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# ABSTRACT

## Beyond Training: Worker Agency, Informal Learning, and Competition

*This paper reconsiders how labor market competition shapes skill development — integrating the perspectives of both firms and workers. While existing models often predict that firms will underinvest in training due to a fear of poaching, we show that competition can instead serve as a catalyst for learning. It creates outside opportunities which incentivize workers to invest in their own skills, and it imposes innovation pressure that raises the value of training for firms. Using linked Norwegian survey and administrative data together with vignette experiments, we find that workers in more competitive markets accumulate skills faster than workers in concentrated markets—primarily through informal, self-directed learning—and that these gains are concentrated in higher-order, transferable skills. Firms in competitive environments also invest more in formal training, treating it as a strategic necessity rather than a dispensable cost. Experimental evidence complements these findings by showing that both workers and managers expect greater returns to learning and human capital investments in competitive markets. Together, these results challenge the canonical view of competition as a source of market failure in training, and instead highlight its role in facilitating both worker-led and firm-led investments in human capital.

**JEL Classification:** J24, J31, J42
**Keywords:** competition, human capital, skills

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# 1 Introduction

Wages rise far into adulthood, long after formal education ends. This well-documented pattern points to the labor market not simply as a place where skills are used, but as a key setting in which they are cultivated (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 not only as a driver of productivity and economic growth, but also as a foundation for equality of opportunity, social mobility, and spatial inequality.

Nonetheless, in contrast to the voluminous literature on the returns to education, we know little 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 common view holds that when firms fear poaching, they underinvest in general skills — those valued across employers — because they may not capture the return. As a result, firm competition can lead to market failures and systematic underinvestment in training (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 often 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.

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. Drawing on novel data that link large-scale surveys, administrative records, and survey experiments, we depart from firm-centered models that emphasize formal training. Instead, we show that workers are the primary agents of skill development—accumulating skills informally through experience, adaptation, and task-based learning. This process is shaped less by direct firm investments and more by external incentives such as outside options. Firms still influence the structure of learning, but it is ultimately workers who decide whether, how, and what to learn.

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, with detailed measures of formal training, informal learning, and the transferability of skills across firms, occupations, and industries; 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. The design distinguishes sharply between formal and informal learning, and records both the intensity and the context of skill development. Alongside these detailed measures, our primary benchmark outcome is deliberately simple: whether workers perceive themselves to have become better at their job over the past year.

A central innovation of this project is that all survey responses are linked to rich 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. This linked survey-administrative data provides a robust foundation for descriptive analysis on how workers, firms, and markets interact to drive human capital accumulation in the labor market.

To gain insight on the behavioral foundations behind our results, we field separate vignette experiments with thousands of workers and managers. In the worker experiment, respondents are randomly assigned to scenarios describing either a competitive or a concentrated labor market, and then asked how they would engage in skill development. Likewise, in the manager survey respondents are randomly assigned to either competitive or concentrated conditions, and asked how they would how and why they would invest in skills. These vignette experiments also include questions about perceptions regarding the associations between competition, firm investments, informal learning, and worker motivation, as well as a series of hypothetical location choice scenarios, where both workers and managers indicate which type of labor market they would prefer to operate in and why.

Our central finding is that labor market competition acts as a catalyst for human capital accumulation—not a constraint. In more competitive markets, firms invest more, workers learn more, and higher-order skills become more prevalent. Critically, informal learning — rather than formal training — emerges as the fundamental engine of skill development. Vignette experiments targeting both workers and managers provide causal evidence that competition amplifies investments on both sides of the market. Firms increase training because they view such investments as essential to survive in rapidly evolving markets. At the

same time, workers increase effort in response to improved outside options. These findings challenge canonical predictions that competition discourages training and suggest instead that competition accelerates the formation of productive, portable skills.

We present five key findings in support of this result. First, we show that workers accurately perceive their surrounding labor market conditions. We construct an outside-opportunity index (OOI) by collapsing the responses from twelve individual items measuring workers' outside options across local labor markets, as defined by occupations and commuting zones. This measure exhibits a strong (negative) correlation with the most prevalent structural measures of labor market concentration — the Herfindal-Hirschman index ($\rho$ = -0.46). Among the twelve items underlying the OOI, the statement about whether pay reflects outside options shows the strongest correlation with both the OOI and the HHI. That workers respond to labor market conditions is a foundational assumption in labor economics — but whether they perceive those conditions remains an open and critical question. For example, 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. In contrast, we find a much stronger alignment between perceived outside options and structural measures of concentration. This provides the first belief-based validation of the Herfindahl-Hirschman Index (HHI)—one of the most widely used indicator of market concentration in both academic and policy work.

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. This association is also present whether we use our OOI or the HHI.

Several additional findings reinforce the link between competition, learning, and wage growth — both within and beyond the survey sample. First, workers who report improving at their job experience faster year-on-year wage growth. Second, labor market competitiveness is positively associated with wage growth in the full population. Third, firms in more competitive environments generate greater wage growth even for non-surveyed workers. Finally, survey-based measures of learning closely align with out-of-sample estimates of firm effects on wage growth—strengthening the link between perceived learning and actual returns. Together, these results point to competitive markets as key environments for workplace learning — structuring the conditions under which skill formation takes place.

Third, we examine how workers learn and document substantial heterogeneity in learning modes. 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 moderately 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 strength of the relationship is stronger between informal learning and competition. Moreover, informal learning explains a far greater share of overall learning than formal training, positioning self-initiated learning as a central driver of skill accumulation. At the same time, the fact that formal training also increases with competition is a novel and unexpected finding, challenging the view that competitive pressure discourages employer investment. As we show, this occurs because, even if firms expect to retain a smaller share of the return to training in competitive markets, the total value of that return increases with competition. In line with our interpretation that firms and workers face distinct incentives to invest in human capital, we find that investments in formal training are most sensitive to competition in the product market while worker investments in informal learning are most sensitive to labor market competition. Since product markets and labor markets are often correlated, the key insight is not that firms lose the incentive to train in competitive labor markets, but that these are often markets where they cannot afford not to.

Fourth, we show that formal training and informal learning map onto the development of distinct types of skills. Informal learning disproportionately drives the development of higher-order skills such as communication, leadership, decision-making, and teamwork, while formal training is more closely associated with basic or task-specific skills. Although both basic and higher-order skills increase with competition, the largest gains occur in higher-order skills, which are also more strongly correlated with wage growth and self-reported job improvements. That is, competition fosters the skills which are increasingly vital to labor markets — and informal learning is the primary channel through which they are developed.

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 (1) jobs, (2) firms, and (3) 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 even with the addition of a large set of controls.

A plausible explanation is that outside opportunities encourage workers to invest in the skills that yield the highest private returns—those that transfer most readily across employers. This would be in line with our earlier result that worker — rather than firm — investments appear most critical for learning. However, we also find that even formal, firm-led training generates more transferable skills in competitive markets. As we discuss below, this may reflect that while competition reduces the share of returns firms can retain, it also increases the overall return to skill investment, potentially offsetting the loss in retention. In other words, competition may shrink the firm's slice of the pie but enlarge the pie itself.

To microfound our results, we turn to our two independent vignette experiments. In the worker experiment, we find that workers assigned to competitive market conditions anticipate substantially greater human capital accumulation. They report higher motivation to engage in both formal and informal learning, and express greater willingness to invest both in developing basic and higher-order skills. Interestingly, workers report that higher-order skills require substantially greater effort to acquire, and our results indicate that heightened motivation in competitive environments plays a central role in their formation. Workers also view learning as more critical for labor market success, firm performance, and career advancement. We complement these results with a hypothetical location choice elicitation, where we show that workers would prefer to start their careers in competitive markets — citing workplace learning as a key reason for this choice.

In the manager experiment, we find that firms in competitive markets assign greater strategic importance to training — not only to improve productivity, but also to recruit, retain, and remain viable in high-pressure environments. In other words, competition makes firms perceive skill investment as a strategic necessity. Importantly, managers are no less likely to invest in transferable skills in the face of competition, suggesting that the perceived value of training outweighs concerns about retention. The key insight is not that firms lose the incentive to train as competition increases, but that they cannot afford not to. When given a choice of where to establish a firm, managers indicate a preference for more competitive markets — citing workplace learning and employee motivation as key reasons for this choice.

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] But 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, making it hard to gauge the relative importance of each of these channels (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

[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).

related to our work, several papers have suggested that competition can prevent firms from investing sufficiently in their worker's skills, for fear that they might be poached (e.g. Becker, 1962; Acemoglu and Pischke, 1998, 1999a; 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., 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. This represents a substantial contribution in itself, with independent value beyond our specific analysis, as it sheds light on an important but previously difficult-to-observe aspect of learning. 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 also challenge long-standing 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). Building on insights from Lazear (2000), we argue that even when firms expect to retain a smaller share of the return, competition may still raise the total return to training—by increasing the productivity payoff of skilled workers. More fundamentally, we extend the analysis to workers, showing that competitive markets not only shape firm behavior but also strengthen individual incentives to invest in their own skills. This helps explain our empirical finding that more learning occurs in competitive markets, particularly for higher-order, transferable skills. This learning is primarily driven by worker—not firm—investments.

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 worker agency and competition—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 leg-

islation 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 provides a useful 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. This linkage allows us to connect self-reported learning experiences to real economic outcomes at both the individual and firm levels - a linkage unmatched in prior studies.

In addition to its data infrastructure, Norway's institutional features make it a valuable setting for broader analysis. The combination of competitive labor markets, high worker mobility, strong welfare protections, and an active upskilling agenda reflects patterns seen across many high-income countries, particularly in Europe. This makes Norway a relevant case for understanding how institutional context shapes skill formation. Ultimately, however, the core questions we ask—how firms train workers, how individuals learn on the job, and how market structure affects these processes—are not specific to Norway. The ideas we emphasize—informal learning, higher-order skills, and worker agency—apply across labor markets, even if institutions shape the exact costs or constraints. In this sense, Norway offers not only internal validity, but also broader relevance for understanding workplace learning and labor market competition.

## 2.2 Linking Market Structure and Skill Formation

In this section, we develop a simple stylized framework for understanding human capital formation in the labor market — and how it is shaped by market structure. The goal is not to provide a formal structural model, but rather to lay out a simple, tractable set of mechanisms that clarify how skill formation occurs inside firms and how it responds to competitive conditions.

We start from the premise that skill formation is a joint outcome of firm behavior and worker choice. Firms shape the learning environment by influencing the cost, accessibility, and structure of opportunities to learn. Workers then decide whether, when, and how to invest in developing their skills.

