concentration alters not only firm behavior but also worker incentives—affecting when, how, and whether individuals engage in informal learning. From the perspective of workers, investment in skills is more rewarding in competitive markets. These dynamics matter not only for wage-setting but also for long-run productivity growth, labor market adaptability, and inequality—especially in light of rising labor market concentration and falling labor shares across advanced economies (Stansbury and Summers, 2020).

Fourth, we build on recent work highlighting that skill development is multidimensional — and that focusing on a single index of "skill" risks missing important variation in how different types of skills are formed. In particular, higher-order skills such as teamwork and decision-making are increasingly valued in modern labor markets but are more difficult to acquire (e.g. Deming and Silliman, 2024; Woessmann, 2024). At the same time, canonical models of firm training predict underinvestment in general or transferable skills in competitive markets, as firms may fear poaching (Pigou, 1912; Becker, 1962; Acemoglu and Pischke, 1998, 1999a,b). While recent research suggests that multidimensional skills develop with work experience (Dorn et al., 2024), our analysis makes two contributions. First, we provide a direct, data-driven measure of skill transferability across multiple dimensions: firms, occupations, and industries. Second, we use these measures to show that a broad range of skills—especially higher-order ones—are cultivated in the workplace, often informally through learning-by-doing, and are more transferable than basic skills. These results help explain why higher-order skills develop in the workplace despite their portability across jobs (Lazear, 2009; Dodini et al., 2024). Importantly, both workers and managers recognize that cultivating higher-order skills requires effort and initiative from the worker, not just training by the firm.

Our results differ from some predictions in the literature on skill formation. Canonical models suggest that firms in competitive markets underinvest in training, particularly in general or transferable skills, due to poaching concerns and limited ability to capture returns (Pigou, 1912; Becker, 1962; Acemoglu and Pischke, 1999a). Most fundamentally, we consider how competition shapes worker incentives and informal learning. Where labor market competition can sometimes reduce firm investments in training – which we do see for some sectors – the relative importance of formal training is minimal when compared to informal learning. Further, on average, formal training is actually more common in competitive markets, consistent with the idea that even if firms capture a smaller share of returns, competition raises the total payoff to skill investment, making training worthwhile despite thinner rents (Lazear, 2000).

More broadly, our findings contribute to macroeconomic debates regarding the drivers of productivity growth and inequality in labor markets. Seminal work underscores the importance of industrial agglomeration in explaining geographic inequalities (Marshall, 1920; Ellison et al., 2010). With few exceptions (e.g. Rotemberg and Saloner, 2000; Almazan et al., 2007), this literature is largely silent on how agglomeration affects the dynamics of human capital accumulation. Critically, as endogenous growth models emphasize human capital accumulation as a key factor shaping long-run growth (Lucas, 1988; Romer, 1990), understanding the dynamics of geographic divergence requires bringing these two literatures together. Moreover, as modern labor markets demand a growing degree of higher order skills (Deming and Silliman, 2024; Woessmann, 2024), it is increasingly important to understand how these types of skills are generated in the labor market. Our results extend these literatures by showing that competitive labor markets—closely associated with agglomeration—play a key role in helping places keep up with the pace of structural transformation (Autor et al., 2006; Acemoglu and Autor, 2011; Deming, 2017; Aghion et al., 2019). Together, our framework—emphasizing competition and worker incentives—links together these key literatures to offer a new explanation for why today's cities are increasingly important not just as places of economic activity, but also as the engines of human capital accumulation (Glaeser and Maré, 2001; Roca and Puga, 2017; Florida et al., 2018).

2 Background

2.1 Norway as an Empirical Testbed for Workplace Skill Formation

Our analysis focuses on Norway, a Nordic welfare state that combines generous employment protections, universal healthcare, free education, and family policies with a long-standing emphasis on skill development and workforce inclusion. While employment protection legislation is relatively strict, it is comparable to other OECD countries such as Italy, Sweden, and Denmark (Huttunen et al., 2018). Labor markets are generally competitive—often more so than in the United States—but operate alongside high union density and broad collective bargaining coverage (Dodini et al., 2023). Norway also maintains a strong policy focus on lifelong learning and upskilling (Bennett, 2025), in line with broader OECD efforts and guidelines.

Norway thus provides a valuable empirical setting to study how market structure, firm behavior, and worker agency jointly shape skill development. Its data infrastructure allows us to link large-scale, nationally representative survey responses to detailed longitudinal register data on wages, employment histories, education, firm characteristics, and workplace transitions—connecting self-reported learning experiences to real economic outcomes at both the individual and firm levels. Even though institutional features may influence the precise magnitudes of the effects we estimate, the underlying questions—how firms train, how individuals learn on the job, and how market structure shapes these processes—apply broadly across advanced economies.

2.2 Linking Market Structure and Skill Formation

In this section, we present a simple analytical framework to organize ideas about how human capital is formed in the workplace and how labor market structure shapes this process. The purpose is not to offer a formal model, but to clarify the mechanisms that connect competition and the accumulation of human capital. We depart from models that treat skill formation as a firm-led investment problem and instead view firms and workers as jointly producing human capital.

For intuition, we can think of a worker's accumulated skills as depending jointly on informal, worker-led, learning and formal, firm-led, training, both shaped by the degree of labor market competition:

$$A_{if} = f(L_i, T_f, \theta),$$

where A_{if} denotes the skills a worker i develops while employed at firm f, L_i captures informal learning initiated by the worker, T_f represents formal training provided by the firm, and θ indexes the level of market competition.

Worker Agency and Informal Learning. Workers choose how much to invest in informal learning — which consists of, for example, learning-by-doing and peer exchange - given the opportunities and constraints of their environment. In that sense, informal learning can be viewed as an individual optimization problem under constraints, where workers allocate effort to maximize the expected returns to their own skill accumulation. These choices determine L_i, the worker-led component of skill formation.

In equilibrium, the worker's choice of L_i reflects the structure of the labor market—specifically how competition links productivity to wages. In competitive labor markets, where wages reflect marginal productivity, the direct link between performance and pay aligns incentives and strengthens workers' motivation to invest in skill development: improvements in skill directly translate into higher wages and broader career opportunities, both within and beyond the firm.

These ideas can be expressed in a simple expression, in which L_i denotes the amount of learning undertaken by worker i, chosen to maximize expected returns:

$$\max_{L_i} \left\{ \pi(\theta) \cdot H(\theta, L_i) - \Phi(L_i, \theta) \right\}.$$

In this formulation, $H(\theta, L_i)$ captures the *gross return to learning* - the increase in productivity and market value that results from acquiring new skills. This return rises with labor market competition θ, since skills are more fully utilized and tend to command higher rewards when markets are competitive. The term $\pi(\theta)$ reflects the *share of gross return retained by the worker*, which also increases with competition as stronger outside options improve workers' bargaining power and tighten the link between productivity and pay.

The final term, $\Phi(L_i, \theta)$, represents the *cost of learning*, encompassing both effort and opportunity costs. These costs decline as competition increases, since stronger competitive pressure improves access to feedback, task variety, and high-quality peers, effectively making informal learning cheaper and more efficient.[2]

What About Formal, Firm-led Training? In addition to workers' own informal learning, firms make active decisions about formal training—structured investments designed to raise worker productivity. Just as workers choose how much to learn given the opportunities and constraints of their environment, firms choose their optimal level of training T_f to maximize expected returns:

$$\max_{T_f} \left\{ \rho(\theta) \cdot R(\theta, T_f) - C(T_f, \theta) \right\},$$

where $R(\theta, T_f)$ is the gross return to training, $\rho(\theta)$ the share of that return the firm can retain, and $C(T_f, \theta)$ the cost of providing it. Market structure influences all three components—the value of training, the ability to retain its returns, and the cost of provision.

The retention component is central in classic models which focus on how firms finance training (e.g. Becker, 1962; Acemoglu and Pischke, 1998). As markets become more competitive, skilled workers are easier to poach, forcing firms to raise wages or offer promotions to retain them and effectively passing part of the return to the worker. This limited ability to internalize returns is often taken to imply underinvestment in general skills.

[2]This occurs because firms facing tighter margins must allocate talent and information more efficiently, creating environments where learning-by-doing and peer exchange become natural by-products of performance pressure.

Yet competition can also increase the *gross* return to training. One intuitive way to see this is through the firm's production possibilities. In competitive markets, firms operate close to their production frontier: there is little slack, and marginal improvements in worker ability translate directly into output or cost savings. In concentrated markets, by contrast, weaker innovation pressure and institutional inertia often keep firms inside their frontier, leaving part of their human capital underused. Competition not only reduces slack but can also shift the frontier outward by forcing faster technology adoption, process improvement, and organizational innovation. Training investments therefore yield higher returns in competitive settings—not only because skills are fully utilized, but because the underlying production possibilities are expanding. This dynamic explains why the gross return to training may rise even as firms capture a smaller share of it.

Costs are simply the total costs of training provision. For the most part, the costs of training do not differ across markets. That said, more competitive local economies may have more outside training providers, and if workers are more motivated in competitive markets, the costs of training them may be reduced.

Predictions. This analytical framework yields several testable implications. First, the accumulation of workplace human capital should vary with market structure through both worker-led informal learning and firm-provided formal training. Second, stronger competition strengthens the incentives for workers to invest in their own skills, as the link between productivity and pay tightens, implying more intensive informal learning in competitive markets. Third, because competition strengthens outside options and raises the value of transferable skills, it should particularly foster human capital accumulation in higher-order, general skills that yield returns across firms and occupations. Fourth, the effect of competition on formal training is ambiguous: operating close to the production frontier can raise the need for training to remain competitive and stay in business (gross return goes up), but weaker rent capture and poaching risk can dampen firms' willingness to invest (retention of return goes down). Finally, the composition of formal training may also adjust with competition. Competitive pressure reduces firms' ability to retain the returns to training (retention goes down), which can push them toward more firm-specific investments to mitigate poaching risk. At the same time, competition raises the gross return to all training—potentially even more for higher-order, general skills (return goes up)—since these are most valuable in dynamic, frontier environments. The net effect on training composition is therefore ambiguous, reflecting a trade-off between return and retention.

3 Data

We draw on three complementary data sources to study how skills are developed in the labor market and how market structure shapes learning. First, we field a nationally representative worker survey with detailed measures of skill acquisition, learning modes, workplace culture, work structure, and workplace incentives. Second, we link these responses to administrative register data spanning over two decades. Third, we conduct randomized vignette experiments with workers and managers to test behavioral responses to shifts in market competition (between-subject design), and solicit respondents' location choice preferences as a function of local market structure. This section describes each data source in turn and outlines the construction of key measures used in our analysis.

3.1 Survey Data

We field a nationally representative survey of approximately 20,000 workers in Norway, administered online by Norstat in late 2023. The survey was designed to capture how skills are developed on the job, with particular attention to types of skills, modes of learning, incentives for learning, and transferability. It takes approximately 20 minutes to complete and was sampled to be representative of the Norwegian workforce. Critically, we are able to link the survey to administrative data for nearly 90 percent of survey respondents. Focusing on workers employed in the private sector—which is the focus of our analysis—yields 9,955 matched respondents, covering employees from nearly 80 percent of Norwegian firms with 100 or more employees (Table A.2).

The survey consists of three primary components (see Appendix B for the full survey). The first part focuses on the structure and content of daily work, capturing information on tasks, autonomy, collaboration, time use, and workplace conditions. The second part centers on learning at work, covering both formal firm-led training and informal learning mechanisms such as learning-by-doing, self-study, peer interaction, and mentoring. Third, to complement these measures focused on skill use and development, the survey collects information on internal mobility, training access, perceived fairness, management practices, pay satisfaction, and incentive structures.

We construct several core measures from the survey to capture human capital development at the workplace, labor market structure, and firm culture.

A key requirement for our purposes is the ability to measure the extent of skill development across heterogeneous work contexts. This is inherently challenging, as the skill content of jobs varies widely, making comparisons across domains difficult. Our primary outcome is a self-assessed measure of learning: whether respondents report being better at their job than one year ago. While this single-item measure inevitably involves some measurement error, it provides a simple and interpretable proxy for on-the-job skill accumulation.

To understand the skill content of workplace learning, the survey also contains domain specific-measures of skill development. Respondents are asked to report learning for a broad range of skills. We construct two skill development indices, one for basic skills and one for higher-order skills. Each index is defined as a weighted average of self-reported learning on a given sub-skill and the importance of that sub-skill for the worker's job. Basic skills include manual work, analytic thinking, service provision, computer programming, adaptation to new technology, working under pressure, and operation of specialized machinery. Higher-order skills include teamwork, leadership, decision-making, communication, and learning quickly. These indices are standardized to have mean zero and standard deviation one. Following Deming and Silliman (2024), the distinction reflects whether skills are directly used within a production process (basic) or shape how workers interact with or influence that process (higher-order).

In addition, the survey asks workers to assess the transferability of their skills across (1) firms, (2) occupations, and (3) industries. This allows us to classify the transferability of each skill dimension using a data-driven approach, providing direct evidence on a critical but previously difficult-to-observe aspect of workplace learning. By linking transferability to both basic and higher-order skill development, we can examine not only how much workers learn, but also how far that learning carries across firms, occupations, and industries.

Further, the survey provides insight into how skills are developed. Capturing both firm-led formal training and worker-led informal learning is critical, since responses from workers around the world suggest informal learning is ubiquitous (Figure A.1). After respondents report improving a particular skill, they are asked how they acquired it. They may select from a non-mutually exclusive list of learning modes — with the full list available in the Appendix. Respondents can also select "Other" if their experience falls outside these categories. Notably, fewer than 2 percent identify "Other" as their primary mode of skill development, suggesting that the survey effectively captures the full range of workplace learning channels.

To reduce the dimensionality of forms of learning, and to extend these beyond the specific dimensions of skills included in the survey, we create two learning mode indices. The first captures informal learning and is based on reported engagement in learning-by-doing, self-directed study, co-worker learning, and mentoring as well as general closeness with colleagues (Gächter et al., 2015) and the extent that workers are exposed to varied tasks. The second captures firm investment in formal training and includes exposure to internal training programs, external courses, formal education sponsored by the employer, and the time elapsed since training. These survey measures are complemented with measures of firm spending on training from the administrative data. Both indices are standardized to have a mean of zero and standard deviation of one.

To capture both perceived and structural labor market competitiveness, we construct two complementary indices. The first is based on survey data and reflects workers' perceptions of their external opportunities. The second is based on our registry data and discussed in detail below. These are central measures, as our analytical framework builds on the premise that workers respond to labor market dynamism when making skill investment decisions — but such responsiveness is only possible if workers actually perceive those opportunities.

To measure perceived outside options, we construct an Outside Options Index derived from a battery of belief-based survey questions. Specifically, the index includes whether the respondent perceives that they are interchangeable; whether they could find a job at another firm, in another occupation, or in another industry within a reasonable commute; whether their baseline or current skills would be useful in finding other jobs; whether they value workplace learning for its external returns; whether they believe their firm's salaries reflect productivity or outside options; and whether outside options create incentives to learn, alongside pay and pay growth satisfaction. The index is first averaged at the individual level and then aggregated to the two-digit occupation–commuting zone level, where it is rank-transformed to lie between 0 and 1.

In addition to measuring competitiveness directly, we also examine whether labor market structure shapes the internal organization of firms — in particular, the environments in which learning occurs. To capture this, we construct an index of firm culture, based on whether workers report being treated fairly by their manager, feeling respected, and being given responsibility at work. This measure is standardized to have mean zero and unit standard deviation. It allows us to test whether competitive pressure is associated not only with more learning, but with learning-supportive environments — a potential channel linking market structure to skill formation by lowering the cost of informal learning.

3.2 Administrative Data

All survey responses are linked to detailed administrative register data from Statistics Norway, covering the period from 2000 to 2023. These records provide comprehensive annual information on earnings, employment histories, occupations, education, demographics, and geographic location for every individual in the sample. Crucially, respondents are also linked to the firms that employ them, allowing us to observe firm-level characteristics including size, industry, financials, workforce composition, and organizational structure.

This linkage enables us to construct structural measures of labor market concentration, assign workers to specific occupation–commuting zone cells, and estimate firm-level wage-setting patterns.

While the administrative data do not extend beyond the time of the survey, the long retrospective window provides a uniquely detailed view of each respondent's long-run labor market experience. We can trace how individual wages, occupations, and job transitions evolved prior to the survey, and examine how these trajectories differ across firm types, industries, and market structures. This panel structure allows us to assess the extent to which workers' current skill levels and learning environments reflect cumulative exposure to different types of firms and labor market conditions.

The ability to connect survey-based measures of learning to long-run administrative data represents a key innovation of this project. Whereas most prior research relies either on subjective assessments or on administrative outcomes alone, our design allows for an integrated analysis of how skills are built in practice and how they map onto real economic outcomes. This linkage enables us to begin opening the black box of workplace learning and to study not only how people say they learn, but also how that learning is reflected in their actual labor market trajectories.

To complement and validate our measure of perceived outside opportunities, we turn to administrative data and construct one of the most widely used structural measures of labor market concentration: the Herfindahl-Hirschman Index (HHI). The HHI is calculated as the sum of squared firm employment shares within two-digit occupation–commuting zone cells.[3] For comparability with the Outside Options Index (OOI), both measures are rank-transformed to lie between 0 and 1. Following Bassier et al. (2022), we also extend the analysis to firm-level labor supply elasticities as an alternative measure of employer power.

Table A.3 summarizes key characteristics of the survey sample and compares them with the full administrative population, separately for individuals (Panel A) and firms (Panel B). On average, survey respondents are slightly older, more highly educated, and have higher earnings. The firms in the survey also tend to employ a slightly larger share of white-collar workers. However, these differences are relatively modest, and the survey sample is broadly comparable to the population overall. Throughout the analysis, we focus exclusively on the private sector.

Finally, we construct various measures of wage-growth in the administrative data. Since Mincer (1958), a common interpretation has been that wage growth at the firm and worker level reflects worker learning (e.g. Arellano-Bover and Saltiel, 2024; Deming, 2023). We use individual and firm level measures of wage growth to validate our survey based measures. For the individual, we construct measures of wage growth by differencing our measure of earnings across two years. At the firm level, we estimate the extent that firms consistently

[3] We follow Gundersen et al. (2019) in our definition of commuting zones.

raise the wages of their workers by estimating firm fixed-effects on wage growth. Specifically, we estimate the following model:

$$\Delta Y_{ift} = \lambda_f + \beta_1 \text{age}_i + \beta_2 \text{age}^2_{it} + \beta_3 \text{experience}_{ift} + \beta_4 \text{experience}^2_{ift} + \beta_5 \text{college}_i + \pi_t + e_{ift} \quad (1)$$

where the outcome is the change in income from one year to the next. To avoid conflating firm effects with average worker characteristics, we control flexibly for age, tenure, and educational attainment. The coefficient vector λ_f captures firm-specific wage growth residuals, interpreted—following Arellano-Bover and Saltiel (2024)—as reflecting firm contributions to on-the-job learning. Critically, we estimate all firm-effects on wage growth exclusively for workers outside of our survey sample – this can help to break a mechanical link between bias in the self-reports of survey measures and realized wage growth.

3.3 Additional Survey Data for Experimental Results

To complement the observational analysis and examine the behavioral foundations behind our results, we field two randomized vignette experiments: one with 1,026 workers and one with 1,001 managers. These survey instruments, documented in full in Section B, consist of three parts: (1) perceptions of how competition affects training investments, learning, and motivation; (2) the vignette experiments themselves, along with detailed follow-up questions on how competition shapes skill formation; and (3) stated preferences over competitive versus concentrated labor markets, and the reasons behind those preferences.

The core of these surveys is a pair of vignette experiments—one for workers and one for managers (between-subject design). Each respondent is presented with a hypothetical market scenario that varies in the overall level of competitive pressure. Treatment is binary: respondents are randomly assigned to either a high or low competition condition. We deliberately describe the competitive environment without specifying whether it reflects labor- or product market concentration. In reality, these dimensions are strongly correlated, and the design aims to mirror workers' and managers' integrated perceptions of competitive pressure.[4]

In the competitive condition, the market is described as offering high outside options, strong innovation pressure, and a heightened risk of losing employees to rival firms. In the concentrated condition, the environment is characterized by low mobility, greater retention, and limited competitive pressure. The framing emphasizes differences in worker mobility and the economic environment, while holding constant other job attributes.

Following the vignette, respondents are asked a series of questions designed to elicit their behavioral responses to the market environment. Workers report how much they would expect

[4]The experiments are preregistered in the AEA RCT Registry: AEARCTR-0015616 and AEARCTR-0015618.

to learn over time, how motivated they would be to invest in different types of skills, which learning channels they would pursue, and how important they believe various skills would be for their success. Managers are asked how they would allocate training resources, whether they would invest in general or specific skills, how they expect workers to respond, and how important they believe skill formation is for firm performance, recruitment, and retention.

The vignettes are designed to better isolate the effect of perceived market structure on learning-related behaviors and expectations. By holding job content constant and randomizing only the competitive environment, the experiments allow us to obtain suggestive evidence on how both workers and firms update their beliefs about skill investment, learning effort, and the value of different types of human capital. This approach provides more causal insight into the behavioral foundations of our framework—highlighting how competition influences not only firm strategy but also individual learning decisions and perceived returns to skill development. Across both worker and manager experiments, the main outcome pre-registered in the AEA RCT registry is whether or not workers will be better at their jobs each year.

In addition to the experimental component, the surveys also include questions that shed light on how workers and managers perceive the relationships between competition, formal training, informal learning, motivation, and human capital accumulation. They also elicit preferences over where to start a career (for workers) or establish a firm (for managers)—in either a competitive or a concentrated labor market—and ask respondents to explain the reasoning behind their choices.

4 Results

Before turning to how market structure shapes skill accumulation, we begin by documenting three empirical patterns that motivate our focus on workplace learning. First, consistent with evidence across a range of contexts (e.g. Lucas, 1988; Deming, 2023), earnings rise steadily over much of the life cycle, implying that skill accumulation continues well beyond formal education (Figure A.2). Second, our survey data show that most workers report having improved at their jobs over the past year (Figure 1a), indicating that learning on the job is pervasive and persistent. Third, self-reported improvement is strongly associated with subsequent wage growth (Figure 1b), validating our measure as a proxy for meaningful human capital accumulation and reinforcing the link between learning and earnings dynamics.[5] Together, these patterns highlight the importance of understanding how skills are formed at work—and how this process responds to different competitive environments.

[5] We further assess the validity and robustness of this measure in the analyses that follow.

Figure 1: Skill accumulation and wage-growth

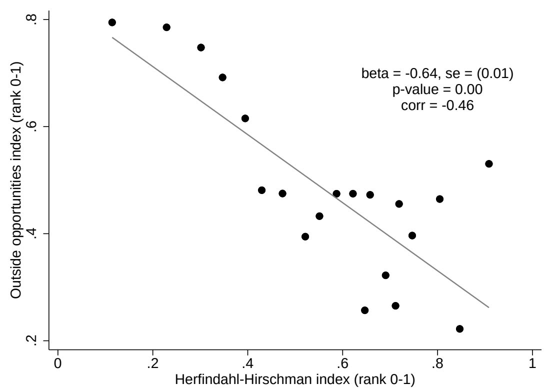
Notes: Figure 1a reports survey responses measuring self-perceived improvements in human capital. Figure 1b relates wage growth to self-reported improvements in human capital. Self-reported improvements in human capital are measured with a 10-point Likert scale, with workers asked to respond to the extent they agree with the statement "I am better at my job than I was a year ago". Given the sparsity of observations to the very left of the scale, the point at "2" on the bin-scatter in Figure 1b represents a weighted average of the observations in its vicinity. The data underlying these figures is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of nearly 9,955 workers employed in the private sector, as detailed in Table A.3.

Market Structure, Perceptions, and Earnings. In our framework, perceived competition strengthens workers' incentives to invest in their human capital. This occurs because, in competitive markets, productivity improvements translate more directly into wage growth and career advancement. For this mechanism to operate, workers must be able to recognize and internalize the competitive conditions they face.

We begin by examining whether workers are aware of the market structure around them. Figure 2 compares our survey-based measure of perceived outside opportunities—the Outside Opportunity Index (OOI)—with the Herfindahl-Hirschman Index (HHI), the standard administrative measure of labor market concentration. The two measures are strongly negatively correlated, indicating that workers do perceive and internalize meaningful variation in market structure.

The strong correlation between the OOI and the HHI indicates that our perception-based measure captures meaningful variation in market structure, while also suggesting that the HHI reflects behaviorally relevant aspects of competition. Despite its central role in both research and policy, the HHI is often treated as a black box: it abstracts from search costs, network frictions, and firm heterogeneity, and may not reflect how workers actually experience employer power. The strong correspondence between perceived and structural measures suggests that, despite these limitations, the HHI captures key aspects of the competitive environment as understood and acted upon by workers. This behavioral validation offers an important complement to existing structural and theoretical evidence on labor market concentration.

Figure 2: Worker perceptions of market competitiveness: The Outside Options index (OOI)



Notes: Individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. Sample restricted to the private sector. The Figure relates our Outside Options index (OOI) constructed with the survey data to the Herfindahl-Hirschman Index (HHI) constructed with the administrative data. The OOI measures perceptions of outside opportunities in the labor market — how competitive a labor market is — by combining responses from 12 questions answered by 19,678 people in the authors' survey into a single index, aggregated up to the 2-digit occupation by commuting zone level. The index is correlated with its underlying items in Table A.4. The HHI measures how concentrated a labor market is, calculated as the sum of squared labor shares at the two-digit occupation by local labor market level, using administrative data from Statistics Norway. The data underlying these figures is based on individual-level administrative data from Statistics Norway linked to surveys conducted by NorStat. These indices are constructed using the full sample of workers in the linked-survey administrative data sample, but sample in the correlation is restricted to private sector workers, as detailed in Table A.3.

That said, we caution against treating the HHI as a conceptual "north star." It remains a black-box construct with well-known limitations. These concerns have motivated a growing literature that moves beyond concentration ratios toward alternative measures of labor market structure, including job transition matrices, occupational similarity, and skill-distance metrics (e.g. Caldwell and Danieli, 2024; Schubert et al., 2024; Dodini et al., 2024).

The correlation also implies that workers hold relatively accurate beliefs about their outside opportunities—something that should not be taken for granted. For example, Jäger et al. (2024) find only a weak correspondence between a single-question measure of workers' expected wages and actual wages at nearby firms in German data. In contrast, our measure shows a much closer alignment between perceived outside options and structural market conditions. This distinction matters because competition authorities and litigation consultants in Europe and the United States routinely rely on the HHI to guide assessments of labor market power, yet its behavioral relevance has rarely been directly examined.

We further probe the OOI in two ways. First, we decompose the index into its components (Appendix Table A.4) and find that the aggregate measure tracks structural concentration more closely than any single item, suggesting that workers draw on multiple signals when forming beliefs about competition. This helps explain why prior work relying on single-item perception measures—such as Jäger et al. (2024)—finds weaker alignment between beliefs and objective market conditions. Second, we assess whether the OOI replicates established empirical relationships. Figure A.3 shows that both perceived (OOI) and structural (HHI) concentration measures display a clear negative and monotonic association with average wages. This pattern is consistent with prior research (e.g. Azar et al., 2022; Rinz, 2022) and suggests that the OOI captures a meaningful dimension of labor market power.

To better understand the properties of our OOI measure, we also compare it with other indicators of market power (Table A.5). Although defined at the occupation–commuting zone level, the OOI correlates positively with firm-level measures based on labor supply elasticities (Bassier et al., 2022). It also shows the expected negative association with product market concentration: markets with greater outside opportunities for workers tend to feature less powerful firms. While labor- and product market HHIs are themselves strongly correlated, the OOI remains more closely aligned with the labor market dimension. This pattern supports interpreting the OOI as a perception-based measure that captures real variation in competitive conditions.

Where Do Workers Learn? One of the central predictions of our framework is that competitive market environments promote skill development, primarily by shaping conditions for informal, worker-led learning. Competition strengthens the link between productivity and pay, increases the share of returns workers can retain, and lowers the effective cost of learning by improving access to feedback, peers, and opportunities for development on the job. In this section, we test this prediction by examining whether workers in more competitive labor markets are more likely to report having improved their skills at work. Recognizing worker agency and informal learning shifts attention beyond firm training decisions to the broader environments in which skills are accumulated.

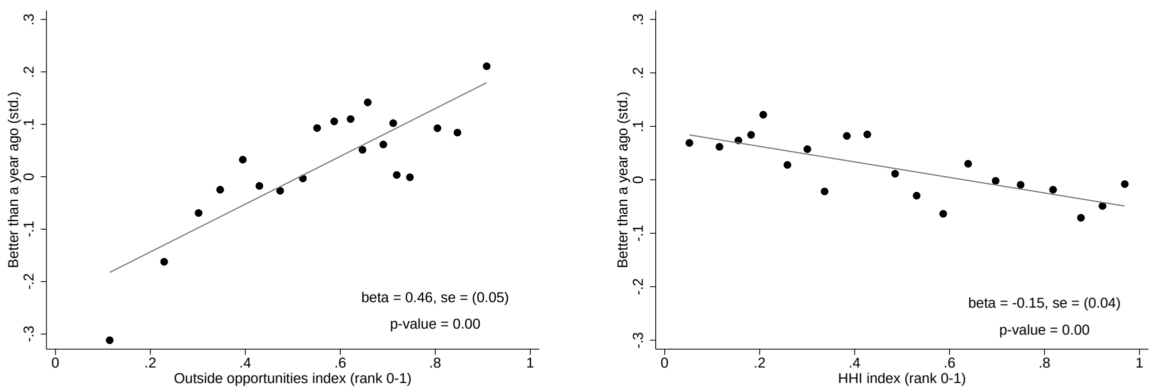
We begin by examining whether competition is associated with greater self-reported learning on the job. Figure 3a shows that the OOI is strongly positively associated with learning: workers in more competitive markets report substantially greater skill development, with those in median-competitiveness markets reporting 0.23 standard deviations less learning than those in the most competitive ones. Figure 3b shows a similar pattern using the HHI: as concentration rises, the probability that workers report being better at their jobs declines.

These relationships are consistent with the framework's predictions and remain robust when controlling for worker demographics, occupation, region, tenure, firm characteristics, and industry (see Row 1 of Tables A.7 and A.8), indicating that they are not driven by compositional differences across labor markets. Taken together, these findings provide clear evidence that competitive labor markets are associated with greater on-the-job learning. Whether measured through objective concentration indices or workers' perceptions of outside options, competition appears to act as a catalyst—rather than a constraint—for skill development.

Figure 3: Human capital accumulation and market structure

(a) Outside opportunity index (OOI)

(b) Herfindahl-Hirschmann Index (HHI)



Notes: Figure 3 reports the relationship between market a self-reported measure of human capital development – the extent that workers perceive themselves to better at their job compared to last year – and labor market structure, as measured both by the OOI and the HHI. The data underlying these figures is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers employed in the private sector, as detailed in Table A.3.

To assess whether these patterns reflect labor market competition specifically—rather than broader features of competitive local economies—we compare the predictive power of the OOI with that of a product market HHI, measured using firm revenue shares within sector–commuting zone cells. Row 1 of Table A.9 shows that both measures are positively associated with learning, but the OOI coefficient is substantially larger and remains stable when the product market HHI is included. This indicates that labor market competition plays a more direct role in shaping skill development, even after accounting for product-side dynamics, consistent with the idea that competition raises the return to learning and strengthens worker incentives.

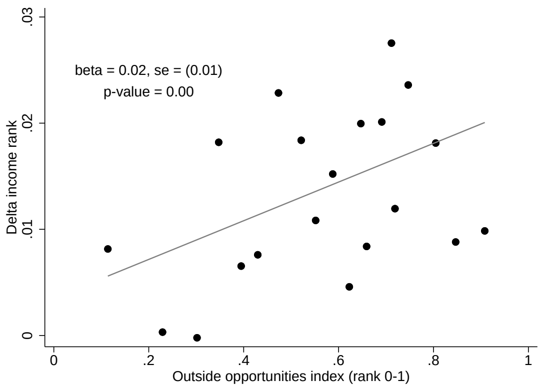
If workers in more competitive markets learn more, we should also expect them to experience greater earnings growth. Figure 4a confirms this: workers in high-competition markets not only report more learning, but also show faster wage progression. This link between competition, self-reported learning, and actual wage growth suggests that competition affects not just perception—but productivity and economic advancement.

To unpack where this learning occurs, we next turn to the role of firms. Do firms in more competitive markets contribute more to worker development? Using administrative data, we estimate firm-specific effects on wage growth—net of worker characteristics and excluding the survey sample. Figure 4b shows that firms in more competitive markets generate faster wage growth for their employees, with magnitudes about half the size of the individual-level wage–competition gradient. Figure 4c links these firm-level wage effects to worker-reported learning: employees at firms with higher wage-growth effects are also more likely to report becoming better at their jobs. This triangulation reinforces our interpretation that self-reported learning captures meaningful human capital accumulation, and that competition shapes both individual incentives and firm practices. Taken together, these findings show that workers in competitive markets learn more, earn more, and are more likely to work in firms that foster learning and wage progression—suggesting that competition promotes not only individual development but also shape the institutional context in which learning occurs.

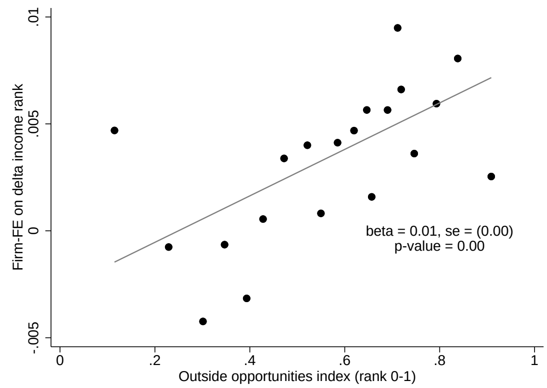
The results in this section show that competition acts as a catalyst for skill development rather than a constraint on growth. This finding aligns closely with our framework: competitive pressure raises the gross return to learning, increases the share of that return workers can retain, and lowers the effective cost of acquiring skills—particularly through informal learning. For firms, the effects are more ambiguous: while the gross return to training may rise, the ability to capture those returns can decline. Prior work has largely abstracted from these informal and worker-led margins, focusing instead on firm-provided training and the composition of skills rather than the overall level of learning or the distinction between gross returns and retention. Our results highlight this broader channel of skill development as central to understanding how competition shapes human capital formation. The next question, then, is how workers acquire these skills, what kinds of skills they build, and why they choose to do so.

Figure 4: Market structure, wage growth, and human capital accumulation

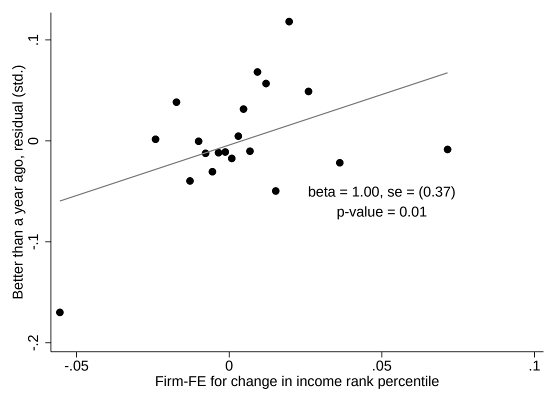
(a) Wage growth and OOI



(b) Firm-FE on wage growth and OOI



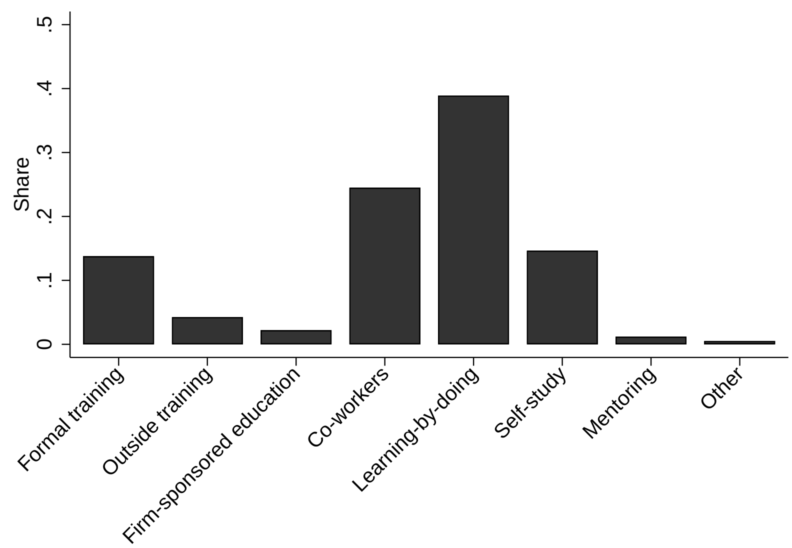
(c) Learning and firm-FE on wage growth



Notes: Figure 4a reports the relationship between worker wage growth and mean labor market-level perceptions of outside opportunities. Figure 5b reports the relationship between the extent that firms consistently generate earnings growth for their workers (outside the survey sample), and labor market concentration as measured through our survey. Figure 4c reports the relationship between survey measures of human capital accumulation and out-of-sample estimates of firm-specific wage growth. The data underlying these figures is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. The survey outcomes are from our survey sample, whereas the wage growth measures are from the sample of workers not in the survey, as detailed in Table A.3.