Competition affects both sides of this equation. It alters firm incentives by changing both the value of training and the extent to which firms can retain its returns. It affects worker

behavior through the same forces—by shifting the value of learning, the share of returns workers can keep, and the cost of acquiring skills. By linking market structure to these underlying mechanisms, we provide a conceptual basis for interpreting how skills are formed, which types are emphasized, and how they evolve across different labor market environments.

We organize the discussion in two parts. First, we consider the firm's decision to invest in skill formation and how that decision is shaped by market conditions. Then, we turn to the worker's learning decision, treating firm behavior as an input to the cost of individual learning effort.

**How Firms Shape the Learning Environment.** We begin by modeling the firm's decision to invest in training. Let $T_f$ denote the level of training investment chosen by the firm. The firm maximizes expected returns to training by solving:

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

where $R(\theta, T_f)$ represents the gross return to training, which depends on both the competitive environment $\theta$ and the level of investment $T_f$; $\rho(\theta)$ denotes the firm's ability to retain the returns to training (e.g., through worker retention); and $C(T_f, \theta)$ is the cost of providing training, which may also vary with market conditions.

Market structure influences all three components of the firm's training decision: the value of training, the ability to retain its returns, and the cost of providing it. With respect to the retention component, competition reduces firms' ability to hold on to the returns from training. When workers acquire valuable skills, they become more attractive to other employers—especially in competitive markets with many firms hiring for similar roles. To retain them, firms need to raise wages or offer promotions, effectively passing part of the return on to the worker. In this case, the firm bears the training cost but captures only part of the benefit. This mechanism has been emphasized in classic models of firm training (e.g. Becker, 1962; Acemoglu and Pischke, 1998), where the inability to fully internalize the return discourages investment — particularly in transferable skills.

Yet competition may also increase the gross return to training. In high-pressure environments with no slack — where firms must adapt, innovate, or improve efficiency to survive—the value of skilled, adaptable workers can rise sharply. A firm in a competitive market may derive more from each unit of worker skill because productivity gains are more valuable when margins are tight and customer expectations are high. For example, in a fast-moving logistics firm, a well-trained employee who can manage delays, adopt new technologies, or coordinate teams may generate large performance gains. Crucially, these gains are more likely to be realized in competitive settings, where firms cannot afford to underutilize talent.

One intuitive way to see this is by considering how competition affects the effective use of skills within a firm's production possibilities. In competitive markets, firms operate closer to their production frontier: there is little slack, and marginal improvements in worker productivity translate directly into output or cost savings. By contrast, firms in less competitive environments often operate inside their frontier — where skill investments may be underutilized due to weaker innovation pressure or institutional inertia. Moreover, competitive pressure does not just tighten slack — it also accelerates the outward shift of the frontier itself. Firms in these environments adopt new technologies more quickly, improve internal processes, and innovate more aggressively. As a result, training investments yield higher returns not only because skills are fully utilized, but also because the underlying production possibilities are expanding. This dynamic helps explain why the gross return to training may rise with competition, even if firms capture a smaller share of it.

Whether competition raises or lowers training investment, then, depends on which force dominates: the reduced ability to retain returns (which lowers the investment incentive), or the increased value of skill (which means that they may not afford not to train). This trade-off lies at the heart of our empirical analysis. We examine it through two complementary approaches: survey data on actual firm behavior across markets with varying competition, and vignette experiments that ask managers how they would respond under different levels of competitive pressure, implemented in a between-subjects design.

The framework above does not assume a specific type of skill. A central question in the literature, particularly in the work of Becker (1962) and Acemoglu and Pischke (1998, 1999a), is whether competitive pressure leads firms to invest more in general skills, which are portable across firms, or in specific skills, which are harder to transfer and more likely to be retained. On one hand, firms facing higher mobility risk may shift toward specific skills to reduce the chance of losing their investment. On the other hand, competitive markets may disproportionately raise the gross return to general skills — especially when innovation, adaptability, or customer responsiveness matter — making such investments more valuable even if retention is lower. The direction of this response is unclear a priori and depends on the balance between retention and gross return. This is another core ambiguity we assess empirically.

While much of the literature focuses on formal training, firms also shape the conditions for informal learning — through task design, peer dynamics, mentoring, and workplace collaboration. Competitive pressure may influence these channels by pushing firms to restructure work in ways that expose employees to broader tasks, increase peer interaction, and require greater individual initiative—conditions that both enable and demand learning on the job. These effects are less directly modeled in standard profit-maximizing frameworks but are

central to understanding how skill formation actually occurs. In the next subsection, we turn to how workers respond to these environments through their own learning behavior and decisions.

Finally, our illustrative expression also contains a direct term for training cost, $C(T_f, \theta)$. While we focus primarily on how competition affects returns and retention, the cost channel is also theoretically ambiguous. On one hand, more motivated or higher-ability workers in competitive markets may lower training costs by requiring less supervision or by raising worker effort. On the other hand, heightened competitive pressure may increase training costs by requiring more complex, tailored, or innovation-oriented programs. These underlying cost components are difficult to observe separately, but the key point remains: even along this dimension, theory does not yield a clear prediction.[2]

**How Workers Respond to the Environment.** We now turn to the worker's decision to acquire skills. Let $L_i$ denote the amount of learning undertaken by worker $i$, chosen to maximize expected returns:

$$\max_{L_i} \{\pi(\theta) \cdot H(\theta, L_i) - \Phi(L_i, E_f, \theta)\}$$

Here, $H(\theta, L_i)$ is the gross return to learning, which depends on the competitive environment $\theta$ and the level of learning $L_i$; $\pi(\theta)$ denotes the share of the return that the worker retains—through wage growth, internal advancement, or mobility; and $\Phi(L_i, E_f, \theta)$ captures the cost of learning, shaped by firm-provided environments $E_f$, market conditions $\theta$, and the learning level itself. Note that the firm's role enters primarily through the cost component: by shaping the work environment—via task assignment, feedback structures, and access to training—firms influence the ease, efficiency, and burden of skill acquisition. But the decision to invest ultimately lies with the worker.[3]

Market structure affects each of these components. First, competition can raise the return to learning by increasing both the demand for new skills and the likelihood that those skills are put to immediate use. In dynamic, high-pressure environments, firms must innovate continuously to remain viable, and workers are more directly exposed to shifting tasks, evolving technologies, and tighter performance expectations. As a result, even modest

[2]The illustrative framework treats training as a productivity-enhancing investment: firms train to raise output and retain part of the return. In practice, however, training may also serve as a strategic tool for recruitment and retention—especially in competitive labor markets. Firms that offer meaningful training may attract higher-quality applicants, reduce turnover, or improve their reputation as employers. These motivations fall outside the model's structure but are empirically relevant. Our vignette experiments allow us to probe for these broader considerations and we provide direct evidence on them in the final section of the paper.

[3]An analogy is education: we can place children in classrooms, but unless they are willing to learn, little will be achieved. Similarly, workplace structures provide opportunities, but agency determines outcomes.

learning investments can yield substantial productivity gains, because they are both urgently needed and readily applied. As firms compete for skilled labor in competitive markets, they bid up wages up to the marginal productivity of labor – which in turn incentivizes workers to increase their productivity. In contrast, in concentrated markets with relatively fixed technologies and underutilized labor, the same investment may have little impact, as new skills are less likely to be used or needed.[4] And, consequently, if workers do not expect to be paid their marginal productivity, they have little incentive to invest in their skills.

Second, competition raises $\pi(\theta)$, the retention of returns. In more competitive labor markets, workers with higher productivity face more job opportunities and stronger fallback options. This enhances both their external mobility and internal bargaining power, allowing them to retain a greater share of the returns to their skills. As a result, the incentive to invest in learning increases, particularly when skills can be translated into wage gains, promotions, or movement to better jobs.

Third, competition may lower the cost of learning $\Phi$, both directly and indirectly. Competitive environments often foster dynamic work arrangements — task rotation, peer interaction, collaborative problem-solving — that make informal learning more accessible. These mechanisms reduce the marginal cost of acquiring new skills, even in the absence of formal training. In addition, firm behavior around formal training, as discussed above, may directly reduce the cost of participation. Organizational culture can also matter: firms that emphasize mentorship, peer support, or continuous improvement may lower both the psychological and logistical barriers to skill acquisition. Such cultural features may be particularly pronounced in competitive markets, and especially important for enabling informal learning, which often depends on voluntary initiative and social reinforcement rather than formal incentives or structure.

Finally, the type of skill matters. The private return to firm-specific or non-transferable skills may be relatively stable across market structures, since their use is confined to the current employer. In contrast, the return to general, transferable skills rises sharply with competition—offering workers greater mobility, bargaining power, and access to high-value tasks. Crucially, these higher-order skills also help workers adapt to evolving production processes and innovation-driven environments, where flexibility, decision-making, and communication are essential. As competition increases, we should expect a shift toward these types of skills

[4]One way to formalize this intuition is to model the return to learning $H(\theta, L_i)$ as increasing in firm-level capital intensity or innovation pressure. For example, let the marginal productivity of learning be a function of the effective capital stock $K_f$ or an innovation index $\iota_f$, such that $\partial H/\partial L_i = h'(L_i; K_f, \iota_f)$, with $\partial^2 H/\partial L_i \partial K_f > 0$. In this setup, learning is more valuable in firms with more complementary capital or in sectors undergoing rapid technological change. Competition may amplify these dynamics by forcing firms to make more efficient use of human capital, raising the productivity gains from even modest skill improvements. This provides a natural mechanism by which competitive environments could increase the gross return to learning, particularly for higher-order or transferable skills.

— contrasting sharply with canonical models that focus on firm-provided training and the underprovision of general skills.

# 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 rich 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). We also 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. Restricting to workers employed in the private sector, this leaves us with 9,955 respondents who we are able to link to administrative data. In total, the survey captures workers from nearly 80 percent of Norwegian firms with 100 or more employees (Table A.1).

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 and 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.

## 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 measure 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.[5] For comparability with the Outside Options Index (OOI), both measures are rank-transformed to lie between 0 and 1. We will also (Bassier et al., 2022) to extend the analysis and look at other firm level measures of power.

Table A.2 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.

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

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

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

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 $\lambda_f$ 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 actualized 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 labor market scenario that varies in the level of competition. Treatment is binary: respondents are randomly assigned to either a competitive or a concentrated market condition.[6]

In the competitive condition, the labor market is described as characterized by high outside options, pressure to innovate, and elevated risk of losing employees to rival firms. In the concentrated condition, the environment is framed as one of 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 to learn over time, how motivated they would be to invest in different types of skills, which

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

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.

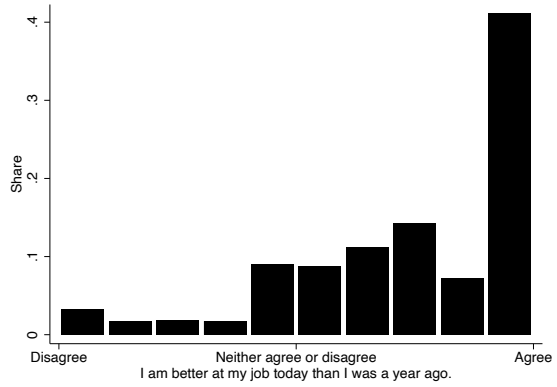
# 4 Results

Before turning to the role of market structure and skill accumulation, we begin by documenting three empirical patterns that motivate our focus on workplace learning. First, consistent with findings across a range of contexts (e.g. Lucas, 1988; Deming, 2023), we observe that earnings rise over much of the life cycle—suggesting that skill accumulation continues well beyond the end of formal education (Figure A.2). Second, our survey data shows that the vast majority of workers perceive themselves as having improved at their jobs over the past year (Figure 1a), indicating that learning on the job is both widespread and persistent. Third, self-reported improvements at work are strongly associated with subsequent wage growth (Figure 1b), lending support both to our survey measure as a proxy for meaningful human capital accumulation and to the common interpretation of wage growth as reflecting, at least in part, learning.[7] While suggestive, these patterns underscore the importance of understanding how skills are formed at work—and how this process responds to different economic environments.

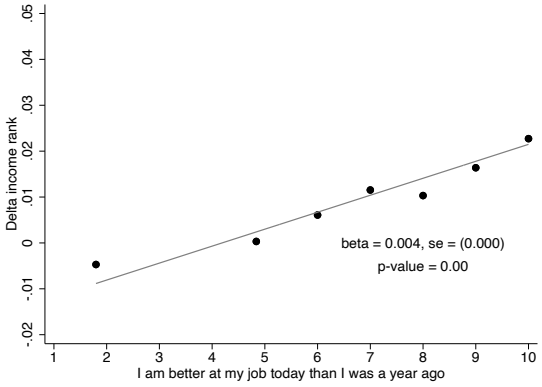
[7]We further assess the validity and robustness of this skill accumulation measure in the analyses that follow.

Figure 1: Skill accumulation and wage-growth

(a) Self-perceived skill development




(b) Wage growth and skill-development




*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.2.

**Market Structure, Perceptions, and Earnings.** In our framework, workers respond to market incentives and become more motivated to invest in their human capital when they perceive competition in their local labor market. For this mechanism to operate, workers must be able to observe and internalize the structure of the market they operate in.

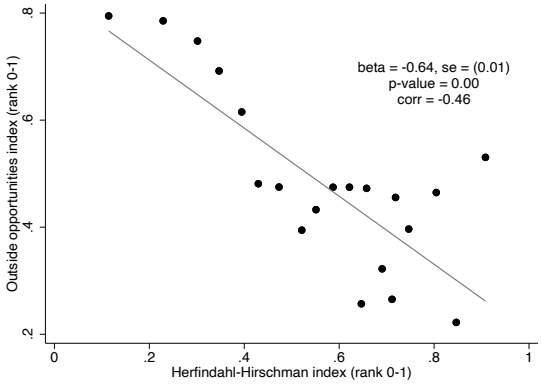
We begin by examining whether workers are aware of the market structure around them. Figure 2 plots our survey-based measure of perceived outside opportunities—the Outside Opportunity Index (OOI)—against the Herfindahl-Hirschman Index (HHI), the most widely used administrative measure of labor market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

The correlation between the OOI and the HHI not only validates our perception-based measure, but also provides rare behavioral evidence in support of the HHI. Despite its widespread use in both academic and policy settings, the HHI remains a black-box construct with known limitations. It abstracts from search costs, network constraints, and firm-level heterogeneity, and may not reflect how workers actually experience employer power. The strong alignment between perceived and structural measures suggests that, despite these limitations, the HHI captures important aspects of the competitive environment as it is

understood by workers. This validation carries independent value: to our knowledge, it is the first large-scale belief-based confirmation of the HHI's relevance for understanding labor market behavior.

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).

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.3. The HHI measures how concentrated a labor market is, calculated as the sum of scared 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.2.

The strong correlation between our OOI and the HHI suggests that workers hold relatively accurate beliefs about their outside opportunities in the labor market—something that should not be taken for granted. For instance, 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, we observe a much closer alignment between worker perceptions of outside options and structural measures of labor market concentration. This constitutes a key contribution beyond our immediate analysis. Competition authorities and

litigation consultants in Europe and the United States routinely rely on the HHI to guide decisions related to labor market power, yet its behavioral relevance has rarely been directly examined.

To better understand the properties of our OOI measure, we examine its correlation with other commonly used measures of market power (Table A.4). We show that, while our measure is calculated at the occupation-by-commuting zone level, it is also correlated with firm level measures of power (Bassier et al., 2022). Additionally, we study the relationship between our measure of outside opportunities in the labor market and market power in the product market by comparing it to a sector-by-commuting zone HHI measure of product market power (based on firm revenue shares). While the correlation is weak (but statistically strongly significant), it goes in the expected direction – more outside opportunities in the labor market are associated with firms having less power in the product market. The table also shows that while labor and product market HHI measures exhibit a strong positive correlation, our OOI measure is still more strongly correlated with the labor market HHI. Together this pattern of correlations provides strong support for interpreting the OOI based on survey data as capturing a real phenomenon.

We further probe the properties of the OOI in two ways. First, we examine the specific components that make up the index. Appendix Table A.3 shows the correlation between each subcomponent and the HHI, allowing us to assess which belief items most closely track structural concentration. While each item is individually informative, the strongest relationship emerges from their aggregation—suggesting that workers form perceptions of market structure based on a broad set of signals, rather than any single indicator. 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 examine how the OOI compares to the HHI in replicating established empirical relationships. Figure A.3 shows that both measures exhibit a clear, monotonic negative relationship with average wages: workers in more concentrated markets, whether measured structurally (HHI) or perceptually (OOI), tend to earn less. 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.

This finding has broader significance. It suggests that workers possess a good understanding of their competitive environment—one that plausibly shapes their behavior and investment decisions. This alignment between subjective and objective measures highlights the need for deeper empirical attention to how workers perceive labor market conditions and how these perceptions enter into economic decision-making. We view this as a promising direction for future research. While our focus in this paper will be on the OOI, we offer complementary

analysis of key results also based on the HHI throughout the Appendix.

**Where Do Workers Learn?** One of the central hypotheses of this paper is that competitive market environments may promote skill development—not only by influencing formal training decisions, but by altering the broader conditions under which learning occurs. This section provides the first direct test of that idea. We examine whether workers in more competitive labor markets are more likely to report having improved their skills on the job—capturing whether, and where, learning takes place. This is a core prediction of our conceptual framework: competition raises the return to learning, increases the share of that return workers can retain, and lowers the cost of acquiring skills, especially informally. While the implications for firms are more ambiguous (competition may raise the value of training but reduce retention of that return), recognizing worker agency and informal learning shifts attention away from firm incentives alone. If these mechanisms are at play, we should observe more learning in competitive markets.

We begin by examining whether competition is associated with greater self-reported learning on the job. Figure 3a shows that the OOOI is strongly positively associated with learning: workers in the most competitive markets report significantly greater skill development than those in less competitive markets. Specifically, a worker in a median-competitiveness labor market reports 0.23 standard deviations less learning than one in the most competitive markets.

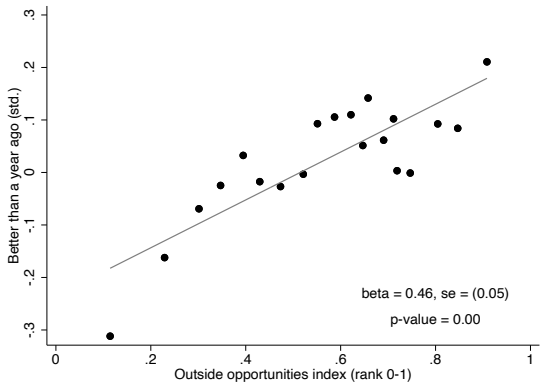
Figure 3b shows that this relationship is not unique to the perception-based OOI. Using the HHI, we observe a similarly negative association with learning: as concentration rises, the probability that workers report being better at their job falls.

Both 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.6 and A.7). These patterns are, therefore, not explained by compositional differences across labor markets in observable characteristics.

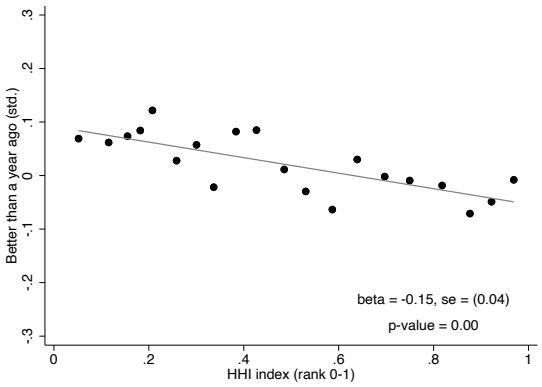
Taken together, these findings provide clear evidence that competitive labor markets are associated with greater on-the-job learning. Whether measured through objective concentration indices or workers' own perceptions of outside options, competition appears to act as a catalyst —not a constraint— for 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.2.

To probe whether our findings reflect labor market competition specifically—rather than a broader feature of competitive local economies—we compare the predictive power of the OOI to that of a product market HHI, based on firm revenue shares within sector–commuting zone cells. Row one of Table A.8 shows that both measures are associated with learning. However, the coefficient on the OOI is considerably larger and remains stable when the product market HHI is included. This suggests that labor market competition plays a more direct role in shaping skill development, even when accounting for product-side dynamics. This is consistent with the idea that competition raises the return to learning and strengthens worker incentives. We return to this question in the next few subsections.

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? To investigate this, we estimate firm-specific effects on wage growth using administrative data—net of worker characteristics and excluding the survey sample. Figure 4b shows that firms in more competitive markets generate higher wage growth for their workers on average. The magnitude is substantial: about half the size of the individual-level wage–competition gradient.