How Do Workers Learn? Having shown that competition is associated with greater skill development, we now turn to the mechanisms through which that learning occurs. Understanding how workers build skills on the job is central to our broader argument and to the illustrative framework introduced earlier—especially because much of that learning takes place outside formal training programs. A key advantage of our survey is that it distinguishes between formal, firm-led training (e.g., internal programs, external courses, or employer-sponsored education) and informal learning channels (e.g., learning-by-doing, peer interaction, self-study, and mentoring). Distinguishing these channels is essential, as a large share of workplace skill development globally occurs through informal means (Figure A.1).

Figure 5: How do people learn skills in the labor market?



Notes: Figure 5 displays the extent that workers learn through different channels. These shares are based on the weighted average of the extent that workers learn each skill in our survey, and the ways in which they learn these skills. The data underlying this figure is individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers employed in the private sector, as detailed in Table A.3.

Figure 5 summarizes how workers acquire skills on the job. Respondents who report learning new skills over the past year indicate the channels through which this occurred, selecting all that apply. Informal mechanisms (learning-by-doing, peer interaction, mentoring, and self-study) dominate by a wide margin. While many workers report some exposure to firm-provided training, informal learning is both more prevalent and more consistently cited. Notably, self-study, arguably the channel requiring the most initiative and autonomy, is among the most common modes, underscoring the active role workers play in their own skill development. Fewer than two percent of respondents choose “other,” suggesting that the survey captures nearly the full range of workplace learning activities.

These findings suggest that most skill development occurs through informal channels—and that focusing exclusively on formal, firm-led training provides a narrow understanding of how human capital is built in the labor market. Informal learning is not a solely complementary mechanism; it appears to be the dominant mode through which workers develop their skills. While our survey is focused on Norway, these results likely have broader reach: in almost all

OECD countries, workers cite informal learning as much more common than participation in firm-led training (Figure A.1).

Having documented the main channels of workplace learning, we next assess how these modes relate to one another and to workers' perceived skill improvement. Table A.6 shows that formal and informal learning are only weakly correlated (about 0.3), indicating that they capture distinct dimensions of workplace learning. More importantly, informal learning is far more predictive of self-assessed human capital growth: its correlation with perceived improvement is roughly 0.4, compared to just 0.1 for formal training. These results highlight the central role of informal learning as a primary mechanism of skill accumulation and suggest that formal training explains only a small share of variation in perceived development.

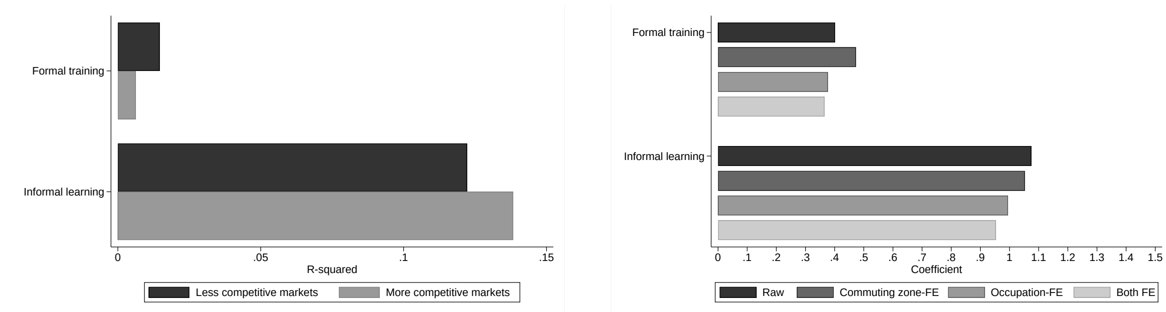
Figure 6a examines how the relationship between learning mode and perceived skill improvement varies across market structures. Informal learning is more strongly associated with self-assessed improvement than formal training, both in competitive and in concentrated labor markets. The relative strength of these associations, however, depends on market structure: formal training is somewhat more predictive of improvement in concentrated markets, while informal learning is more predictive in competitive ones.

Figure 6b examines how the prevalence of each learning mode varies with competition. Both formal training and informal learning increase as labor markets become more competitive, but the rise is substantially steeper for informal learning. While prior work has focused on how competition affects the type of training, our framework highlights why it also raises the level of learning. Competition increases the gross return to productivity improvements, allows workers to retain a larger share of those returns, and lowers the effective cost of acquiring skills—especially through informal channels such as learning-by-doing and peer interaction. These forces make worker-led learning particularly responsive to competitive pressure. For firms, the effects are more nuanced: competition raises the gross return to training as firms operate closer to the production frontier, yet it reduces their ability to capture those returns as poaching and wage pressure intensify. The result is a clear but asymmetric pattern—formal, firm-led training rises with competition, while informal, worker-led learning rises much more sharply. This pattern is consistent with the joint production view of human capital formation outlined in our framework, where competition amplifies both individual incentives and the organizational environments that sustain them.

The relationship is not driven by occupation, or commuting zone – as evidenced by the robustness of this result to the inclusion a large number of fixed effects. Further, rows two and three of Table A.7 and Table A.8 show that the relationship between competition and learning modes is robust to the inclusion of a large array of covariates and not sensitive to how we measure labor market power. The strong, positive association between competitive market environments and informal learning persists even under saturated specifications controlling for occupation, commuting zone, workforce composition (education and age), and firm size.[6]

Figure 6: Informal learning, formal training, and market structure

(a) Human capital accumulation by mode of learning (b) Mode of learning and market structure



Notes: Figure 6a reports the extent that each mode of learning is associated with worker's perceptions that they are better at their job than last year. This is measured as the R-squared from separate bi-variate regressions between mode of learning and being better at one's job than the prior year, by market structure – defined by the OOI, split at the median. Figure 6b reports the regression coefficients from a regression between market structure (OOI) and the learning mode, first with no control variables, then with commuting-area fixed effects, then fixed effects for two-digit occupation code, and then both simultaneously. Informal learning and is measured by reported engagement in learning-by-doing, self-directed study, co-worker learning, and mentoring as well as general closeness with colleagues (Gächter et al., 2015) and the extent that workers are exposed to varied tasks. The second captures firm investment in formal training and includes exposure to internal training programs, external courses, formal education sponsored by the employer, and the time elapsed since training, as well as measures of firm spending on training. Both indices are standardized to have a mean of zero and standard deviation of one. The data underlying these figures is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers employed in the private sector, as detailed in Table A.3.

We next compare how learning responds to labor- and product market competition to clarify which market forces drive skill formation. Rows 2 and 3 of Table A.9 show that informal learning is highly responsive to labor market competition but largely unaffected by product market concentration. In contrast, formal training responds to both dimensions. This pattern suggests that worker-led learning is governed mainly by labor market incentives—where competition raises the returns to productivity growth, increases the share workers can retain, and lowers learning costs—whereas firm-led training is also shaped by product market pressures that influence profitability and innovation demand.

To better understand what drives informal learning, we distinguish between two comple-

[6]Disaggregating by industry reveals wide variation in average learning levels but a consistent pattern overall: more competition leads to more learning, and informal learning remains the dominant, more responsive channel (Figure A.6). Two industries—finance and real estate, and organizations—show a negative relationship between competition and formal training, providing support for the idea that firms can underinvest in training in competitive markets (Pigou, 1912; Becker, 1962; Acemoglu and Pischke, 1998, 1999a). By and large, however, most industries exhibit an increased level of training in competitive markets.

mentary mechanisms: worker initiative and firm environment. We begin with worker initiative, focusing on the most direct expression of individual effort—self-study. Figure A.7 shows that workers in more competitive labor markets are substantially more likely to engage in self-study or training outside formal channels. This provides clear evidence that competition strengthens motivation and raises the returns to personal investment in skill development.

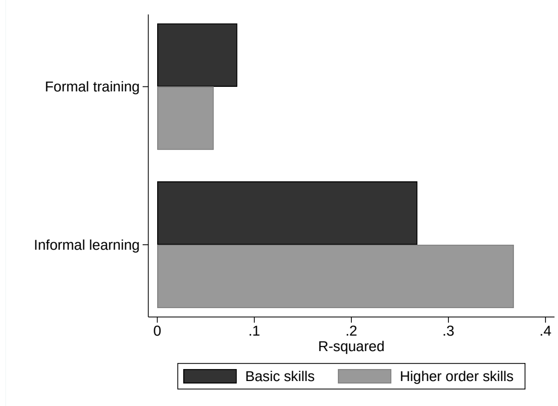
At the same time, informal learning depends on the conditions firms create. In our framework, these environments improve organically with competition, as firms operate closer to the production frontier and rely more on collaboration, feedback, and knowledge sharing. To examine this channel, Table A.11 applies a simple mediation approach. Panel A shows that workers in more competitive markets report stronger, growth-oriented firm cultures. Panels B–D then test whether accounting for culture attenuates the relationship between outside options and learning outcomes (self-assessed improvement, informal learning, and formal training). In each case, the coefficient declines, suggesting that competition fosters learning both by motivating workers directly and by strengthening the organizational environments that enable it.

In sum, workers learn mainly through informal channels, and this form of learning becomes especially prominent in competitive labor markets. Firms still invest in formal training, but their main contribution lies in creating the environments that enable informal, worker-led learning. We next turn to the question of what types of skills workers acquire, and how these patterns vary by market structure and learning mode.

What Do Workers Learn? We now examine what kinds of skills workers acquire through different learning modes and under different market structures. This distinction is central to understanding the broader consequences of skill formation: different skills contribute differently to productivity, earnings growth, career progression, and firm performance. Identifying how market structure shapes the development of specific skills is therefore key to interpreting the economic implications of our findings.

Before turning to a data-driven approach for skill-classification, we follow Deming and Silliman (2024) and distinguish between basic skills — such as manual work, service provision, and task-specific technical competencies — and higher-order skills, such as communication, leadership, teamwork, and decision-making. This distinction builds on Bloom et al. (1956), where higher-order skills demand more from individuals to develop, but also allow individuals to take an active role in the production of more complex tasks. Interestingly, formal educational programs have exhibited a mixed ability in developing higher-order skills (e.g., Deming and Silliman (2024)). As these skills are becoming increasingly rewarded in the labor market, understanding how these types of skills can be developed in the workplace is essential for meeting the labor market demands of the coming decades.

Figure 7: Explaining improvements in skill type, by learning mode

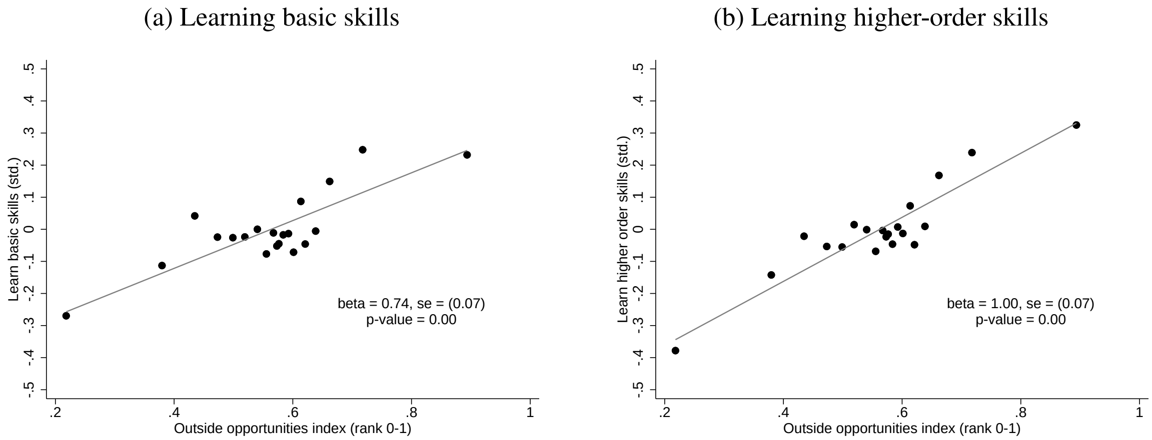


Notes: Figure 7 reports the R-squared from bivariate regressions which relate skill development – either in terms of an index of basic or higher order skills – and learning mode – either firm investments or informal learning. Basic skills are measured as an average of manual work, analytic thinking, service provision, computer programming, adaptation to new technology, working under pressure, and operation of specialized machinery. Higher-order skills are measured as an average of teamwork, leadership, decision-making, communication, and learning quickly. Both indices are standardized to have mean zero and standard deviation one. The data underlying these figures is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Figure 7 examines how formal and informal learning modes are associated with different types of skill development. Informal learning is strongly correlated with both basic and higher-order skills, but the association is much stronger for higher-order skills. In contrast, formal training is more modestly correlated with skill development and is more closely tied to basic, task-specific skills. These patterns reinforce a central implication of our framework: higher-order skills – which are transferable across markets, and increasingly in-demand – are developed primarily through informal learning, because these skills yield the greatest overall returns to workers and are most fully rewarded in competitive environments.

Figure 8 shows how reported learning of basic and higher-order skills varies with market structure. Both types of skills increase as labor markets become more competitive, but the gradient is much steeper for higher-order skills. This suggests that competitive environments do not simply promote more skill development overall—they also tilt the composition of learning toward potentially more transferable skills. This pattern aligns closely with our conceptual framework, where stronger outside options raise worker incentives to invest in flexible skills that enhance long-term mobility and value. From the point of view of firms, cultivating higher-order skills can also be essential for firms to remain competitive (Aghion et al., 2019).

Figure 8: Competition and improvements by skill type



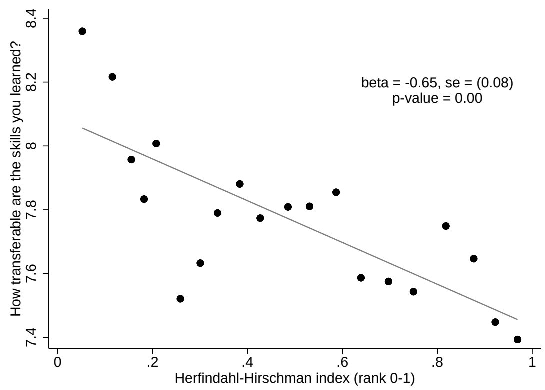
Notes: Figure 8 exhibits the relationship between market structure, as measured by the Outside Opportunity Index, and multidimensional skill development for (a) basic skills, and (b) higher order skills, separately. The data underlying these figures is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Having established how market structure relates to the development of basic and higher-order skills, we next examine the role of skill transferability in shaping human capital accumulation. A central insight from Acemoglu and Pischke (1999a) is that firms may be less willing to invest in transferable skills in competitive labor markets, since they capture a smaller share of the returns. Our framework adds an additional mechanism on the firm side: competition can also raise the gross return to skill, as proximity to the production frontier increase the productivity payoff to worker ability. At the same time, on the worker side, our framework emphasizes that transferable skills become more attractive from the worker's perspective when competition increase, as this expands the worker's outside options and increases the share of returns that the worker can retain. This distinction is crucial: market structure may affect firms and workers in fundamentally different ways, particularly in the domain of informal learning, where workers play an active role in acquiring skills.

In our survey, we ask workers how the skills they learned on the job in the last year would transfer across occupations. Figure Figure 9 shows that the mean extent of self-reported transferability rises with competition.[7] This reinforces the idea that competition not only increases learning, but also shifts its composition toward more portable and higher return skills.

[7]To avoid mechanical correlation with the OOI - which includes transferability items in its construction - we use the HHI as the measure of market structure in this analysis.

Figure 9: Transferability and market structure



Notes: Figure 9 reports the relationship between the extent that workers consider that the skills they learned at the workplace in the last year as transferable and labor market concentration, as measured by the Herfindahl-Hirschmann Index. Since the outcome variable is a component of the Outside Opportunity Index, we do not report the relationship between the OOI and how transferable workers perceive their learning to be. Figure A.8 provides a more in-depth analysis at the relationship between skill transferability and market structure by whether or not skills are learned through formal training or informally, and conditional on occupation. The data underlying these figures is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Skill transferability depends not only on the intrinsic content of skills but also on the surrounding labor market institutions and competitive environment. As Acemoglu and Pischke (1999b) and Lazear (2009) emphasize, skills that are technologically general can become effectively specific depending on context. This distinction is important for interpreting the patterns in Figure 9. To assess how workers and firms invest in skills with intrinsically transferable content, we take a data-driven approach. Specifically, we regress self-reported overall transferability of recent learning on the intensity of learning across different skill dimensions. This yields the marginal contribution of each skill type to perceived transferability, allowing us to classify skills by their intrinsic portability—net of the context in which learning occurs.

Table A.12 presents the average transferability of each skill across three margins: firms, occupations, and industries. Higher-order skills are consistently more transferable than basic skills across all three dimensions. This highlights their potential role in supporting mobility and reducing labor market frictions—and again points to the centrality of informal learning, which disproportionately produces these types of skills.