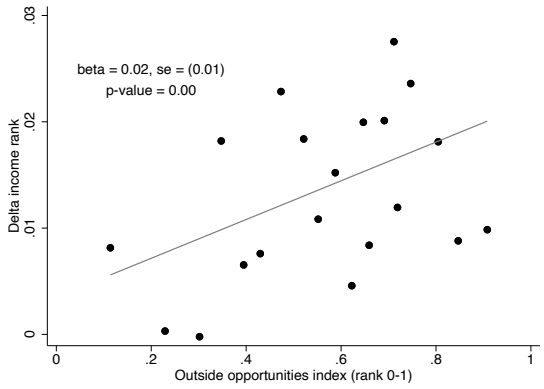
Figure 4c connects these firm-level wage effects to worker-reported learning. Workers employed at firms with higher wage-growth effects are also more likely to report becoming better at their jobs. This triangulation strengthens our interpretation: self-reported learning tracks meaningful differences in human capital accumulation, and competition appears to shape both individual incentives and firm practices.

Together, these findings extend our core insight. Workers in competitive markets learn more, earn more, and are more likely to work at firms that foster learning and wage progression. In short, competitive market environments not only promote individual development but also shape the institutional context in which learning occurs.

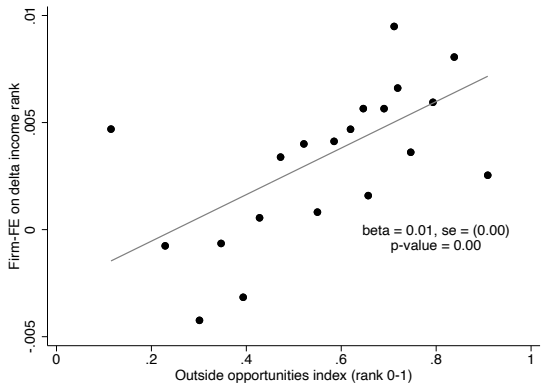
The results from this section provide clear evidence that competition acts as a catalyst for skill development—rather than a constraint to growth. This is a central result, closely aligned with our conceptual framework: competitive pressure increases the worker's gross return to learning, raises the share of that return they can retain, lowers the cost of acquiring skills (in particular through informal learning), and strengthens learning incentives. For firms, the effects are more theoretically ambiguous—while the gross return to training rises, the ability to retain that return may decline. Prior work has largely abstracted from informal learning and worker agency, focusing instead on how competition may shape the type of skills provided through formal, firm-led training. Even in that setting, it has paid little attention to the level of learning that occurs and the difference between gross returns and retention. Our findings highlight this broader margin of skill development as critical. The next question, then, is how workers actually 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

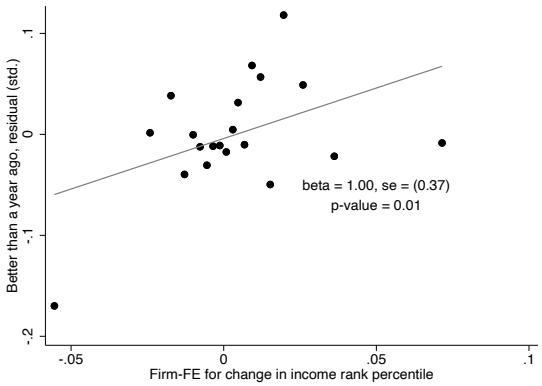
(a) Wage growth and OOI




(b) Firm-FE on wage growth and OOI




(c) Learning and firm-FE on wage growth

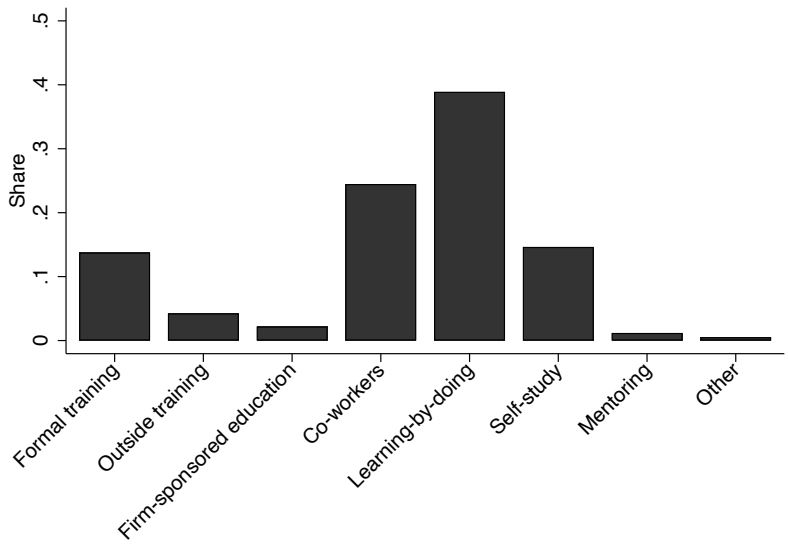



*Notes:* Figure 4a reports the relationship between worker wage growth and mean labor market-level perceptions of outside opportunities. Figure 5b reports the relationship between the extent that firms consistently generate earnings growth for their workers (outside the survey sample), and labor market 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.2.

**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 the broader argument of this paper and the illustrative framework introduced before—especially since much of that learning may take place outside formal training programs. A key advantage of our survey is that it allows us to distinguish 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). Understanding the relative roles of these channels is critical, given that a substantial 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.2.

Figure 5 presents descriptive evidence on how workers acquire skills on the job. Respondents are first asked whether they have learned new skills at work over the past year. If they answer yes, they are then asked to indicate through which channels that learning occurred. Respondents may select multiple channels. The figure reports the prevalence of each learning mode across the full sample. Informal mechanisms—such as learning-by-doing, peer interaction, mentoring, and self-study—are far more common than formal training. While many workers report some exposure to firm-provided training, informal learning is both more widespread and more consistently cited. Strikingly, self-study—arguably the channel requiring the most initiative and autonomy—ranks among the most frequently reported modes. This highlights the active role many workers play in their own skill development. Finally, fewer than 2 percent of respondents select "other" as a learning mode—underscoring that the categories provided in the survey capture nearly the full range of workplace learning.

These findings have important implications. They 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 may have global 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 channels through which workplace learning occurs, we next examine the relationship between them—and assess the extent to which each predicts self-assessed human capital improvement. Specifically, we analyze how strongly formal and informal learning are correlated, and how each maps onto workers' perceptions of skill development over the past year. Table A.5 explores these relationships. We find that formal and informal learning are only weakly correlated (correlation of approximately 0.3), suggesting that they capture distinct dimensions of workplace learning. More importantly, informal learning is far more predictive of perceived skill development. The correlation between informal learning and self-assessed improvement is approximately 0.4, while the corresponding figure for formal training is just 0.1. These results emphasize the central role of informal learning as a primary mechanism of skill accumulation, and suggest that formal training explains relatively little of the variation in perceived improvement.

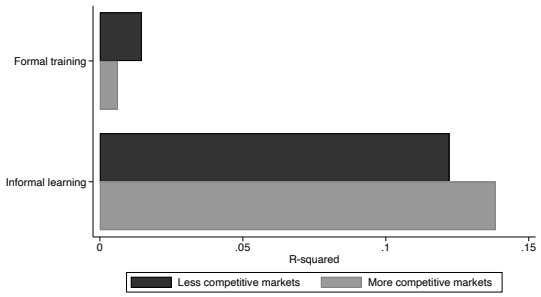
Figure 6a explores how the relationship between learning mode and perceived skill improvement varies across market structures. Informal learning is considerably more strongly associated with self-assessed improvement than formal training. This is the case in both more and less competitive labor markets. Still, the relative strength of this association depends on market structure: formal training appears more predictive of improvement in concentrated markets, while informal learning is more predictive in competitive ones. This suggests that market structure may shape not only the quantity of learning, but also the effectiveness of different learning modes.

Figure 6b then examines how the prevalence of each learning mode varies with competition. We find that both formal and informal learning increase as labor markets become more competitive—but the rise is substantially steeper for informal learning. This is a central result. While prior work has emphasized how competition may affect the type of training, little is known about how it shapes the level of learning. Our findings show that formal firm-led training increases with competition, and that informal learning rises even more sharply. 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.6 and Table A.7 show that the relationship between competition and learning

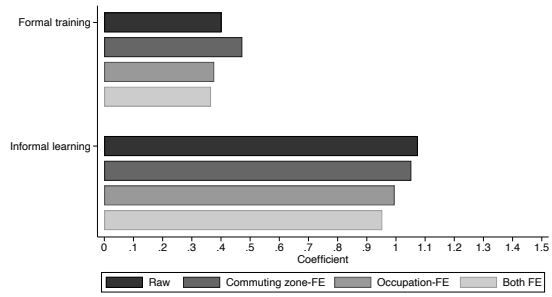
modes is robust to the inclusion of a large array of covariates and not sensitive to how we measure labor market power. The strong, positive association between competitive market environments and informal learning persists even under saturated specifications controlling for occupation, commuting zone, workforce composition (education and age), and firm size.

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.2.

Interestingly, when we disaggregate the analysis by industry, we find substantial heterogeneity in average learning and performance levels—but striking consistency in the underlying relationships (Figure A.6): more competition leads to more learning; informal learning is more strongly associated with self-assessed improvement than formal training; and informal learning is more responsive to OOI. Interestingly, two industries – finance and real estate as well organizations – show a negative relationship between competition and formal training (Figure A.6e), 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. Further, Figure A.6e shows that formal training appears much less responsive to competition in white collar industries than in industries like agriculture and manufacturing. Together, these patterns suggest that competition shapes how workers learn—not just who is working

where.

These patterns align with our conceptual framework: competition raises the gross return to learning, increases the retention of that return for workers, and lowers the cost—especially for informal modes of learning. The dominant margin of response occurs through mechanisms shaped not by firms, but by workers themselves. At the same time, the fact that formal training also increases suggests that, in this setting, the rise in the gross return to training outweighs the decline in firms' ability to retain that return. This provides rare empirical evidence on a long-standing theoretical ambiguity: even when retention of returns falls, productivity gains from training may be large enough to induce greater firm investment.

To further probe the relationship between how firms versus workers might respond to market structure, we study how informal learning and formal training differentially respond to labor versus product market power. Rows two and three of Table A.8 report how these two dimensions of market power shape informal learning and formal training, respectively. These results indicate that informal learning is much more responsive to labor market competition than concentration in the product market; in contrast, formal training is nearly as responsive to labor market competition as to product market concentration. This pattern aligns with our framework: worker-led investments in human capital are shaped by labor market incentives and career concerns, while firms' training decisions may be more sensitive to product market pressures.

To better understand the drivers of informal learning, we next ask: to what extent is skill development in competitive markets shaped by workers' own initiative versus firm-provided opportunities and learning environments? We begin by focusing on one dimension where worker agency is clearest: self-study. Figure A.7 shows that workers in more competitive labor markets are significantly more likely to report engaging in self-study or training outside formal channels. This pattern suggests that competitive environments encourage workers to take a more active role in their own skill development.

But informal learning is not purely individual. It depends critically on the tasks workers perform, the discretion they are given, and the culture in which they operate—all of which are shaped by firms. As such, the roles of workers and firms in enabling informal learning are tightly linked and not easily separable.

To explore whether firm practices help mediate the relationship between competition and learning, we turn to firm culture. Table A.10 follows a simple mediation logic. Panel A shows that workers in more competitive labor markets report stronger, more growth-oriented firm cultures. Panels B through D then examine whether accounting for firm culture attenuates the relationship between outside options and learning outcomes—measured by self-assessed improvement, informal learning, and formal training. In each case, the inclusion of culture

reduces the estimated effect of outside options, suggesting that competitive markets may foster learning not only by changing worker incentives, but also by shaping the organizational context that supports learning.

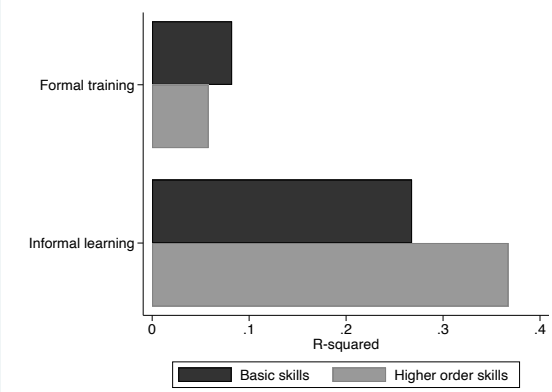
While descriptive, this analysis reinforces the idea that informal learning arises from the interaction between individual agency and firm structure. Competition appears to affect both.

Taken together, these findings point to a consistent result: workers learn primarily through informal channels, and this mode of learning becomes especially salient in competitive labor markets. While firms continue to invest in formal training, the dominant pattern of skill development is driven by informal processes. Interestingly, however, these informal pathways are not solely individual—they also are shaped by the structure, norms, and cultures that firms help establish. These patterns underscore the importance of worker agency, but also highlight the role of firms in enabling or constraining informal learning. Together, they point to the need for a broader focus—beyond training inputs—on the full learning dynamics that shape human capital accumulation in practice. Next, we 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 turn to the question of what kinds of skills workers acquire through different learning modes and across different market structures. This distinction is central to both theory and evidence. Understanding which skills are developed—through which channels, and in which environments—is essential for interpreting the broader consequences of skill formation. Different types of skills matter differently for productivity, earnings growth, career progression, and firm performance. Understanding how market structure shapes the differential formation of various skills is therefore crucial.

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

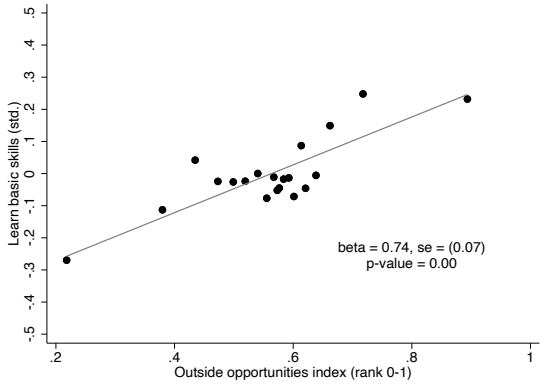



*Notes:* Figure 7 reports the R-squared from bivariate regressions which relate skill development – either in terms of an index of basic or higher order skills – and learning mode – either firm investments or informal learning. Basic skills are measured as an average of manual work, analytic thinking, 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.2.

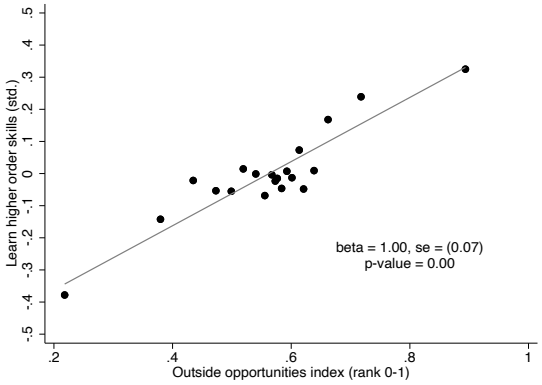
Figure 7 examines how formal and informal learning modes are associated with different types of skill development. Informal learning is strongly correlated with both basic and higher-order skills, but the association is much stronger for higher-order skills. In contrast, formal training is more modestly 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.

Figure 8: Competition and improvements by skill type

(a) Learning basic skills




(b) Learning higher-order skills




*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.2.

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).

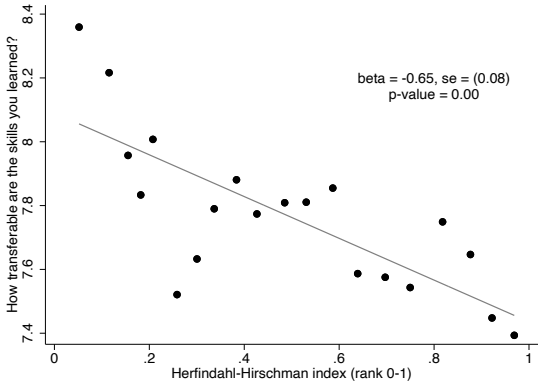
After having disentangled the relationship between market structure and basic/higher-order skills as classified by Deming and Silliman (2024) and inspired by Bloom et al. (1956), we zoom in on the question of skill transferability and how that transferability shapes human capital accumulation in the labor market. In this domain, a key insight from Acemoglu and Pischke (1999a) seminal paper is that firms may be less likely to invest in transferable skills in competitive labor markets because they can capture less of the return.

In contrast to the canonical view that competition discourages firm investment in transferable skills due to lower retention, our framework emphasizes that competition can also raise the gross return to skill — potentially offsetting those disincentives. At the same time, transferable skills become more attractive from the worker's perspective when competition between firms 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 and deploying skills. As we document above, much of skill development occurs through informal channels, making it essential to account for how both firm incentives and worker behavior respond — potentially asymmetrically — to changes in competitive conditions.

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.[8] This reinforces the idea that competition not only increases learning, but also shifts its composition toward more portable and higher return skills.

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.2.

The extent to which skills are transferable across firms or occupations (are "general") depends not only on their intrinsic content, 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 in certain

[8]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.

contexts. This distinction is important when interpreting the patterns in Figure 9. To better understand the extent that workers and firms invest in skills whose content makes them transferable (i.e. technological general skills), we use a data-driven approach to classify transferability across contexts. Specifically, we regress self-reported overall transferability of recent learning on the intensity of learning across different skill dimensions. This allows us to estimate the marginal contribution of each skill type to perceived transferability—offering a classification of skills by their intrinsic portability, net of the particular context a worker is in.

Table A.11 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 extent that the skill content of training and learning is transferable, we examine how the transferability of acquired skills varies by learning mode and competition (Figure A.8). We find that the transferability of both formally and informally acquired skills increases as competition rises. This is a key result: it stands in direct contrast to canonical predictions from Becker (1962) and Acemoglu and Pischke (1998, 1999a), which suggest that competitive pressure should discourage formal firm investment in transferable skills. Instead, our findings indicate that such investment persists—and even grows—in competitive settings. One plausible interpretation is that competition raises the gross return to skill formation enough to offset reduced 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 further study these patterns, we zoom into workplace skill development across the granular skills included in our survey (Table A.9). For each skill, we regress reported learning on indicators for informal learning and formal firm-provided training, including both in a horse-race specification. We then order skills by their average reported transferability. Two main findings emerge. First, highly transferable skills—such as leadership, problem-solving, and communication—are disproportionately developed through informal learning. Second, the ratio of the coefficients on informal versus formal learning rises with skill transferability. These results sharpen the interpretation above: informal learning is not only more prevalent overall, but it plays a particularly central role in the development of skills that enable mobility,

flexibility, and long-run value.

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 has shown that human capital appears to accumulate faster in competitive labor markets, that this learning occurs primarily through informal channels, and that the resulting skills—especially higher-order and transferable ones—are shaped by both the structure of the labor market and the behavior of workers and firms. These patterns align closely with our conceptual framework and provide new evidence on how market structure influences human capital accumulation. However, while our observational data provide insights into patterns of skill development, they cannot identify causal relationships, or fully isolate the underlying mechanisms that drive these patterns. In particular, we cannot directly observe whether competition affects learning through changes in firm behavior, worker incentives, or both.

To deepen our understanding of these mechanisms, we field two complementary surveys targeting (1) workers and (2) firm managers. Each survey contains three components. First, a set of targeted questions elicits beliefs about the role of formal training, informal learning, competition, and motivation in shaping skill development—providing a structured way to interpret the patterns observed in the descriptive data. Second, the core of each survey is a vignette experiment designed to isolate how labor market competition influences investments in human capital. These vignettes offer a clean and internally valid way to test causal intuitions that are difficult to identify in observational data. Third, we elicit preferences over competitive versus concentrated labor markets—either as a setting to start a career (for workers) or to establish a firm (for managers)—and ask respondents to explain the reasoning behind their choices. This combination of belief elicitation, experimental variation, and preference mapping provides new insight into how market structure shapes learning incentives from both sides of the labor market.

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

Before turning to experimental evidence on how competition shapes beliefs about human capital investments, 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.** To examine how firms approach human capital development in the workplace, we turn to managers. 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

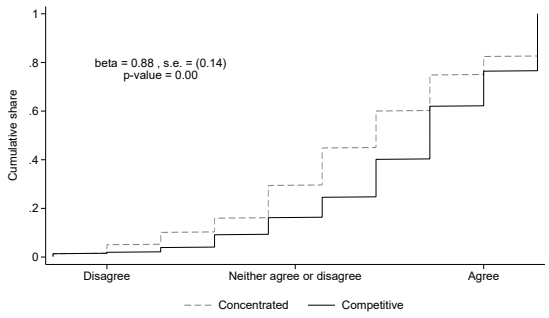
The key evidence isolating the relationship between competition and workplace human capital investment comes from vignette experiments. In these experiments, workers and managers are randomly assigned to hypothetical competitive or concentrated markets and asked how and why they would make decisions regarding human capital investment.

**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. This outcome was pre-registered with the AEA as our primary outcome in the worker analysis.