After classifying the transferability of skill content, we examine how it varies by learning mode and market competition (Figure A.8). We find that the transferability of both formally and informally acquired skills rises with competition. This result contrasts with canonical predictions from Becker (1962) and Acemoglu and Pischke (1998, 1999a), which imply that competitive pressure should discourage firm investment in transferable skills. Instead, our findings suggest that such investment not only persists but expands in competitive environments. Our preferred interpretation is that competition raises the gross return to skill formation enough to offset the lower retention. More broadly, it may be that firms in dynamic labor markets cannot afford not to invest in transferable skills— because failing to do so would compromise productivity and competitiveness in a market with high innovation demand and little labor market slack. And, if firms have monopsony power over the bundle of skills a worker possesses (Lazear, 2009), or if a firm maintains informational monopsony power over the workers' ability (Acemoglu and Pischke, 1998), training may not incur excess turnover costs.

To better understand which skills drive these patterns, we disaggregate workplace learning across the specific skill dimensions included in our survey (Table A.10). For each skill, we regress reported learning on indicators for informal learning and formal firm-provided training, including both in a horse-race specification, and then order skills by their average transferability. Two clear patterns emerge. Highly transferable skills—such as leadership, problem-solving, and communication—are developed mainly through informal learning, and the relative importance of informal over formal learning increases systematically with skill transferability. This reinforces our interpretation above: informal learning is not only more prevalent overall, but it is the primary channel through which competitive markets foster the formation of general, higher-order skills.

Finally, we take into account the role of occupations in shaping the pattern of skill development across markets. Figure A.8c-d shows that when we condition on occupation, the slope between competition and transferability almost fully flattens across both training modes—but is not reversed. That is, more competitive labor markets are associated with the accumulation of more transferable skills, but this appears largely driven by compositional differences in skill type across occupations. Nonetheless, for the standard prediction in Acemoglu and Pischke (1999a,b) to hold, we would need to observe the opposite: a negative relationship between competition and transferability conditional on skill. We do not find this.

5 Behavioral Foundations for the Descriptive Patterns

The preceding analysis shows that human capital accumulates faster in competitive labor markets, that this learning occurs primarily through informal channels, and that the resulting higher-order, transferable skills reflect both market structure and the behavior of workers and firms. While these patterns align with our framework, the observational data cannot isolate causal mechanisms or distinguish whether competition affects learning through firm behavior, worker incentives, or both. To probe these channels directly, we field two complementary surveys—one of workers and one of managers—each combining belief elicitation, a randomized vignette experiment, and preference mapping. The belief module captures views about how competition shapes learning and motivation; the experiment isolates how competition influences human capital investment; and the preference module asks respondents to choose between competitive and concentrated market environments and explain their reasoning. Together, these components provide new evidence on how market structure shapes learning incentives from both sides of the labor market.

5.1 How Workers and Firms View Training, Learning, and Competition

We first present descriptive results on worker and manager perceptions. We begin with workers and then turn to managers.

Workers. Workers generally perceive formal firm investments in training as crucial for their career development (Figure A.9a). However, there is notable variation in their responses. When asked about the effectiveness of different training types, workers indicate that training provided internally is more effective than training offered by external providers (Figures A.9b-c). This suggests that firm-specific training is valued more highly by workers.

In comparison to formal training, workers express significantly greater enthusiasm for the role of informal learning in their careers. Nearly one in four respondents rate informal learning as a 10 out of 10 in terms of its importance for their human capital development (Figure A.9d). In contrast, the modal response for firm training is 7 out of 10, with the mean score nearly half a standard deviation lower. Furthermore, a large majority of workers emphasize that opportunities for career advancement serve as strong incentives for learning in the workplace, highlighting the role of external opportunities in driving worker learning (Figure A.9e).

Firms. Managers are considerably more optimistic than workers about the impact of firm training on productivity (Figure A.10a). Like workers, managers report that internal training is more effective than external training (Figures A.10a-b). This preference for internally provided training suggests that such programs may better address the specific human capital needs required to enhance job performance within the firm. This could be due to the skills being more firm-specific, as described by Acemoglu and Pischke (1999a), or because transferable, higher-order skills critical in the workplace are best developed within the firm's applied context. The difference in enthusiasm between managers and workers — where managers are notably more optimistic about the value of firm-provided training in general — may arise either because firms capture more of the productivity gains than workers (making these gains less visible to workers), or because managers are overly optimistic about training's role.

Managers largely view competition as a key driver for investing in training. The majority of managers believe that competition necessitates increased investment in training (Figure A.10d). This is consistent with the proposed stylized framework, which suggests that competition may require firms to increase their investment in human capital in order to remain productive and competitive. In competitive environments, firms are more likely to see the returns from skilled workers as critical to their survival, which motivates them to invest more in training.

Furthermore, managers recognize that competition between firms can also motivate workers to invest in their own human capital (Figure A.10e). This suggests that in competitive environments, the frictions associated with human capital investments may be lower, making such investments more attractive. By reducing these frictions, competition encourages both firm-led and worker-driven skill development, as workers respond to better outside opportunities by improving their skills.

5.2 Experimental Evidence on Competition and Skill Development

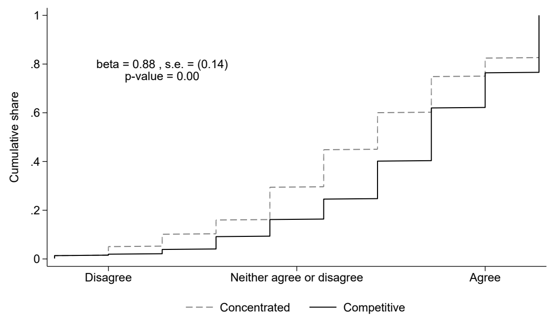
To complement the observational evidence, we turn to vignette experiments that isolate how competition influences workplace human capital investment. In these experiments, workers and managers are randomly assigned to hypothetical competitive or concentrated market environments and asked how—and why—they would make decisions related to learning and skill development.

Workers. Our main outcome in this analysis is whether workers assigned to the competitive market condition believe that an additional year of work will result in more learning than workers randomly assigned to the concentrated market condition.

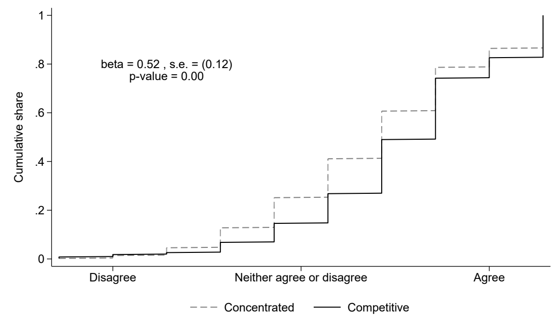
The results show that workers in competitive environments are significantly more likely to expect improvement in their job performance over time, with each additional year of work (Figure 10a). Workers thus anticipate stronger skill accumulation when facing competitive conditions, consistent with the idea that competition raises learning incentives and expectations of growth.

Figure 10: Competition and learning: Behavioral foundations from workers and firms

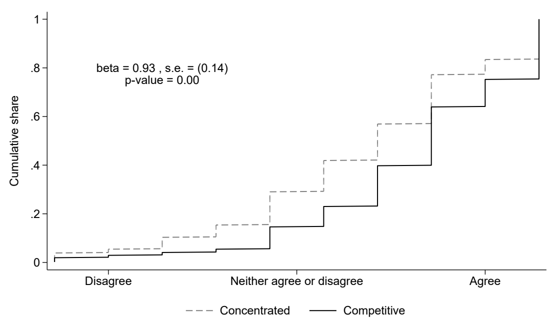
(a) Workers: "Every year I work at this company I will be better at my job."



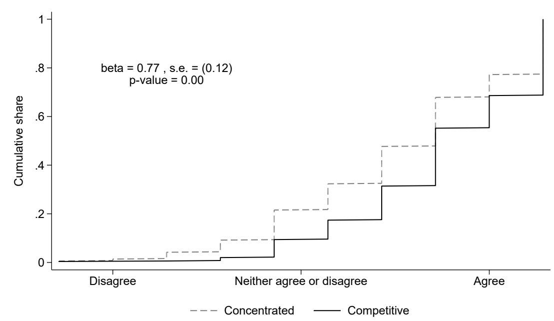
(b) Managers: "Workers in this firm will be better at their jobs after each year."



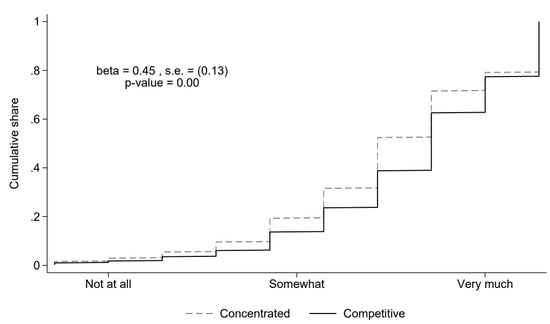
(c) Workers: "Skills are critical for my labor market success."



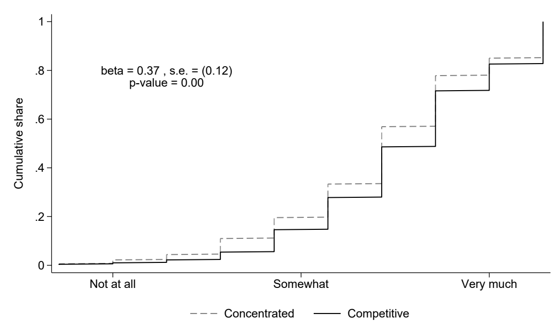
(d) Managers: "Investing in training is critical for succeeding as a business."



(e) Workers: "How motivated will you be to invest in informal learning?"



(f) Managers: "How motivated will your workers be to take up training?"



Notes: Figure 10 reports the main results from the worker and manager vignette experiments. In these experiments, workers and managers are randomly assigned to one of two conditions – a competitive labor market or a concentrated labor market – and asked how they would behave. The results reported in Figures (a) and (b) were pre-registered as the primary outcomes in the AEA RCT registry. The full survey instruments can be found in Appendix B, and the treatment effects on supplemental outcomes are reported in Figures A.11-A.14. These data are from surveys fielded by Norstat to 1,026 workers and 1,001 managers.

We next examine workers' motivation to invest in skill development. Workers believe that competitive markets increase the likelihood that skill improvements will lead to better labor market outcomes (Figure 10c). As a result, they are more motivated to invest in both informal learning and formal training across a broad range of skills (Figures 10e, A.11b). These suggest that competition not only affects access to learning opportunities but also changes how workers weigh the costs and benefits of investing in their skills.

Next, we assess how market structure affects the types of skills workers would invest in. As shown in Figures A.11c-d, exposure to a competitive environment increases reported motivation to acquire both basic and higher-order skills, with statistically significant effects in both domains. The effects are similar in magnitude, suggesting that competition does not shift the type of skills workers prioritize, but simply increases their willingness to invest.

Figure A.15 helps explain why higher-order skills respond so strongly to competitive pressure. Although workers are equally willing to invest in basic and higher-order skills, they perceive the latter as substantially harder to acquire—nearly one point higher on a 1–10 difficulty scale. This distinction is consistent with earlier results showing that higher-order skills are developed mainly through informal learning and sustained individual effort, making them especially sensitive to incentives. When acquisition costs are high, increased motivation becomes a key driver of learning.

Beyond private incentives, workers also appear to internalize firm outcomes. Figures A.12a–b show that they emphasize how skills affect outside options, yet they also believe their learning raises firm productivity (Figure A.11a). This suggests that workers perceive a dual payoff to learning—both personal and organizational—implying that competitive environments may enhance productivity partly by aligning worker and firm incentives.

Taken together, the vignette experiments show that competition acts as a catalyst for human capital investment by strengthening workers' motivation to learn. The results highlight that skill formation is not simply a byproduct of firm training, but a proactive decision shaped by how competition expands the value of skills—both within firms and through outside options.

Firms. We complement the worker experiment with a parallel vignette study targeting managers, designed to examine how perceived market structure shapes firms' training decisions and underlying motivations. As in the worker experiment, managers were randomly assigned to either a competitive or a concentrated market scenario and asked a series of questions about how they would respond in terms of skill investment, training focus, and strategic priorities.

Manager responses indicate that they expect competition to increase human capital accumulation within their organizations (Figure 10b). The effect is statistically strong and mirrors the worker evidence, suggesting that competition promotes, rather than discourages, investment in skill development from both sides of the labor market.

To understand the motivations behind these expectations, we examine managers' qualitative assessments from the vignette experiment. Managers in competitive markets consistently describe human capital investment as essential for business success (Figure 10b), implying that they perceive higher payoffs to training and learning when competition is strong. This behavioral evidence helps explain why firms may increase skill investments even when competitive pressure limits their ability to retain all of the returns.

While managers see competition as making human capital investment critical, their focus extends beyond productivity. As shown in Figure A.13a–b, they emphasize skill development as vital not only for productivity and firm survival but also for attracting and retaining talent. Notably, they place greater weight on recruitment than retention, suggesting that offering opportunities for learning is a key strategy for securing skilled workers. In competitive environments, firms thus treat skill development as both a productivity tool and a means of sustaining performance through effective talent acquisition.

Firms' concern with productivity also extends to the type of skills they invest in. Managers in competitive environments report a greater willingness to invest in transferable skills (Figure A.13c). Although such investments increase the risk of poaching, they can be among the most valuable from the employer's perspective. Moreover, as Lazear (2009) notes, while individual skills may be transferable, the bundle of skills an employee holds can remain firm-specific, allowing employers to capture part of the return. In this view, competition reshapes not only who captures the returns to training, but also what kinds of skill investments firms consider essential for remaining viable in demanding markets.

Beyond highlighting the role of skill development in raising productivity, the manager survey also sheds light on how managers perceive worker behavior. Those assigned to competitive settings expect workers to be more motivated to invest in both formal training and informal learning across a wide range of skills (Figures 10c and A.14a, c, d). This suggests that managers view human capital accumulation as a joint process, shaped by both firm and worker choices—consistent with our broader argument that competition activates workers as independent agents of skill formation. At the same time, managers do not report a greater willingness to raise wages following these investments (Figure A.13d), implying that human capital development may provide an amenity value for workers rather than being directly compensated through pay.

Finally, despite recognizing that competition may motivate workers to invest more in informal training than in firm-provided training (Figure A.14a versus Figure 10f), managers remain confident in the importance of firm-led training. These results stand in contrast to the broader findings in this paper, which highlight the critical role of informal learning in worker development. This discrepancy suggests a potential information friction in how managers perceive and foster workplace human capital accumulation. Given that informal learning plays a key role in skill development, policies aimed at enhancing firm culture (Table A.11) may prove more effective than traditional investments in formal training when it comes to improving worker skills and productivity.

In sum, competitive pressure changes how firms approach training. Managers in competitive markets view skill investment as essential not only for productivity and survival, but also for recruiting and retaining talent. They report a greater focus on transferable skills, reflecting broader strategic adaptation to tighter performance demands and competition for workers. While our stylized framework emphasized that the effects of competition on firm-led training are theoretically ambiguous, these results suggest that the increase in gross returns dominates in practice.

5.3 Worker and Firm Preferences for Labor Market Competition

In addition to the randomized vignette experiments for workers and managers, we also ask the experiment respondents to indicate whether they would prefer to operate (managers) or work (workers) in a competitive or concentrated labor market, and to briefly explain their reasoning. While not part of the experimental design, these stated preferences offer complementary insight into how individuals and firms evaluate market structure and the learning environments it supports.

Workers. Over 70 percent of workers indicate that they would prefer to work in a competitive labor market (Figure A.16a). Compared to those who selected the concentrated market, workers who selected the competitive market are more likely to cite access to non-wage amenities such as learning and training, better career advancement opportunities, and higher wages as reasons for their choice (Figure A.16c). These responses align closely with the survey and vignette findings, and further underscore the role of worker agency in driving skill formation under competitive conditions.

Firms. Among managers, nearly 60 percent preferred the competitive setting (Figure A.16b). When asked why, those selecting competition were significantly more likely to cite factors related to learning and human capital development, including stronger worker motivation to learn, greater incentives for skill acquisition, improved ability to hire junior workers, and better career opportunities within the firm (Figure A.16d). These patterns are consistent with the mechanisms emphasized in our conceptual framework, particularly the idea that competitive pressure increases the value of skill development as a strategy for firm performance and adaptability.

Taken together, these results suggest that both workers and firms associate competitive market environments with stronger incentives for learning and broader opportunities for skill development. While not causal, these patterns reinforce the view that competition shapes not only behavior, but also expectations and preferences around human capital investment.

6 Discussion and Conclusion

This paper investigates how competition shapes human capital development in the labor market. We draw on a novel large-scale dataset that links administrative and survey data, complemented by two auxiliary survey experiments, to provide a detailed analysis of the interactions between competition, firms, and workers in shaping the accumulation of human capital beyond formal schooling. Our findings extend beyond standard approaches that focus solely on firm training and labor market competition, emphasizing instead the role of workers as active agents and highlighting the importance of informal learning, as opposed to top-down, firm-provided training.

Our main finding re-conceptualizes competition as a catalyst for, rather than a barrier to, human capital accumulation. This primary takeaway is supported by several results that help extend existing literatures on labor market structure, the technology of skill formation, and the multi-dimensionality of human capital. First, both workers and firms invest more in workplace learning in more competitive markets. Second, informal learning—rather than firm-provided training—accounts for the majority of skill development, particularly in competitive environments. Third, transferable, higher-order skills are especially responsive to informal learning and market competition. While these patterns are evident in the descriptive data, they are further supported by experimental evidence that isolates the role of competition in shaping how workers and managers make human capital investment decisions.

We interpret these results though a stylized framework in which the human capital of employees provides firms with a critical edge in competitive markets, and where workers are more motivated to develop their skills when they have opportunities for career advancement both within and outside their firm. In this framework, firms view the fear of poaching as secondary to the productivity-enhancing role of human capital investments. From the workers' perspective, skills that are highly valued across a wide range of firms become the most attractive targets for investment. Informal learning —often overlooked in theoretical models but pervasive in practice— emerges as the dominant mode of skill formation. As a result, competition cultivates transferable, higher-order, skills. This takeaway challenges the widely held belief that competition among employers leads to a market failure and underinvestment in human capital; particularly in terms of transferable skills (e.g. Pigou, 1912; Becker, 1962; Acemoglu and Pischke, 1999a).