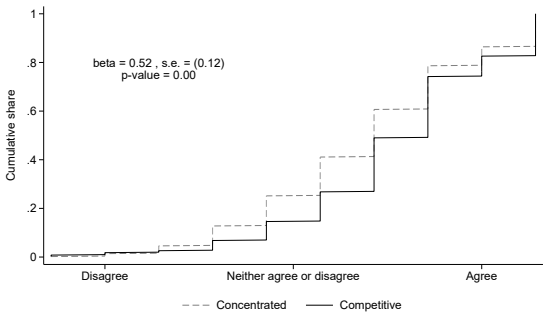
The results show that workers in competitive environments are significantly more likely to expect improvement in their job performance over time, with each additional year of work (Figure 10a). This finding strongly reinforces our survey-based evidence and aligns with the stylized framework proposed in the paper. Specifically, it underscores that in competitive markets, workers are more likely to anticipate continued skill development, highlighting the positive role that competition plays in shaping human capital accumulation.

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

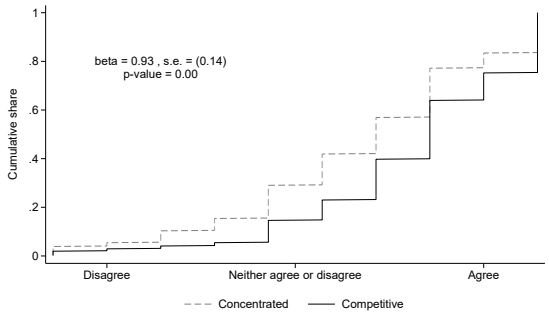
(a) Workers: "Every year I work at this company I will be better at my job."



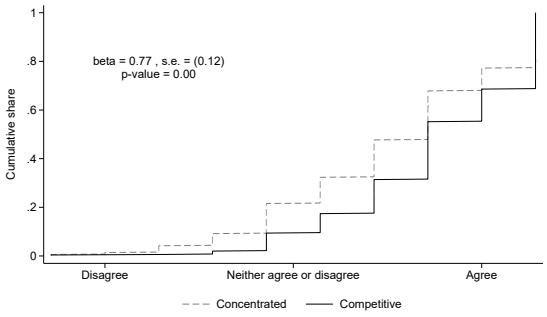

(b) Managers: "Workers in this firm will be better at their jobs after each year."



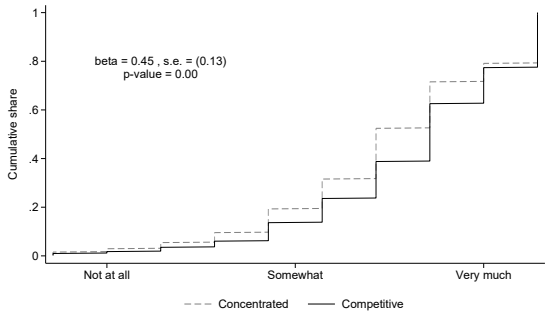

(c) Workers: "Skills are critical for my labor market success."



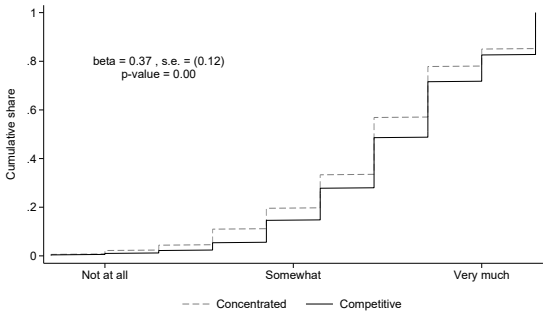

(d) Managers: "Investing in training is critical for succeeding as a business."




(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 findings 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.[9]

One interpretation of these results is that as outside options improve and the chance of career advancement increases, workers become more willing to invest in human capital. This result is important: it underscores the central role of informal learning and worker agency, and highlights the need to move beyond models that focus exclusively on firm-led training.

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 rather increases their willingness to invest across the full range of competencies.

Figure A.15 sheds light on why higher-order skills respond so strongly to competitive pressure, as observed in the survey, despite workers being equally willing to invest in both basic and higher-order skills. Workers perceive higher-order skills as significantly more difficult to acquire than basic skills, rating them nearly one point higher on a 1-10 scale of perceived difficulty. This distinction aligns with our earlier findings on learning modes: higher-order skills are primarily developed informally and require sustained individual effort. As such, they may be particularly sensitive to changes in incentives. When the cost of acquiring these skills is perceived as higher, increased motivation becomes a critical factor in driving learning efforts.

Interestingly, workers appear to place greater emphasis on how skills influence their outside options rather than their wages within the firm (Figures A.12a-b). However, workers also believe that improving their skills will enhance their firm's productivity (Figure A.11a). This is an important finding. While most prior literature focuses on the private returns to learning, these results suggest that workers also perceive their own skill development as contributing to broader firm outcomes. If workers care about firm survival—either directly or indirectly, as a means of maintaining their current job—this perception becomes even more significant. In this sense, competition may boost productivity not only by altering firm behavior but also by shifting how workers view the purpose and impact of skill formation.

Taken together, the evidence from these vignette experiments strongly supports the idea that competition serves as a catalyst for human capital accumulation. Moreover, it provides

[9]Surprisingly, workers view firm-led training as equally effective as informal learning for improving skills (Figure A.12c).

insight into the behavioral mechanisms underlying workers' learning. Competition motivates human capital investment — by expanding the relevance of skills not just in terms of increased productivity and wages in workers' current place of work, but particularly in terms of outside options. These patterns provide direct behavioral support for the mechanisms outlined in our stylized framework and observed in the survey and administrative data: skill formation is not simply a byproduct of formal firm investment, but a proactive, strategic decision made by workers themselves, greatly shaped by the competitive environment.

**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 labor market scenario and asked a series of questions about how they would respond in terms of skill investment, training focus, and strategic priorities. As for workers, the pre-registered primary outcome for managers was whether those who are assigned to the competitive condition are more likely to respond that each year in the workplace will make their workers better at their jobs.

Manager responses provide strong evidence that they believe competition increases human capital accumulation within their organizations (Figure 10b). This finding is both statistically significant and conceptually important, offering broad support for the central finding of the paper: competition facilitates, rather than impedes, human capital development. It also strengthens the connection between the stylized framework, our survey analysis, and the experimental evidence from workers.

Several additional responses from the vignette experiment provide experimental evidence that highlights the behavioral foundations behind this key result from the perspective of managers. Most centrally, managers view investment in human capital in competitive markets as essential for business success (Figure 10b). This is a pivotal finding. It offers direct causal evidence that competition increases the perceived gross return to training — one of the core parameters in our stylized framework.

Further, while managers view competition as making investment in human capital critical for business success, their focus extends beyond the typical productivity-oriented perspective. Existing literature often centers on firms' ability to recoup human capital investments through productivity gains, particularly when these gains are not offset by wage increases due to poaching in competitive markets. In contrast, our findings reveal a more nuanced picture: managers in competitive markets view human capital investment as essential not only for boosting productivity and ensuring firm survival but also for recruiting and retaining skilled workers (Figure A.13a-b). Interestingly, managers in competitive markets place even greater weight on skill investments for recruiting than on retention, suggesting that in order to recruit

the best talents, they need to offer employees viable pathways to develop their skills. This suggests that, in competitive environments, firms see skill development as a key factor in sustaining performance, while also enabling them to attract and retain the talent necessary for long-term success.

The idea that firms care about skill investment because of its effects on productivity, also extends to empirical results concerning the skill-content of firm investments. Managers in competitive environments report an increased willingness to invest in transferable skills (Figure A.13c). One reason for this is that although investments in transferable skills might increase risk of poaching, they can also be the most valuable skill investments from the employer's perspective. In addition, as noted by Lazear (2009), while particular skills may be transferable, the bundle of skills employees possess can still be unique to a particular employer, allowing the employer to capture returns. In this view, competition does not simply alter who captures the returns to training, but also what types of investments firms believe are necessary to remain viable in a more demanding environment.

Beyond illustrating the central role skill development plays in increasing productive capacity, the manager survey also helps provide insight on how managers perceive workers as behaving. Notably, managers assigned to a competitive setting believe that workers will be more motivated to invest both in formal training as well as informal learning across a broad range of skills (Figures 10c and A.14a, c, d). These findings highlight that managers recognize human capital accumulation as a joint process involving both firm and worker decisions. This reaffirms a core argument of the paper: competition activates workers as agents who make independent decisions about investing in their own human capital. Interestingly, while managers view training as crucial for business success, worker motivation, and talent acquisition, they do not report a significant willingness to increase wages following human capital investments (Figure A.13d). This could suggest that human capital investments offer an amenity value for workers, rather than being directly compensated through higher wages.

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.10) may prove more effective than traditional investments in formal training when it comes to improving worker skills and productivity.

Taken together, the manager vignette experiment provides clear evidence that competitive

pressure shapes how firms evaluate and justify training investments. It increases the perceived importance of training not only for firm performance, but also for recruiting and retaining talent—channels often overlooked in standard models. It also shifts stated priorities toward more transferable skills, suggesting that firms may broaden the scope of training in response to competitive conditions. These findings align closely with our survey evidence and are consistent with the mechanisms outlined in the stylized framework: competition raises the gross return to skill investment and changes firm behavior not only through retention constraints, but through heightened performance and recruitment incentives.

## 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 complex 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 workplace learning 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.

Our findings carry important implications. First, they 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. Second, they 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, we offer a new lens on how inequality in opportunity and productivity is generated, and potentially mitigated, inside the workplace.