We contribute to several active research agendas. We extend classical models of training (Becker, 1962; Acemoglu and Pischke, 1998, 1999a) by showing that competition can raise investment levels when it increases the value of skills, even if retention falls. We complement recent work on monopsony and labor market power (Card, 2022; Caldwell and Danieli, 2024; Schubert et al., 2024; Azar and Marinescu, 2024) by demonstrating that market structure shapes not only wages and sorting, but the very process of skill accumulation. We speak to a broader literature on life-cycle human capital formation (Ben-Porath, 1967; Lucas, 1988; Heckman, 2006; Deming, 2023) by showing that informal, effort-driven learning dominates the formation of higher-order skills inside the firm. Finally, we integrate the literatures on skill specificity (Becker, 1962; Acemoglu and Pischke, 1999a; Lazear, 2009; Dodini et al., 2024) and the growing importance of broad, higher-order skills (Deming and Silliman, 2024; Woessmann, 2024) by showing that such skills can be developed through worker-led, experience-based learning — and that because workers perceive them as transferable, this learning is more likely to occur in competitive environments. These insights open a new empirical and conceptual lens on how firms, workers, and markets jointly shape the formation of human capital over the life-cycle.

The results suggest that rising labor market concentration may suppress not only wages but also the development of human capital—especially among workers whose learning depends on dynamic environments. They also point to new levers for policy. Specifically, strengthening competition, enabling mobility, and fostering learning-conducive work structures may be more important for skill formation as expanding access to formal training. Finally, by linking firm behavior, worker agency, and market structure, they offer a new lens on how inequality in opportunity and productivity is generated, and potentially mitigated, inside the workplace.

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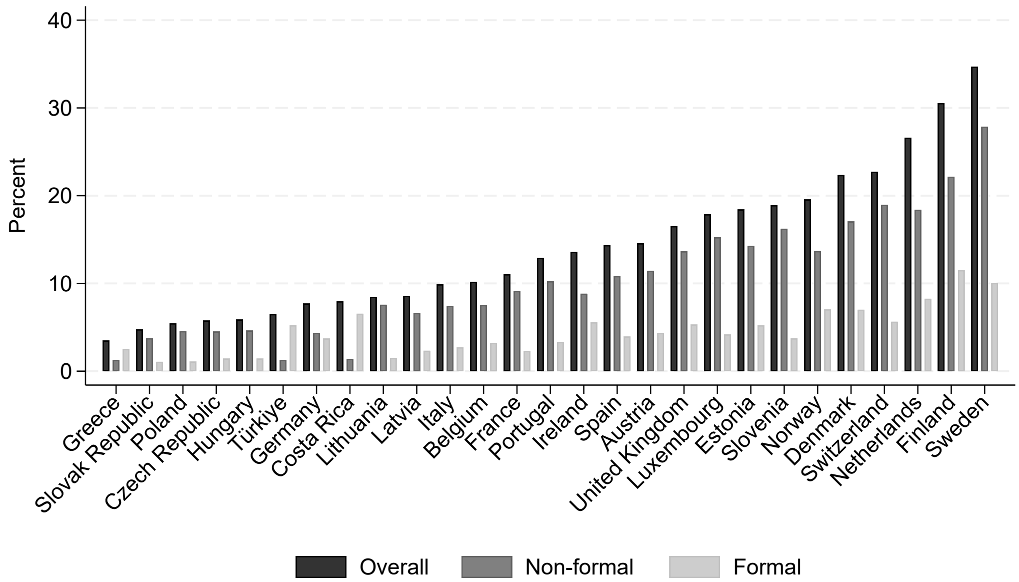
A Appendix Figures and Tables

Table A.1: Overview of Core Measures

Measure	Description	Source	Notes / Construction
Better at My Job	Self-reported improvement over the past year; proxy for on-the-job learning	Survey	Binary indicator (1 = better than last year)
Market Concentration (HHI)	Sum of squared firm employment shares within occ–cz cells	Administrative	Rescaled to the [0,1] range
Outside Options Index (OOI)	Perceived local opportunities and mobility prospects	Survey	Aggregated to occ–cz rank [0,1]
Informal Learning Index	Engagement in learning-by-doing, self-study, peer learning, and mentoring	Survey	Standardized (mean 0, sd 1)
Formal Training Index	Exposure to internal training, external courses, or firm-funded education, and firm training costs	Survey + Administrative	Standardized (mean 0, sd 1)
Basic Skill Index	Self-reported learning in manual, analytic, service, and task-specific skills, weighted by job importance	Survey	Standardized (mean 0, sd 1)
Higher-Order Skill Index	Self-reported learning in teamwork, leadership, decision-making, and communication skills, weighted by job importance	Survey	Standardized (mean 0, sd 1)
Skill Transferability Index	Data-driven measure of how portable skills are across firms, occupations, and industries	Survey	Based on workers' assessments of how recent learning applies to other jobs
Firm Contribution to Wage Growth	Firm fixed effects on annual wage growth	Administrative	Estimated net of age, tenure, and education; out-of-sample

Notes: This table summarizes the core measures used in the analysis. Commuting zone (cz) definition follows Gundersen et al. (2019).

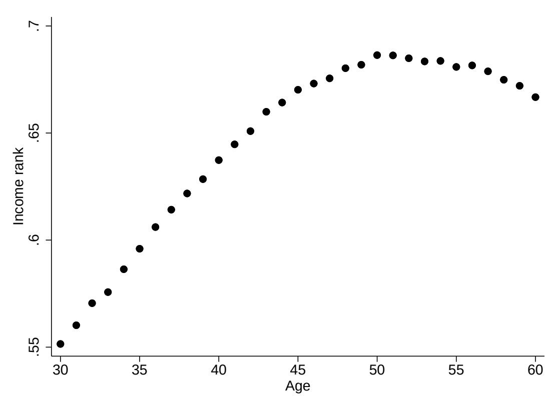
Figure A.1: Participation in adult education in 2021 across OECD countries



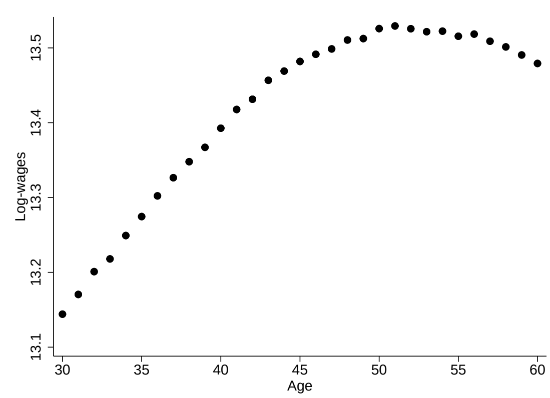
Notes: This figure shows the portion of adults aged 25-65 who participated in adult education in the four weeks prior to the survey. Source: OECD (2023).

Figure A.2: Life-cycle wage growth

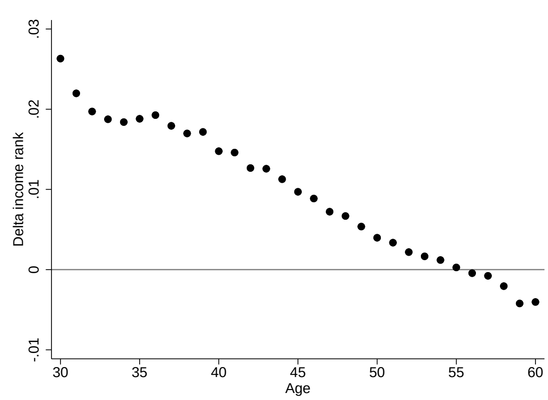
(a) Income rank percentile by age



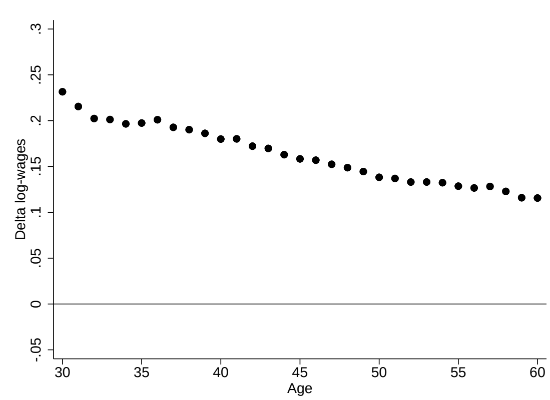
(b) Log wages by age



(c) Change in income rank percentile by age



(d) Change in log wages by age



Notes: Figure A.2a plots the mean income rank percentile (0-1) by age in the full population of working adults. Figure A.2b plots the mean log-wages by age. Figure A.2c plots the mean change in income rank across age-groups. Figure A.2d reports the relationship between the year on year change in log-wages by worker age for the full sample of Norwegian workers aged 30-60 in 2022 in the data at Statistics Norway.

Table A.2: Survey sample

	All firms	Firms > 5	Firms > 10	Firms > 20	Firms > 50	Firms > 100
Share of firms	0.030	0.138	0.213	0.337	0.579	0.766
Share of workers	0.031	0.024	0.020	0.016	0.011	0.009
Number of firms	7,164	6,224	5,549	4,585	3,177	2,209

Notes: This table studies the coverage of the firms in the survey sample. Column (1) compares the survey sample to the full population. Column (2)-(6) report the same figures, but set increasingly more demanding firm-size requirements. Row (1) reports the share of firms in the survey sample compared to the full population. Row (2) reports the median share of workers in each firm in the survey sample. Row (3) reports the total number of firms in the survey sample. The data underlying this table is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We compare the sample of workers in the linked-sample employed in the private sector to the full private sector sample, as detailed in Table A.3.

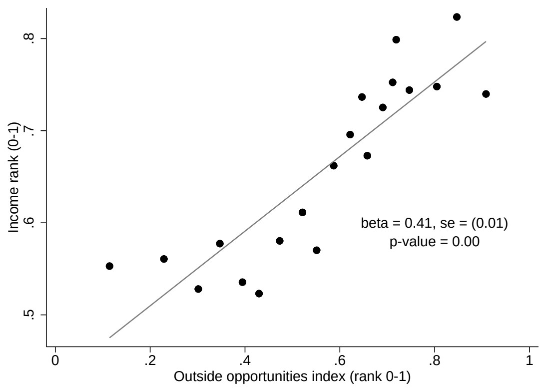
Table A.3: Sample descriptives

	Full sample	Private sector	Survey sample	Survey and Private
	(1)	(2)	(3)	(4)
		Panel A: Individual characteristics		
Age	42.38	41.44	44.66	44.14
	(13.03)	(12.50)	(11.57)	(11.72)
Male	0.51	0.63	0.47	0.57
	(0.50)	(0.48)	(0.50)	(0.49)
College	0.42	0.38	0.59	0.49
	(0.49)	(0.48)	(0.49)	(0.50)
Income rank (0-1)	0.50	0.58	0.64	0.66
	(0.29)	(0.26)	(0.23)	(0.23)
		Panel B: Firm characteristics		
Firm size	2,053.81	477.59	2,487.42	600.26
	(4,570.02)	(1,094.98)	(4,725.49)	(1,219.05)
Mean age at firm	42.31	41.33	42.72	41.91
	(5.22)	(6.78)	(4.66)	(5.68)
Share male at firm	0.51	0.63	0.48	0.59
	(0.27)	(0.30)	(0.26)	(0.27)
Share college at firm	0.42	0.37	0.53	0.45
	(0.28)	(0.31)	(0.27)	(0.30)
Mean income at firm	0.54	0.56	0.51	0.53
	(0.11)	(0.13)	(0.06)	(0.07)
Number of individuals	3,187,032	1,602,608	19,678	9,955
Number of firms	231,181	227,189	7,006	5,632

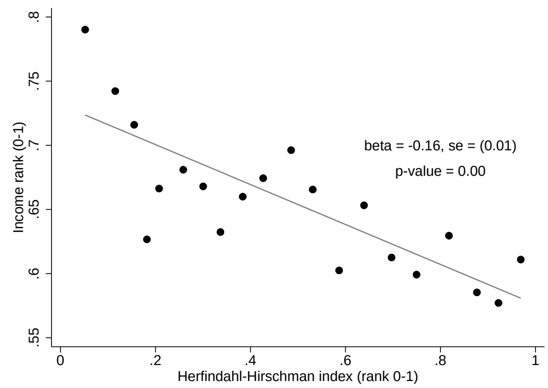
Notes: This table reports the mean characteristics in (1) the full population in Norway in the year 2023, (2) the private sector, (3) the survey sample, and (4) workers at private sector firms in the survey sample. Panel A reports information on individual characteristics, while Panel B reports information on mean firm characteristics, weighted by firm size. The data underlying this table is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat.

Figure A.3: Wages across the OOI versus HHI

(a) Income rank (0-1) and OOI

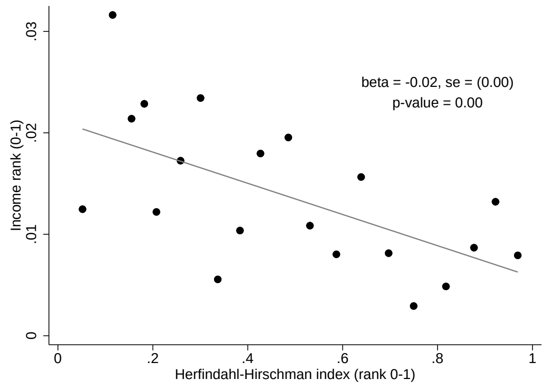


(b) Income rank (0-1) and HHI



Notes: Figure A.3 reports the relationship between income rank percentile and labor market structure, as measured by (a) the Outside Opportunity Index, and (b) the Herfindahl-Hirschman Index. The data underlying these figures is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Figure A.4: Market concentration and wage growth



Notes: Figure A.4 exhibits the relationship between the HHI-index, ranked 0-1, and wage growth. This is the HHI counterpart to Figure 4, replacing our outside opportunities index (OOI) with the HHI. The data underlying this figure is individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Table A.4: Outside options index components: Correlations

	HHI	p-value	OOI	p-value
	Panel A: Individual items			
Salaries at my workplace reflect outside options	-0.14	0.00	0.29	0.00
Salaries at my workplace reflect productivity	-0.15	0.00	0.29	0.00
The skills I had when I started would have been useful for other jobs.	-0.10	0.00	0.23	0.00
The skills I have now are useful for outside job opportunities.	-0.07	0.00	0.16	0.00
I have incentives to learn skills for outside opportunities.	-0.08	0.00	0.16	0.00
I am satisfied with opportunities for pay-growth.	-0.06	0.00	0.23	0.00
I am satisfied with my pay.	-0.08	0.00	0.24	0.00
It would be easy to train someone to do my job. (reverse)	-0.06	0.00	0.19	0.00
The skills I learn at work would transfer to other firms.	-0.10	0.00	0.22	0.00
The skills I learn at work would transfer to other occupations.	-0.08	0.00	0.19	0.00
The skills I learn at work would transfer to other industries.	-0.13	0.00	0.24	0.00
Learning skills for outside options factor in job choice	-0.13	0.00	0.21	0.00
	Panel B: HHI and OOI			
Outside opportunity index	-0.46	0.00		

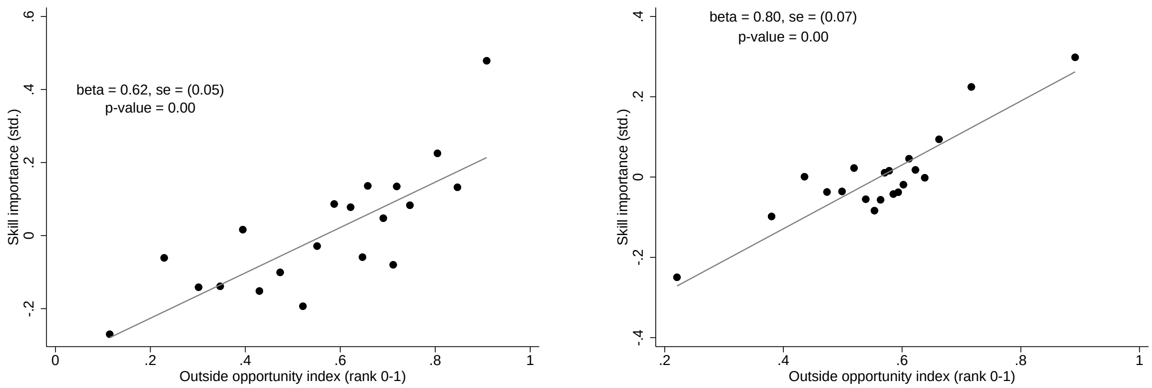
Notes: This table reports correlations between item-level sub-components of the Outside Opportunity Index, as well as the HHI-measure and the OOI index. The OOI measure is constructed as the mean response across all workers in a particular (two-digit) occupation in the same commuting zone, across all the questions in Panel A. Individual responses composing this index are correlated against the Herfindahl-Hirschman Index (ranked, 0-1) – measuring market concentration, and the OOI index – measuring market competition. P-values are reported from bivariate regressions. Panel B reports the overall correlation between HHI and OOI. The data underlying this table is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Table A.5: Comparisons of different measures of market power

	OOI	HHI-occupation	Firm power	HHI-revenue
OOI	1			
HHI-occupation	-0.46	1		
Firm power	-0.20	0.07	1	
HHI-revenue	-0.06	0.31	-0.01	1

Notes: This table reports the pairwise correlation matrix between the OOI index constructed using newly collected survey data and various register-data based measures of market power. The HHI-occupation index is an HHI index based on the share of workers in a particular occupation employed at firms in across a commuting zone. The measure titled "firm power" follows Bassier et al. (2022). The HHI-revenue measures product market power, as defined as the revenue shares of firms in a particular sector and commuting zone. All indices are transformed to ranks (0-1) for comparability. The data underlying this table is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Figure A.5: Skill-intensity across labor markets



(a) Skill intensity across labor markets

(b) Conditional on age, gender, and occupation

Notes: Figure A.5a plots the mean intensity of skill demand across labor markets, as classified by the Outside Opportunity Index. Here, skill-intensity is measured as the total perceived importance over all dimensions of skills, and is standardized to have a mean of zero and standard deviation of one. Figure A.5b reports the same relationship, but includes fixed effects for age, gender, and two-digit occupation code. The data underlying these figures is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Table A.6: Forms of learning: Correlations

	Better at my job	Informal learning	Formal training
Better at my job	1		
Informal learning	0.37	1	
Formal training	0.10	0.29	1

Notes: This table reports the pairwise correlation matrix between the single item measuring whether or not workers perceive themselves to be better at their jobs than a year ago, and indices for informal learning and formal training. The data underlying this table is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Table A.7: Labor market competition (OOI) and human capital accumulation, sensitivity to specification

	No controls	CZ	Occ. 2-dig	Occ. and CZ	Worker education	Worker age	Firm size	All at once
Better at job	0.46	0.41	0.73	0.68	0.42	0.54	0.46	0.62
	(0.05)	(0.05)	(0.07)	(0.08)	(0.05)	(0.05)	(0.05)	(0.08)
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Informal learning	1.07	1.05	0.99	0.95	1.02	1.11	1.08	0.95
	(0.05)	(0.05)	(0.07)	(0.08)	(0.05)	(0.05)	(0.05)	(0.08)
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Formal training	0.40	0.47	0.38	0.37	0.49	0.40	0.41	0.41
	(0.05)	(0.05)	(0.07)	(0.08)	(0.05)	(0.05)	(0.05)	(0.08)
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Learn basic skills	0.34	0.42	0.74	0.78	0.47	0.36	0.34	0.77
	(0.05)	(0.05)	(0.07)	(0.08)	(0.05)	(0.05)	(0.05)	(0.08)
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Learn higher order skills	0.75	0.76	1.00	1.00	0.76	0.79	0.75	0.98
	(0.05)	(0.05)	(0.07)	(0.08)	(0.05)	(0.05)	(0.05)	(0.08)
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	9,907	9,882	9,903	9,878	9,840	9,826	9,907	9,737

Notes: This table reports the relationship between the OOI index (ranked 0-1) and various measures of human capital accumulation, across several specifications. The first column reports the simple bi-variate relationship between the OOI and skill development, while the successive columns include covariates, first separately, and in the last column, all together. The second column includes fixed effects of commuting zone. The third column includes fixed effects for 2-digit occupation. The fourth column includes both commuting zone and occupation fixed effects simultaneously. The fifth column includes measures of worker education. The sixth column includes fixed effects for worker age. The seventh column includes a measure the log of firm size. And the final column includes all the pre-mentioned variables simultaneously. The data underlying this table is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

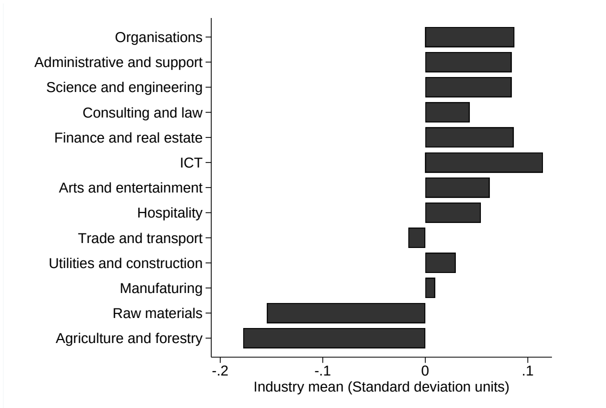
Table A.8: Market structure (HHI) and human capital accumulation, sensitivity to specification

	No controls	CZ	Occ. 2-dig	Occ. and CZ	Worker education	Worker age	Firm size	All at once
Better at job	-0.15	-0.10	-0.15	-0.15	-0.13	-0.19	-0.15	-0.10
	(0.04)	(0.05)	(0.05)	(0.10)	(0.04)	(0.03)	(0.04)	(0.09)
p-value	0.00	0.05	0.00	0.11	0.00	0.00	0.00	0.27
Informal learning	-0.19	-0.05	-0.16	-0.20	-0.17	-0.22	-0.19	-0.21
	(0.04)	(0.05)	(0.05)	(0.09)	(0.04)	(0.04)	(0.04)	(0.09)
p-value	0.00	0.29	0.00	0.03	0.00	0.00	0.00	0.02
Formal training	-0.03	-0.25	0.08	-0.01	-0.05	-0.04	-0.03	-0.09
	(0.04)	(0.05)	(0.05)	(0.09)	(0.04)	(0.04)	(0.04)	(0.09)
p-value	0.36	0.00	0.09	0.88	0.14	0.31	0.38	0.31
Learn basic skills	0.09	-0.11	0.08	-0.08	0.06	0.06	0.09	-0.05
	(0.04)	(0.05)	(0.05)	(0.09)	(0.04)	(0.04)	(0.04)	(0.09)
p-value	0.02	0.03	0.11	0.39	0.09	0.08	0.02	0.58
Learn higher order skills	-0.14	-0.20	-0.02	-0.19	-0.14	-0.16	-0.14	-0.18
	(0.04)	(0.05)	(0.05)	(0.09)	(0.04)	(0.04)	(0.04)	(0.09)
p-value	0.00	0.00	0.68	0.04	0.00	0.00	0.00	0.05
Learning transfers firms	-0.65	-0.79	-0.15	-0.41	-0.63	-0.67	-0.65	-0.38
	(0.07)	(0.09)	(0.09)	(0.18)	(0.07)	(0.07)	(0.07)	(0.18)
p-value	0.00	0.00	0.10	0.02	0.00	0.00	0.00	0.04
Transferability informal	-0.52	-0.64	-0.05	-0.16	-0.51	-0.54	-0.52	-0.16
	(0.04)	(0.05)	(0.05)	(0.09)	(0.04)	(0.04)	(0.04)	(0.09)
p-value	0.00	0.00	0.29	0.07	0.00	0.00	0.00	0.08
Transferability firm training	-0.33	-0.43	-0.02	-0.15	-0.32	-0.35	-0.33	-0.17
	(0.04)	(0.05)	(0.05)	(0.09)	(0.04)	(0.04)	(0.04)	(0.09)
p-value	0.00	0.00	0.64	0.11	0.00	0.00	0.00	0.08
Observations	9,907	9,882	9,903	9,878	9,840	9,826	9,907	9,737

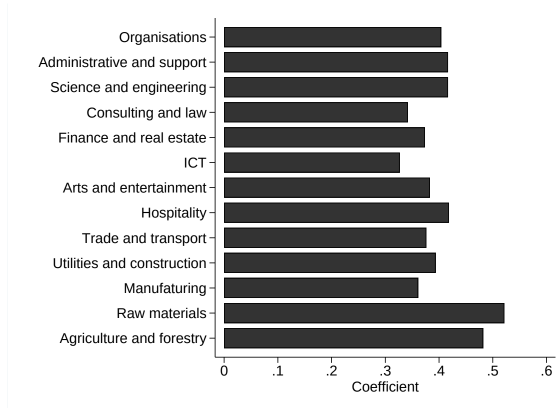
Notes: This table reports the relationship between the HHI index (ranked 0-1) and various measures of human capital accumulation, across several specifications. The first column reports the simple bi-variate relationship between the HHI and skill development, while the successive columns include covariates, first separately, and in the last column, all together. The second column includes fixed effects of commuting zone. The third column includes fixed effects for 2-digit occupation. The fourth column includes both commuting zone and occupation fixed effects simultaneously. The fifth column includes measures of worker education. The sixth column includes fixed effects for worker age. The seventh column includes a measure the log of firm size. And the final column includes all the pre-mentioned variables simultaneously. The data underlying this table is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Figure A.6: Analysis by industry

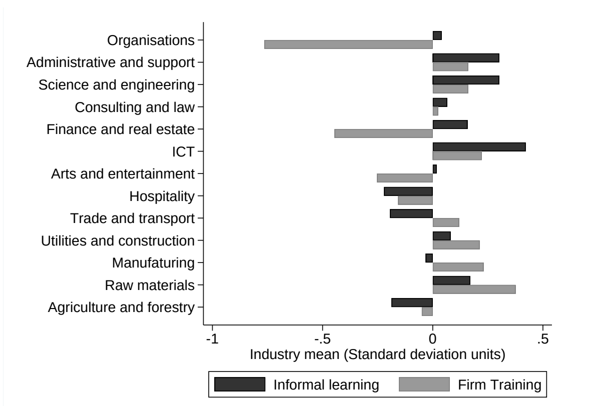
(a) Better than a year ago



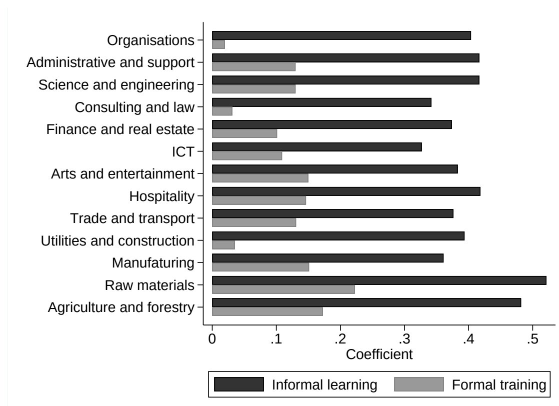
(b) OOI and better than a year ago



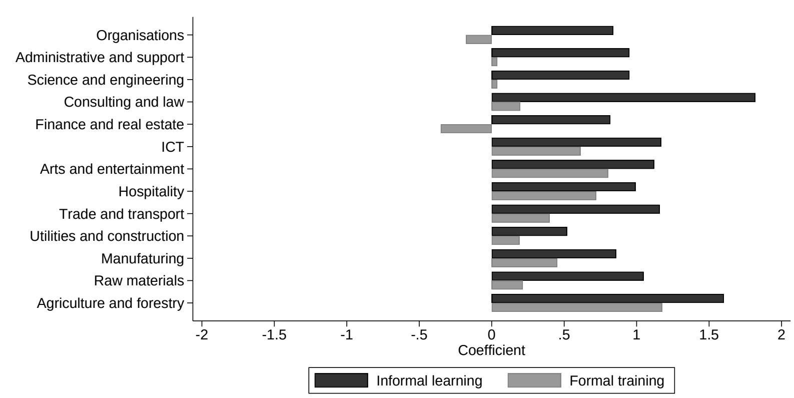
(c) Prevalence of learning mode



(d) Better than a year ago, learning mode



(e) Responsiveness to OOI, by learning mode



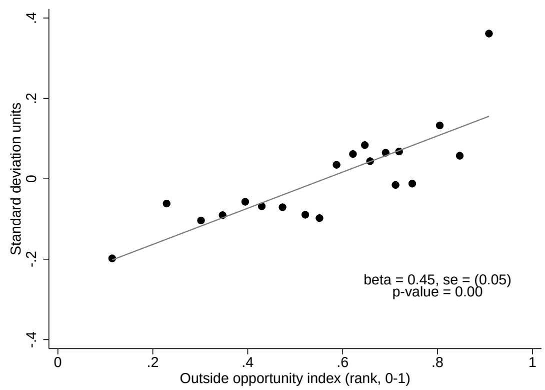
Notes: This figure breaks apart the analysis in this paper by industry. Panel (a) reports the industry mean response to the extent of self reported job-improvement. Panel (b) reports the regression coefficient for how OOI is associated with the responses perceived job improvement. Panel (c) reports the prevalence of each learning mode by industry. Panel (d) reports the regression coefficient from the regression of perceived job improvement on learning mode. Panel (e) reports the regression coefficients from the regression of learning mode on OOI. The data underlying these figures is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Table A.9: Labor market structure vs. product market structure

	OOI (1)	Product market HHI (2)	Difference (3)
Better than last year	0.43	-0.29	0.14
	(0.05)	(0.10)	(0.11)
p-value	0.00	0.00	0.22
Informal learning	1.11	-0.21	0.90
	(0.05)	(0.09)	(0.11)
p-value	0.00	0.03	0.00
Formal training	0.45	-0.39	0.05
	(0.05)	(0.09)	(0.11)
p-value	0.00	0.00	0.63

Notes: This table reports the relationship between different dimensions of market structure – labor market competitiveness, as measured by the OOI, and product market competitiveness, as measured by the HHI based on revenue – and human capital accumulation. The data underlying this table is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Figure A.7: Learning by self-study, across market structure



Notes: This figure reports the relationship between worker learning via self-study and labor market structure, as measured by the Outside Opportunity Index. The data underlying this figure is individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Table A.10: How particular skills are developed

	Informal learning	Formal training	Informal/Formal
	(1)	(2)	(3)
Leadership	1.15	0.21	5.48
	(0.03)	(0.03)	
p-value	0.00	0.00	
Learning quickly	1.07	0.08	13.23
	(0.02)	(0.02)	
p-value	0.00	0.00	
Communication	0.87	0.12	7.49
	(0.02)	(0.02)	
p-value	0.00	0.00	
Teamwork	1.31	0.15	8.58
	(0.02)	(0.02)	
p-value	0.00	0.00	
Decision-making	1.11	0.14	8.17
	(0.02)	(0.02)	
p-value	0.00	0.00	
Technological adaptation	1.07	0.36	2.94
	(0.02)	(0.02)	
p-value	0.00	0.00	
Analytic	1.11	0.15	7.62
	(0.02)	(0.02)	
p-value	0.00	0.00	
Service	0.59	0.27	2.18
	(0.03)	(0.03)	
p-value	0.00	0.00	
Manual	0.56	0.20	2.76
	(0.03)	(0.03)	
p-value	0.00	0.00	
Working under pressure	0.81	0.11	7.73
	(0.02)	(0.02)	
p-value	0.00	0.00	
Computer programming	0.57	0.12	4.93
	(0.02)	(0.02)	
p-value	0.00	0.00	
Using specialized machinery	0.19	0.37	0.53
	(0.03)	(0.03)	
p-value	0.00	0.00	

Notes: This table studies the relationship between modes of learning and (granular) multi-dimensional skill accumulation. The skills in the table are ordered by data-driven approach to measuring transferability, as reported in Table A.12. Columns (1)-(3) report the results from a regression with two righthand-side variables, informal learning and formal training (both standardized to have a mean of zero and standard deviation of one). Column (1) reports the coefficient on informal learning, while Column (2) reports the coefficient on formal training. Column (3) reports the ratio between these two coefficients. The data underlying this table is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Table A.11: The role of firm culture in learning

	OOI_1	OOI_2	Firm culture	$(\text{OOI}_1 - OOI_2)/OOI_1$
	(1)	(2)	(3)	(4)
	Panel A: Relationship between OOI and firm culture			
Firm culture	0.97			
	(0.05)			
p-value	0.00			
	Panel B: Better than a year ago			
Better than last year	0.46	0.20	0.26	0.56
	(0.05)	(0.05)	(0.01)	
p-value	0.00	0.00	0.00	
	Panel C: Informal learning			
Informal learning	1.07	0.58	0.51	0.46
	(0.05)	(0.04)	(0.01)	
p-value	0.00	0.00	0.00	
	Panel D: Formal training			
Firm training	0.40	0.23	0.17	0.42
	(0.05)	(0.05)	(0.01)	
p-value	0.00	0.00	0.00	

Notes: This table studies the role of firm culture in explaining human capital accumulation across markets. First, Panel A reports the relationship between OOI and firm culture from a bi-variate regression. Second, Panel B reports the results from a mediation analysis (Imai et al., 2010), studying the extent that firm culture covaries with market structure in explaining human capital accumulation. Column (1) reports the bivariate relationships between OOI and human capital accumulation. Column (2) and Column (3) report the results from a regression which includes both the OOI and the index for firm culture on the right-hand side of the equation. Column (4) compares the coefficients in Column (1) – i.e. the short regression – with those in Column (2), by calculating the extent that the coefficient on OOI decreases, when the firm culture variable is included in the regression. The results reported in Column (4) can be interpreted as the extent that the relationship between OOI and human capital accumulation can be explained by firm culture. These results should not be interpreted as causal. The data underlying this table is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

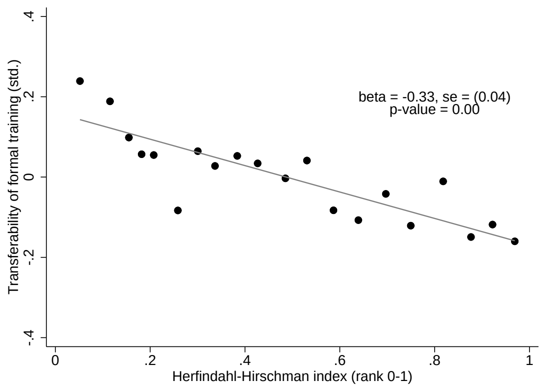
Table A.12: Degrees of skill transferability across levels of market structure

	Transferability of learning across:		
	Firms	Occupations	Industries
Leadership	0.04	0.12	0.12
Learning quickly	0.08	0.10	0.11
Communication	0.06	0.10	0.07
Teamwork	0.07	0.05	0.05
Decision-making	0.05	0.03	0.01
Technological adaptation	0.06	0.02	0.05
Analytic	0.03	0.02	0.04
Service	-0.00	0.01	0.03
Manual	0.01	0.00	-0.03
Working under pressure	0.00	-0.02	-0.01
Computer programming	-0.03	-0.04	-0.03
Using specialized machinery	-0.10	-0.10	-0.12

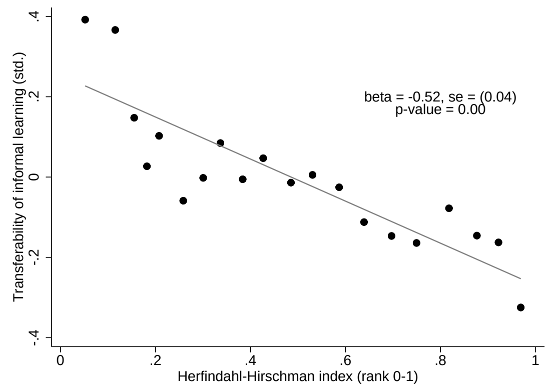
Notes: This table reports estimates of the extent that different skills are transferable across firms, occupations, and industries. These are estimated by regressing workers' perceptions of the transferability (defined across firms, occupation, and industries in three separate regressions) of the skills they have learned on a vector measuring the extent that they have learned each dimension of skill. Skills are ordered by their estimates of transferability across occupations. The data underlying this table is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Figure A.8: Learning mode and skill transferability across market structure