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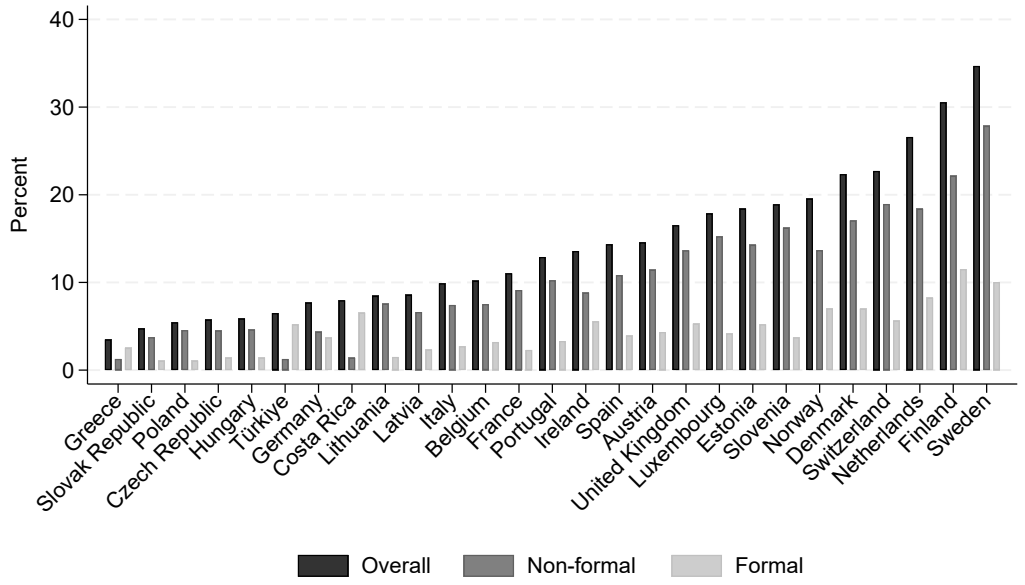
# A Appendix Figures and Tables

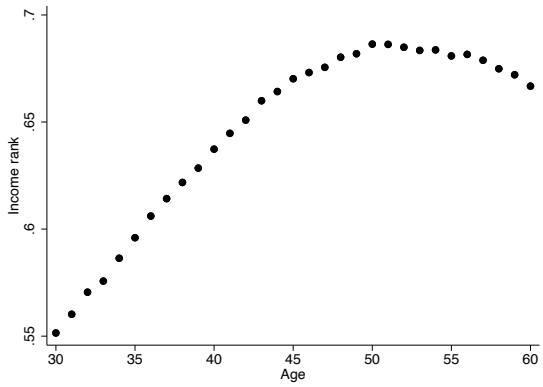
Figure A.1: Participation in adult education in 2021 across OECD countries



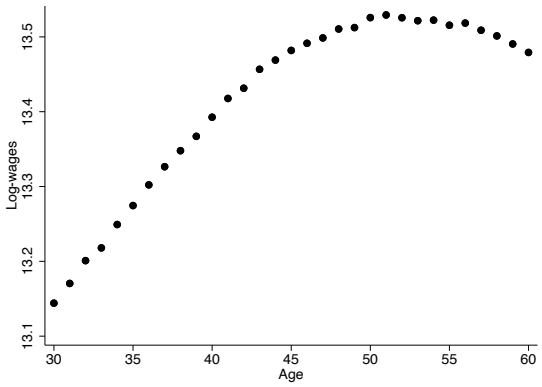

*Notes*: This figure shows the portion of adults aged 25-65 who participated in adult education in the four weeks prior to the survey. Source: OECD (2023).

Figure A.2: Life-cycle wage growth

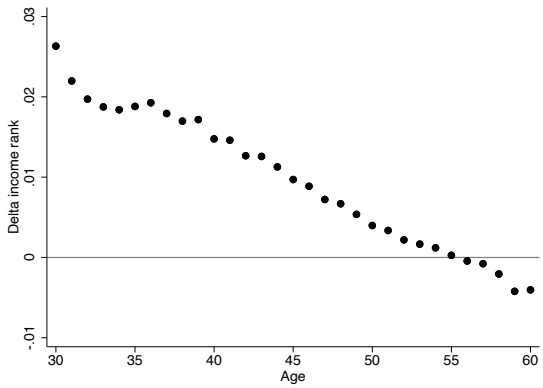
(a) Income rank percentile by age



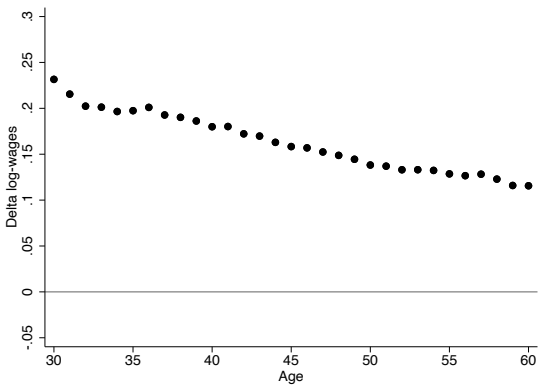

(b) Log wages by age




(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.1: 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.2.

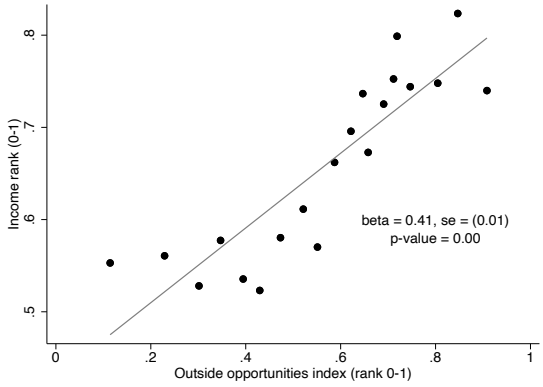
Table A.2: Sample descriptives

| | 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 |

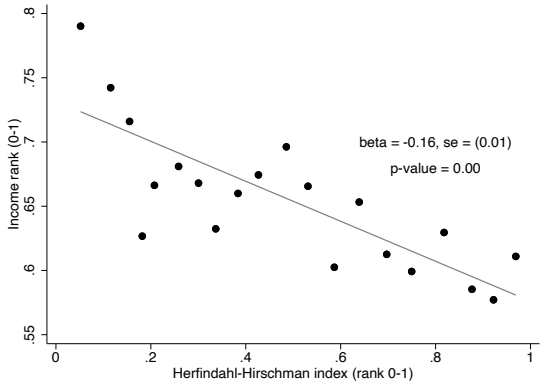
*Notes:* This table reports the mean characteristics in (1) the full population in Norway in the year 2023, (2) the private sector, (3) the survey sample, and (4) workers at private sector firms in the survey sample. Panel A reports information on individual characteristics, while Panel B reports information 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

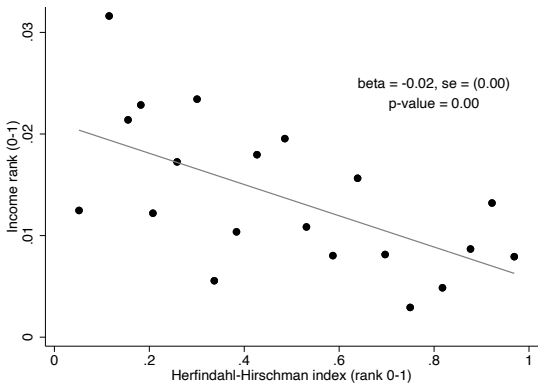



(b) Income rank (0-1) and HHI




*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.2.

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.2.

Table A.3: 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 asy 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.2.

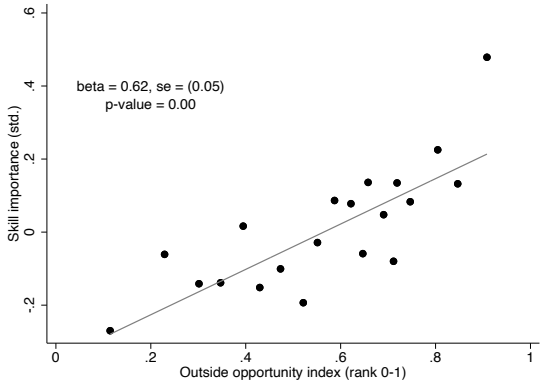
Table A.4: Comparisons of different measures of market power

| | 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 |

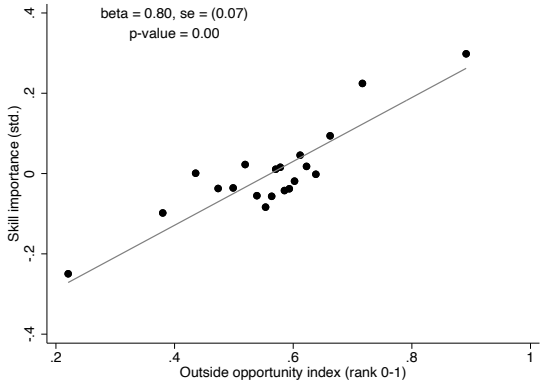
*Notes:* This table reports the pairwise correlation matrix between the OOI index constructed using newly collected survey data and various register-data based measures of market power. The HHI-occupation index is an HHI index based on the share of workers in a particular occupation employed at firms 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.2.

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.2.

Table A.5: 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.2.

Table A.6: 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 |

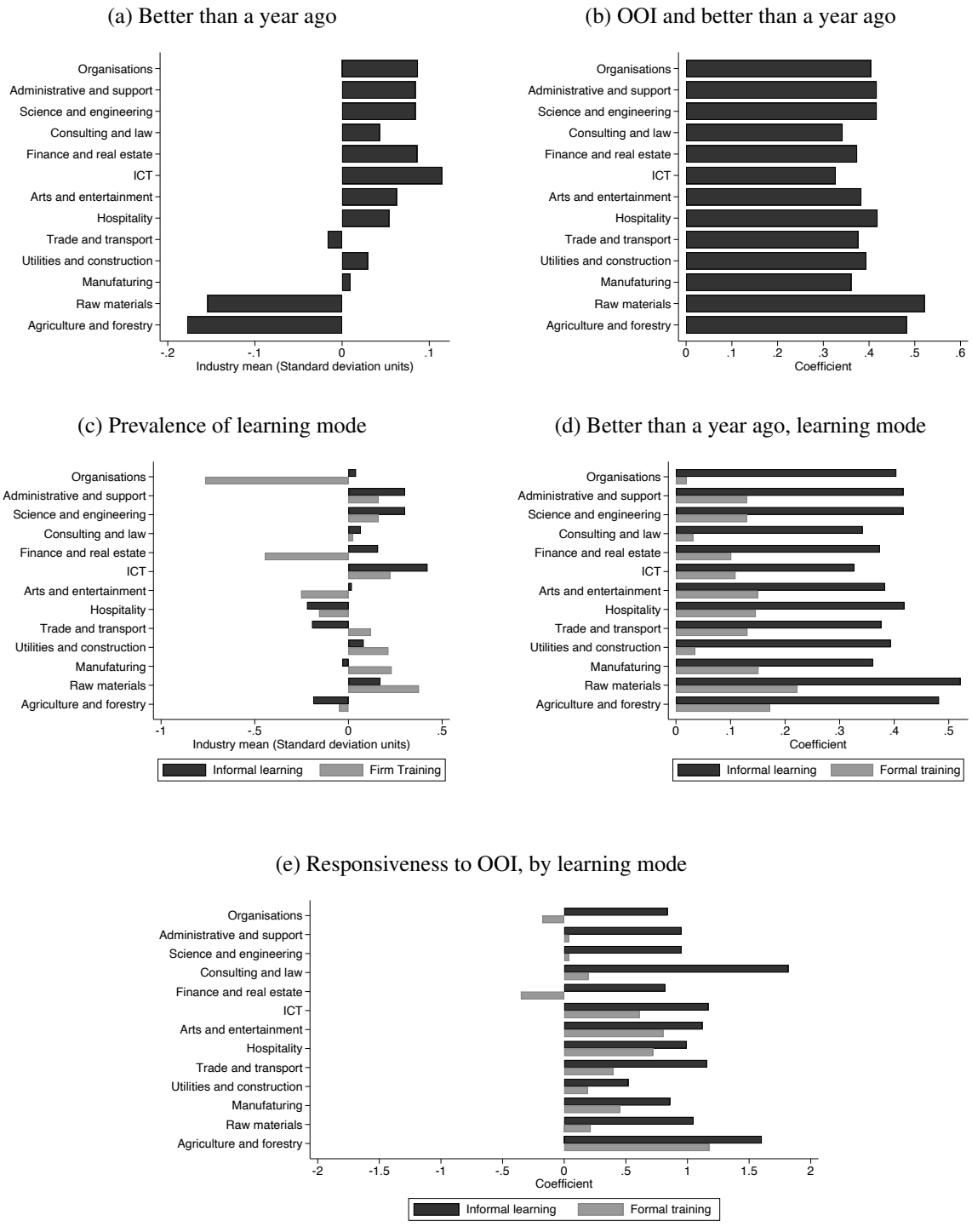
*Notes:* This table reports the relationship between the OOI index (ranked 0-1) and various measures of human capital accumulation, across several specifications. The first column reports the simple bi-variate relationship between the OOI and skill development, while the successive columns include covariates, 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.2.