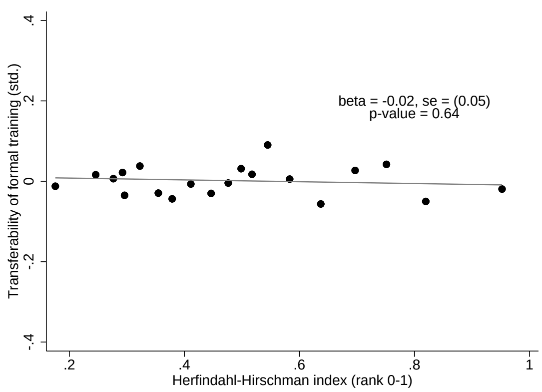
(a) Markets, transferability and formal training



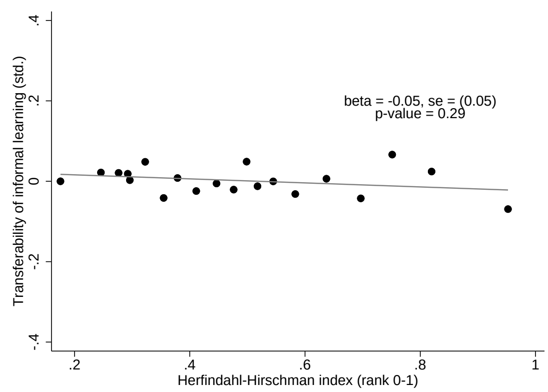
(b) Markets, transferability and informal learning



(c) Markets, transferability and formal training – within occupation



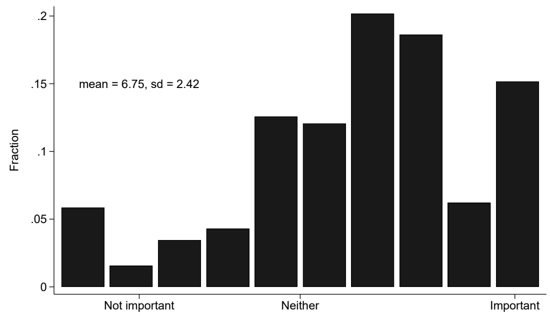
(d) Markets, transferability and informal learning – within occupation



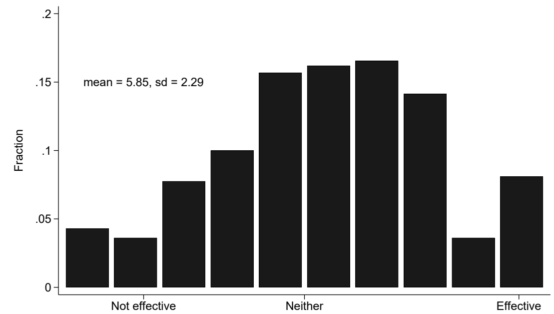
Notes: This figure reports the relationship between the content of learning (transferability), how skills are learned (informal learning vs. formal training), and market structure (HHI). The transferability of skill accumulation is measured by an index based on estimates of learning by skill transferability (based on the data-driven approach from Table A.12). Panels (a) and (b) report the raw relationship between HHI and transferability of learning, while Panels (c) and (d) report this relationship conditional on occupation. The data underlying these figures is based on individual-level administrative data from Statistics Norway linked to surveys conducted by Norstat. We focus on the sample of workers in the linked-sample employed in the private sector, as detailed in Table A.3.

Figure A.9: Workers, perspectives

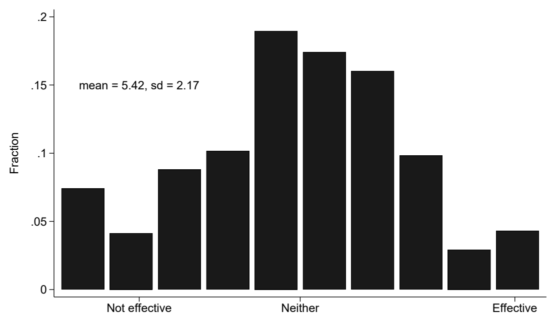
(a) "How important are firm investments in training for your career?"



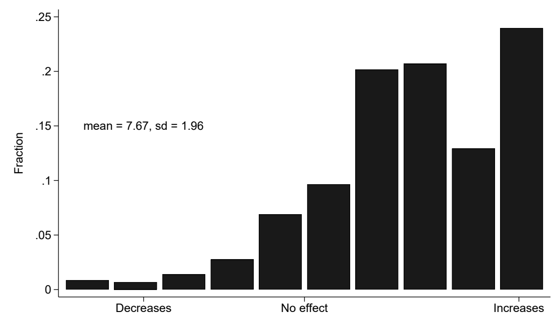
(b) "How effective is training provided by people at your firm (ex. internal or presentations) for improving your productivity?"



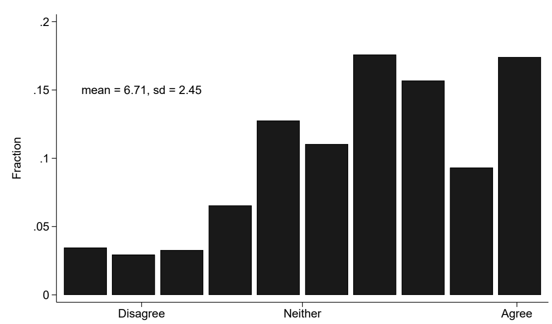
(c) "How effective is training provided by people outside your firm (ex. bringing in outside speakers, attending firm-sponsored workshops) for improving your productivity?"



(d) "How important is informal learning (e.g., learning-by-doing or peer learning) for your career?"



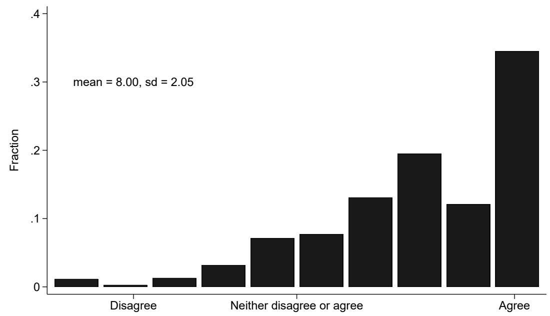
(e) "Opportunities for career progression and advancement affect my incentives and motivation for engaging in learning at work."



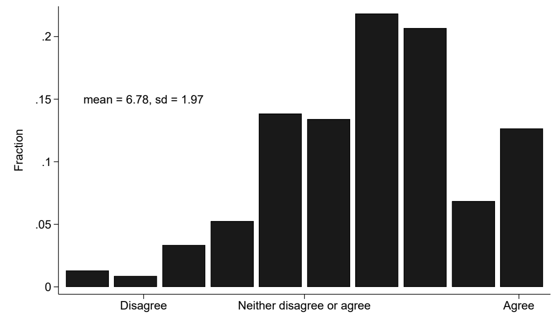
Notes: Figure A.9 presents histograms of worker responses in the auxiliary survey regarding their perceptions of firm investments, informal learning, motivation, and outside opportunities, in developing human capital. These data are from a survey fielded by Norstat to 1,026 workers.

Figure A.10: Managers, perspectives

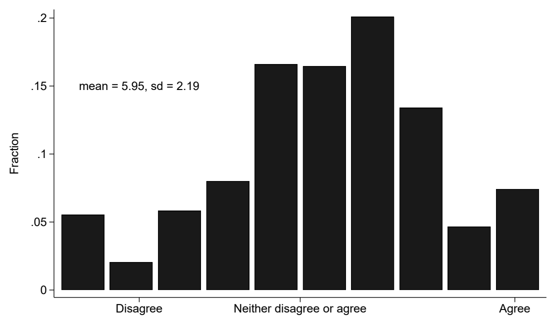
(a) "Investments in training by firms play an important role in improving worker productivity."



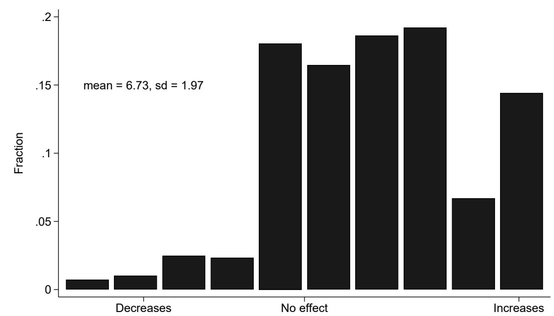
(b) "How effective is training provided by people at your firm (ex. internal workshops or presentations) for improving worker productivity?"



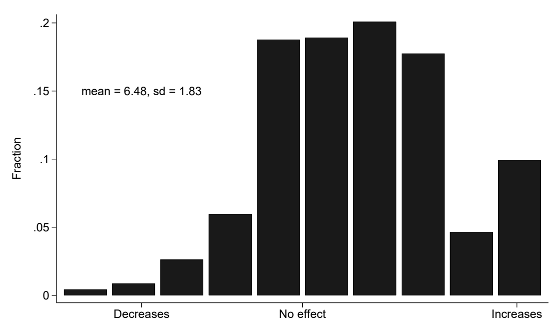
(c) "How effective is training provided by people outside your firm (ex. bringing in outside speakers, attending firm-sponsored workshops) for improving worker productivity?"



(d) "The level of competition between firms influences the amount or type of training firms will provide."



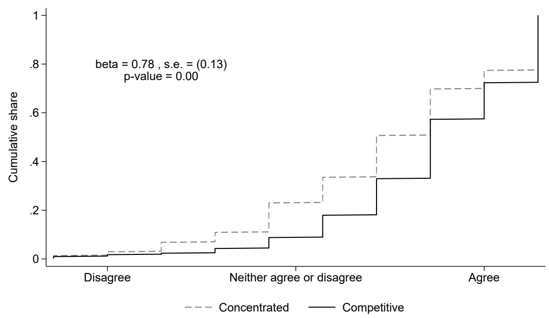
(e) "The level of competition between firms influences the effort and incentives of workers to take up training such as those described above."



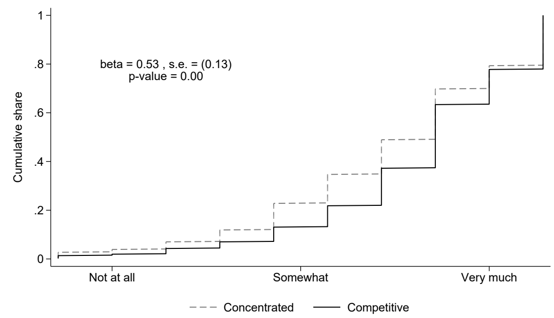
Notes: Figure A.10 presents histograms of manager responses in private sector firms in the auxiliary survey regarding their perceptions of firm investments, informal learning, motivation, and outside opportunities in developing human capital. These data are from a survey fielded by Norstat to 1,001 managers.

Figure A.11: Worker vignette experiment: Mechanisms (A)

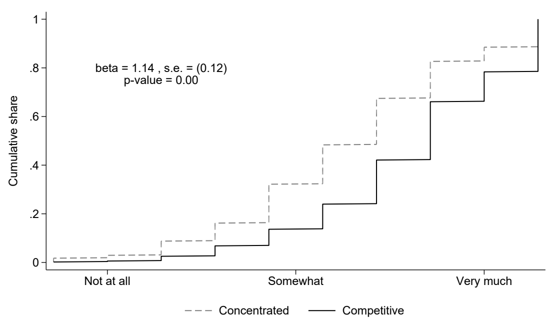
(a) "Skills are critical for my firm's success."



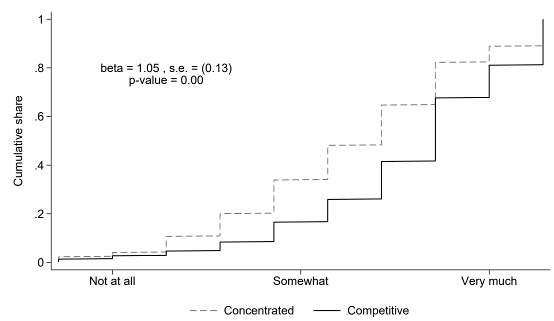
(b) "How motivated will you be to take up firm-provided training?"



(c) "How motivated will you be to improve basic skills?"



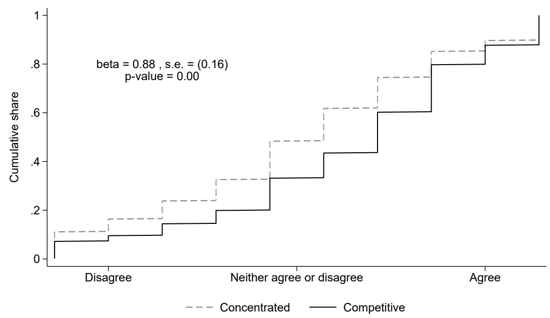
(d) "How motivated will you be to improve higher-order skills?"



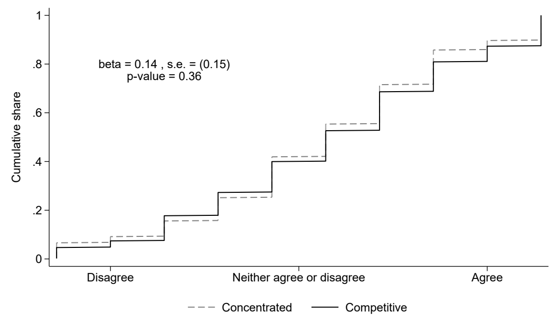
Notes: This figure presents cumulative density distributions of worker responses in the auxiliary survey, by randomized treatment condition – whether they are in a competitive or concentrated market. These data are from a survey fielded by Norstat to 1,026 workers.

Figure A.12: Worker vignette experiment: Mechanisms (B)

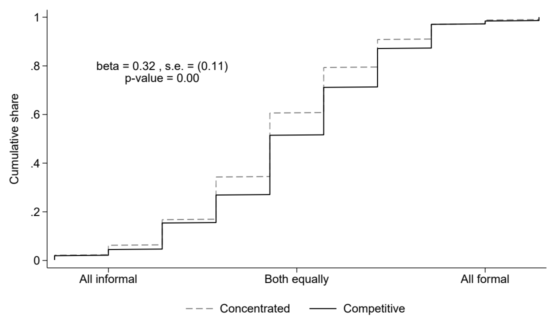
(a) "Improving my ability to do my job improves my outside options."



(b) "Improving my ability to do my job will increase my wages ."



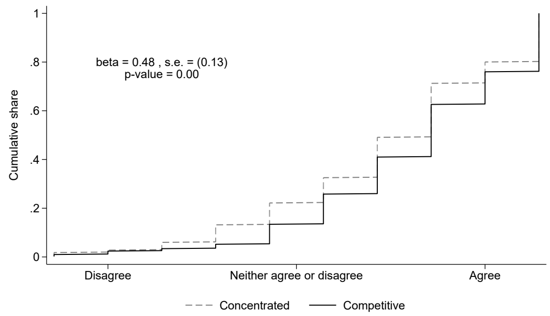
(c) "What share of improvements in skills will come from formal training versus informal learning?"



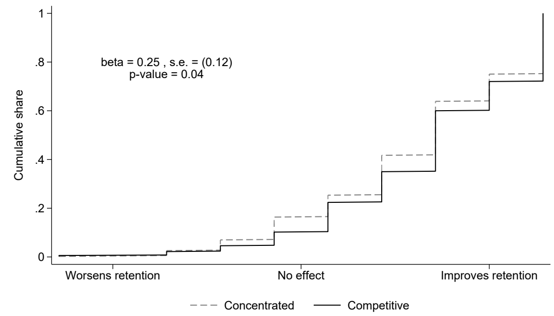
Notes: This figure presents cumulative density distributions of worker responses in the auxiliary survey, by randomized treatment condition – whether they are in a competitive or concentrated market. These data are from a survey fielded by Norstat to 1,026 workers.

Figure A.13: Manager vignette experiment: Mechanisms (A)

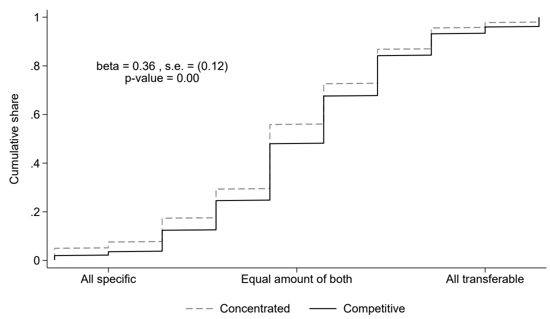
(a) "Investing in training improves my firm's ability to hire workers."



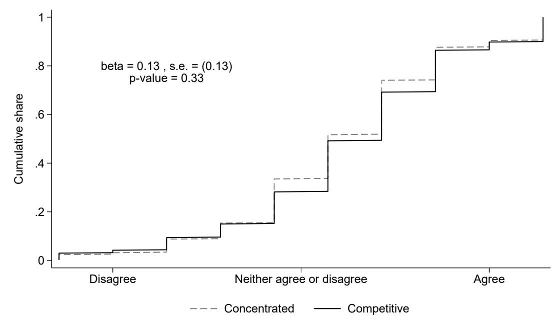
(b) "Investing in training improves my firm's ability to retain workers."



(c) "What share of this training should be focused on transferrable vs. specific skills?"



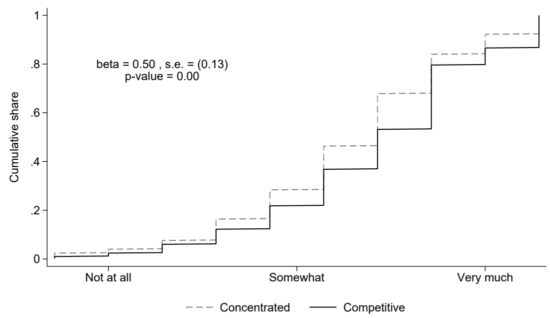
(d) "After these training investments, would you increase wages for workers?"



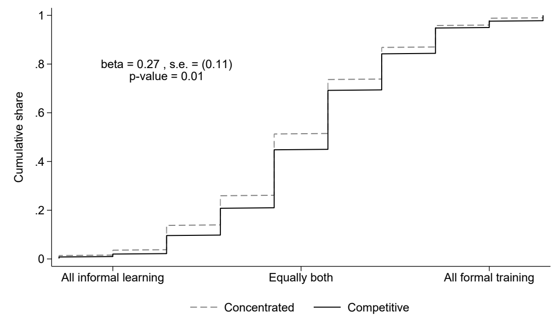
Notes: This figure presents cumulative density distributions of manager responses in the auxiliary survey, by randomized treatment condition – whether they are in a competitive or concentrated market. These data are from a survey fielded by Norstat to 1,001 managers.

Figure A.14: Manager vignette experiment: Mechanisms (B)

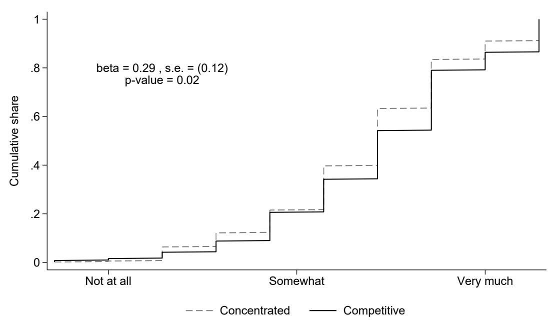
(a) "How much will your workers invest in informal learning?"



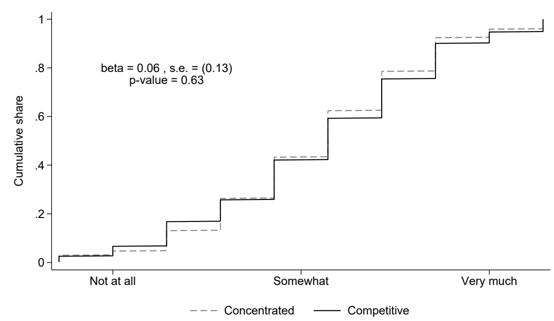
(b) "What share of improvements in worker skills will come from formal training versus informal learning?"



(c) "How motivated will your workers be to improve basic skills?"



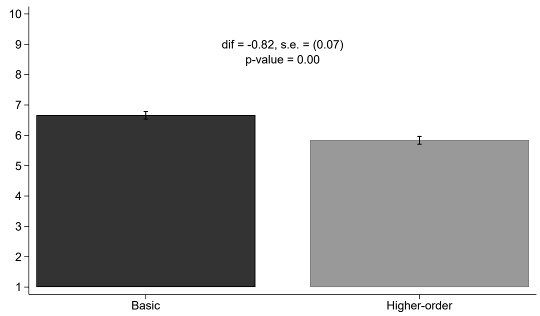
(d) "How motivated will your workers be to improve higher-order skills?"



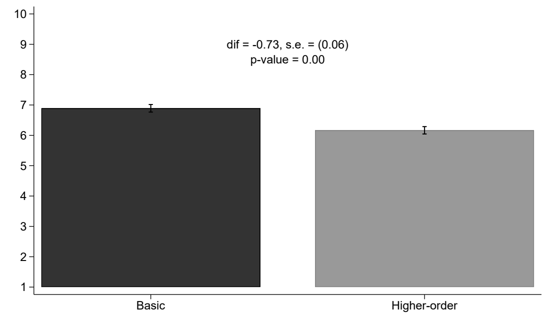
Notes: This figure presents cumulative density distributions of manager responses in the auxiliary survey, by randomized treatment condition – whether they are in a competitive or concentrated market. These data are from a survey fielded by Norstat to 1,001 managers.

Figure A.15: How easy is it to learn the following skills?

(a) Workers



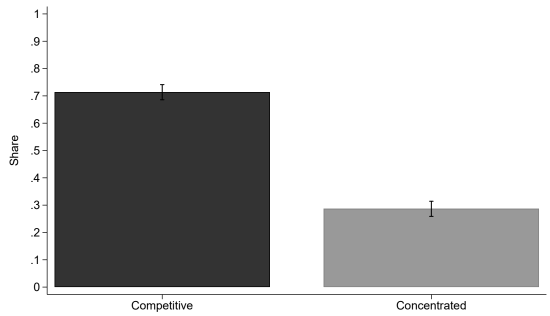
(b) Managers



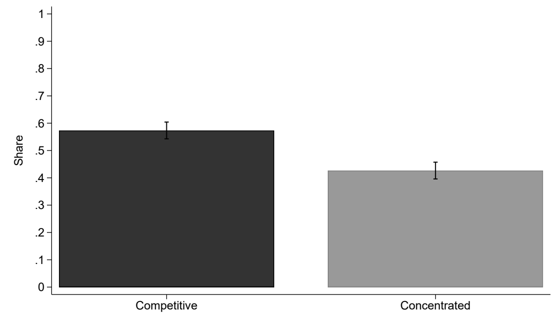
Notes: This figure reports worker and manager perceptions of how easy they perceive it to be to develop basic versus higher order skills. These data are from surveys fielded by Norstat to 1,036 workers and 1,001 managers.

Figure A.16: Location choice: Workers and managers

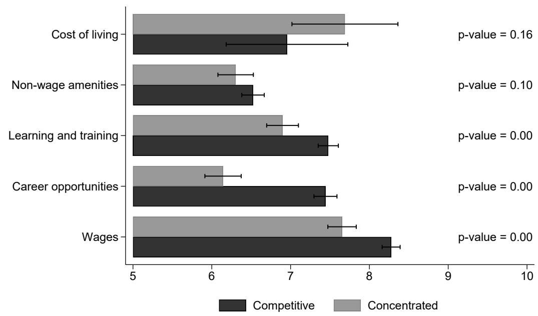
(a) Worker early career preferences



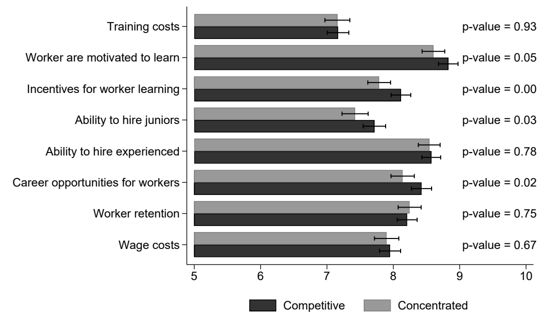
(b) Manager choice of where to start business



(c) Worker reasons



(d) Manager reasons



Notes: Figures (a) and (b) report worker and manager responses from a discrete choice experiment, where they choose whether they would prefer to start their career or establish a firm in a competitive or concentrated market. Figures (c) and (d) report the reasons motivating each choice. These data are from surveys fielded by Norstat to 1,026 workers and 1,001 managers.

B Survey instruments

This section documents the survey instruments underlying all survey components in this paper. *Unless stated otherwise, responses follow a ten-point Likert scale, with the points 1 and 10 indicating extreme responses (None/All or Very much disagree/Very much agree).*

B.1 Main survey

Part 0: Background information – for data linkage

1. What is your name (last name, first name)? Note! This question will exclusively be used for the purposes of data linkages at the Central Bureau of Statistics, and will be deleted before any researcher has access to the data.
2. When were you born (day, month, year)?
3. Which municipality do you currently live in?

Part I: Skills, tasks and the content of work

1. How many hours a week are specified in your work contract?
2. How many hours do you typically work each week?

   Think of your typical workday. How much time do you spend performing the following activities? (These categories are NOT mutually exclusive.)

3. ...working with machines (not computers).
4. ...working with your hands.
5. ...completing physically demanding tasks.
6. ...performing repetitive tasks.
7. ...learning new skills.
8. ... developing existing skills.
9. ...encountering new challenges.
10. ...working with computers.
11. ...analyzing data.
12. ...solving analytic problems.
13. ...working with people at the same level of seniority as myself.
14. ...working with people at a higher level of seniority to myself.
15. ...working with people at a lower level of seniority to myself.
16. ...collaborating on projects.
17. ...completing administrative work.
18. ...working with clients.
19. ...helping others [job-related].
20. ...leading groups.
21. ...working from home or a remote workspace.

22. ...reading.
23. ...writing.

To what extent do you agree with the following statements:

24. I make strategic decisions at work.
25. I have autonomy in my job.
26. There are many people at my company that could do my job.
27. It would be easy for my company to train someone new to do my job.
28. The job provides opportunities to learn new skills.

29. XXX people report to me at my workplace.

How important are the following skills for your job?

30. Manual.
31. Analytic.
32. Teamwork.
33. Service.
34. Leadership.
35. Computer programming.
36. Decision-making.
37. Learning quickly.
38. Adapting to new technologies.
39. Ability to work under pressure.
40. Communication.
41. Working with specialized machines (not computers).

Part II: Learning on the job

1. I am better at doing my job today than I was one year ago.
2. Cycle through the each dimension of skills listed in the above section:
   (a) To what extent do you believe you learn the following types of skills at your place of work?
   (b) If you responded that you have improved in these areas while at your current place of work, which of the following describes how you learned these skills?
      i. Training by the firm.
      ii. Workshops or conferences by people outside the firm.
      iii. Formal education sponsored by your workplace.
      iv. Learning from co-workers.
      v. Learning-by-doing.
      vi. Self-study.

vii. Mentoring.
viii. Other.

Consider the skills you have learned at your job.

3. Would they transfer to other firms or places of work?
4. Would they transfer to other occupations?
5. Would they transfer to other industries?

6. How often are you offered training or opportunities that improve your skills?
7. My workplace offers apprenticeships or internships.
8. How many years ago did you last participate in some form of training at your firm.
9. Enrolling in further education or training would help me progress at my current place of work.
10. Enrolling in further education or training would help me transfer to a different job at the same or a different firm.

Part III: Workplace environment

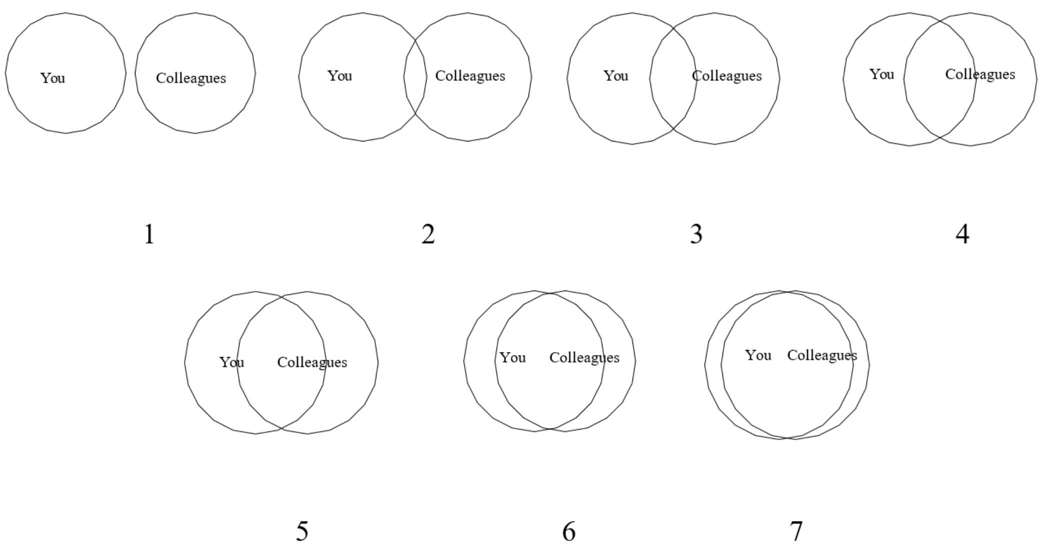
1. I am given opportunities to try new roles and/or tasks.
2. I am given opportunities to take on increasing responsibilities.
3. I am given access to attractive work assignments.
4. I am assigned to take care of "office housework".
5. My workplace rewards new ideas.
6. I have incentives to learn skills because of promotions within my job.
7. I have incentives to learn skills for job opportunities outside my job.
8. The skills I had when I started at my company could have been helpful in landing other jobs in my field within a reasonable commute.
9. If I wanted to, I could find work at the same or better salary within a reasonable commute.
10. I need to keep learning new things to keep my skills relevant.
11. If you stay at your firm, how much do you think you will earn in five years?
12. Does your firm typically hire from within the firm?

To what extent do you agree with the following statements:

13. Salaries at my workplace reflect:
    - Seniority.
    - Productivity.
    - Effort.
    - Loyalty.

- Favoritism.
- Education and/or credentials.
- Past accomplishments.
- Outside options.

14. I have the skills I need to perform my job effectively.
15. More training would allow me to perform my job more effectively.
16. Management treats me fairly at work.
17. I am respected by the management team.
18. I am satisfied with opportunities for pay-growth.
19. I am satisfied with my pay.
20. Promotions at my workplace depend on competition between workers.
21. Please, look at the circles diagram below. Then, consider which of these pairs of circles best represents your connection with your colleagues. By selecting the appropriate number below, please indicate to what extent you and your colleagues are connected.



22. There is a union at my workplace. YES/NO — trigger:
23. The union at my workplace is effective in advancing worker interests.
24. How important were learning opportunities for career progression inside the firm in your choice of workplace?
25. How important were learning opportunities for career progression outside the firm in your choice of workplace?
26. The skills I learned through education are useful in my current job.
27. How important are each of the following skills you learned in school for your current job. (Cycle through skills)

B.2 Manager survey

Part I: General questions

1. Is your current employer a public or private organization?
2. Investments in training by firms play an important role in improving worker productivity.
3. How effective is training provided by people at your firm (ex. internal workshops or presentations) for improving worker productivity?
4. How effective is training provided by people outside your firm (ex. bringing in outside speakers, attending firm-sponsored workshops) for improving worker productivity?
5. The level of competition between firms influences the amount or type of training firms will provide.
6. The level of competition between firms influences the effort and incentives of workers to take up training such as those described above.

Part II: Vignette experiment

Show one of the two vignettes:

Competitive: *You are a manager at a medium-sized firm in a highly competitive market where numerous firms operate. To succeed in this environment, your firm must continuously innovate. You also face intense competition in hiring and retention.*

OR

Monopsonistic: *You are a manager at a medium-sized firm in a highly concentrated market where only a few firms dominate. Market share is stable, reducing the pressure to innovate to remain in business. You also face little competition in hiring and retention.*

Consider the above environment when answering the following questions: (Above statement is shown for each question)

1. Investing in worker training is critical for succeeding as a business.
2. Do you think that investment in training affects your ability to hire workers.
3. Do you think that investment in training affects your ability to retain workers.
4. What share of this training would be focused on skills transferable across firms as opposed to on skills specific to your firm?
5. After these training investments, would you increase wages for your workers?
6. How motivated do you think your workers would be to take-up training?
7. In addition to formal training, workers can acquire skills through informal learning, such as learning-by-doing, or co-worker learning. How much do you think workers will invest in informal learning?

   Basic skills span writing, data-analysis, programming, or using the software at your workplace. Higher order skills include, for example, leadership, collaboration, or decision-making.
   Answer the following questions independent of the market environment:

8. How important are basic skills for your employees?

9. How easy is it for workers to learn these types of basic skills?
10. How transferable are these types of basic skills to other firms?
11. How important are higher order skills for your employees?
12. How easy is it for workers to learn these types of higher order skills?
13. How transferable are these types of higher order skills to other firms?

Now consider the environment pictured above. [remind them of environment they're in]

14. How motivated do you think your workers are to improve their basic skills?
15. How motivated do you think your workers are to improve their higher order skills?
16. Workers in this firm will be better at their jobs after each year.
17. What share of these improvements in worker skills come from formal training versus informal learning?

Part III: Location choice

You are about to start a new business, where you want to maximize worker productivity. You can choose to establish your firm in two types of labor markets:

Descriptions of both: Monopsonistic or Competitive (from vignette)

1. Which do you choose?

   How important were the following in your choice of location?
2. Wage costs.
3. Worker retention.
4. Career opportunities for workers.
5. Ability to hire experienced workers.
6. Ability to hire junior workers.
7. Incentives for worker learning.
8. Workers are motivated to learn.
9. Training costs.

B.3 Worker survey

Part I: General questions

1. Which best describes your occupation? (1-digit occupation codes list)
2. Do you work in the public or the private sector?
3. What best describes your highest level of education?
4. How would you describe the education level of your parents?
5. How important are firm investments in training for your career?
6. How effective is training provided by people at your firm (ex. internal or presentations) for improving your productivity?

7. How effective is training provided by people outside your firm (ex. bringing in outside speakers, attending firm-sponsored workshops) for improving your productivity?
8. How important is informal learning (e.g., learning-by-doing or peer learning) for your career?
9. Opportunities for career progression and advancement affect my incentives and motivation for engaging in learning at work.

Part II: Vignette experiment

Show one of the two vignettes:

Competitive: *You are a worker at a medium-sized firm in a highly competitive market with numerous firms. Advancement and retention in the firm is determined through worker competition. Career opportunities outside your firm are determined by your demonstrated ability.*

OR

Monopsonistic: *You are a worker at a medium-sized firm in a highly concentrated market where only a few firms dominate. There is little room for career advancement at the firm, and there are few opportunities outside your firm.*

Consider the above environment when answering the following questions: (Above statement is shown for each question)

1. Investing in my skill-set is critical for my success in this labor market.
2. Investing in worker training is critical for your firm's success.
3. How motivated will you be to take-up firm provided training (e.g., workshops, presentations, courses)?
4. In addition to formal training, you can acquire skills through informal learning, such as learning-by-doing or peer learning. How much will you invest in informal learning?
5. Informal learning requires more motivation and effort than firm-provided training.
6. Improving my ability to do my job will increase my wages.
7. Improving my ability to do my job will increase my outside options.

Basic skills span writing, data-analysis, programming, or using the software at your workplace. Higher order skills include, for example, leadership, collaboration, or decision-making.

Answer the following questions independent of the market environment:

8. How important are basic skills at your workplace for your career?
9. How easy will it be to learn these types of basic skills?
10. How transferable are these types of basic skills to other firms?
11. How important are higher order skills for your career?
12. How easy will it be to learn these types of higher order skills?

13. How transferable are these types of higher order skills to other firms?

    Now consider the environment pictured above. [remind them of environment they're in]

14. How motivated would you be to improve basic skills?
15. How motivated would you be to improve higher order skills?
16. Each year I spend at this firm will make me better at my job.
17. What share of these improvements come from formal training versus informal learning?

Part III: Location choice

You are about to start your first job. You can choose to start your job in one of two types of labor markets:

Descriptions of both: Monopsonistic or Competitive (from vignette)

1. Which do you choose?
   How important were the following in your choice of location?
2. Wages.
3. Worker retention.
4. Career opportunities.
5. Learning and training.
6. Non-wage amenities besides learning and training.
7. Cost of living.