Table A.7: 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.2.

Figure A.6: Analysis by industry



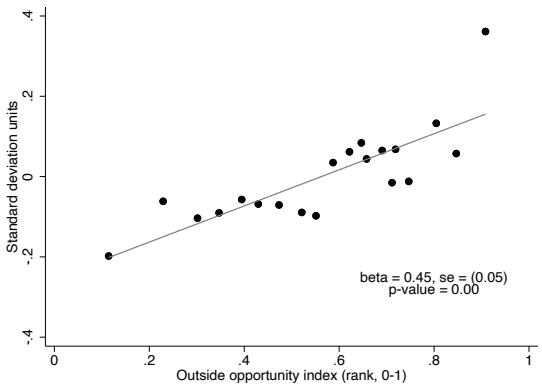

*Notes:* This figure breaks apart the analysis in this paper by industry. Panel (a) reports the industry mean response to the extent of self reported job-improvement. Panel (b) reports the regression coefficient for how OOI is associated with the responses perceived job improvement. Panel (c) reports 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.2.

Table A.8: Labor market structure vs. product market structure

| | OOI | Product market HHI | Difference |
|---|---|---|---|
| | (1) | (2) | (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.2.

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.2.

Table A.9: 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.11. 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.2.

Table A.10: The role of firm culture in learning

| | $OOI_1$ | $OOI_2$ | Firm culture | $(OOI_1 - OOI_2)/OOI_1$ |
|---|---|---|---|---|
| | (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.2.

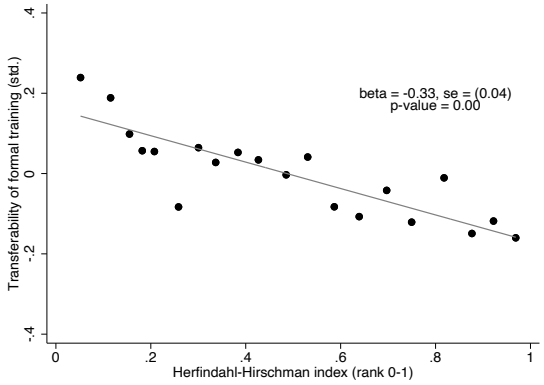
Table A.11: Degrees of skill transferability across levels of market structure

| | 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 |

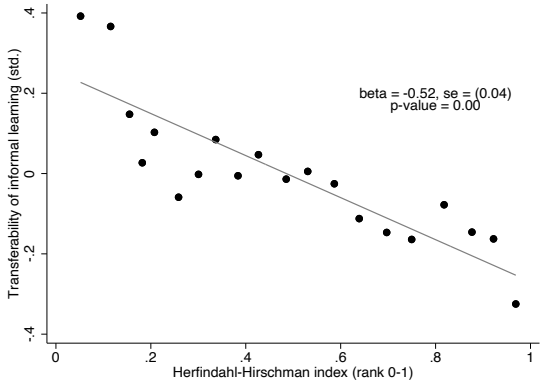
*Notes:* This table reports estimates of the extent that different skills are transferable across firms, occupations, and industries. These are estimated by regressing workers' perceptions of the transferability (defined across firms, occupation, and industries in three separate regressions) of the skills 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.2.

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

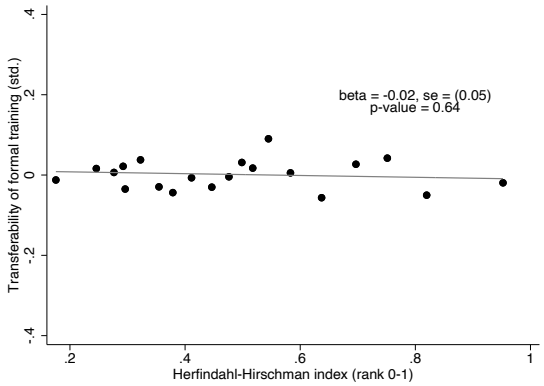
(a) Markets, transferability and formal training



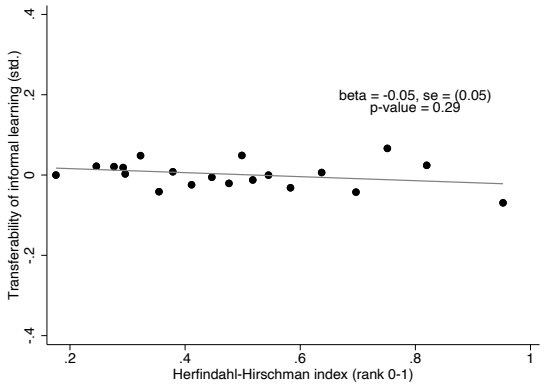

(b) Markets, transferability and informal learning




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



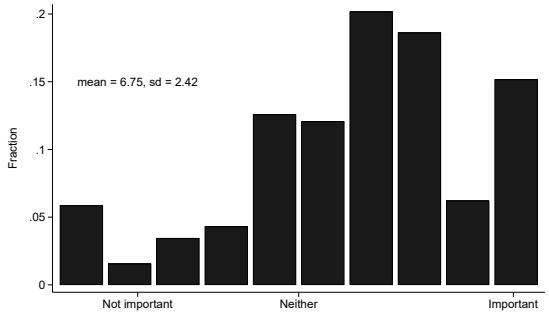

(d) Markets, transferability and informal learning – within occupation



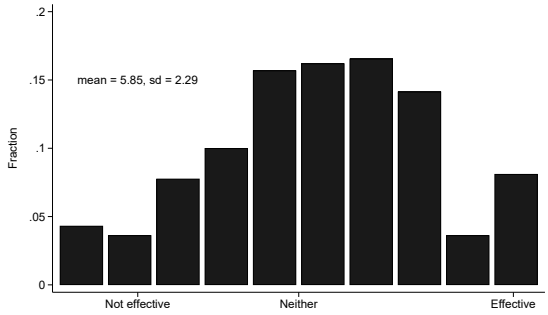

*Notes:* This figure reports the relationship between the content of learning (transferability), how skills are learned (informal learning vs. formal training), and market structure (HHI). The transferability of skill accumulation is measured by an index based on estimates of learning by skill transferability (based on the data-driven approach from Table A.11). 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.2.

Figure A.9: Workers, perspectives

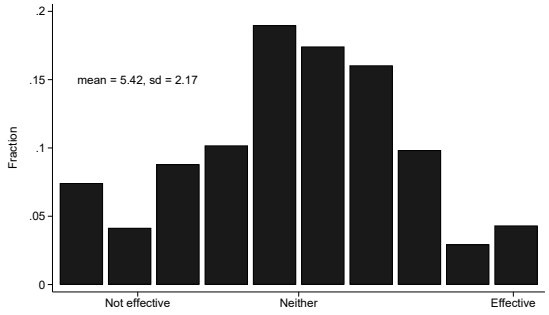
(a) "How important are firm investments in training for your career?"



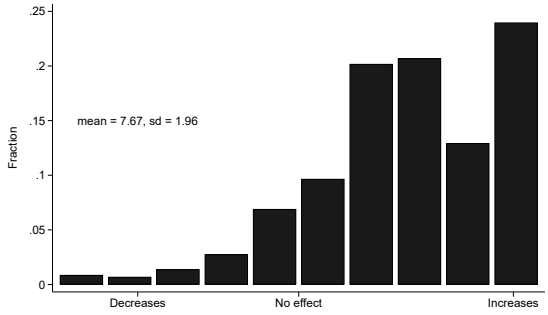

(b) "How effective is training provided by people at your firm (ex. internal or presentations) for improving your productivity?"



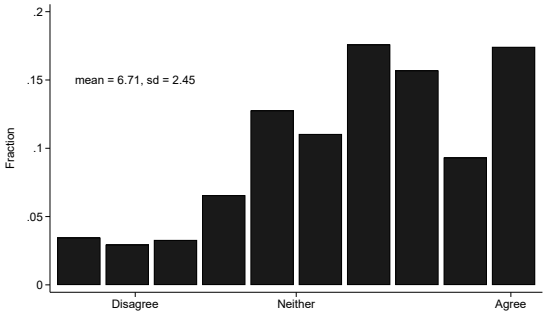

(c) "How effective is training provided by people outside your firm (ex. bringing in outside speakers, attending firm-sponsored workshops) for improving your productivity?"




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



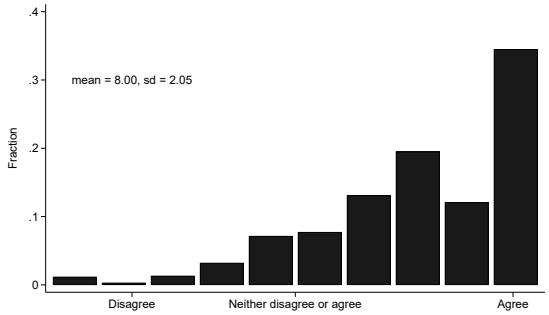

(e) "Opportunities for career progression and advancement affect my incentives and motivation for engaging in learning at work."



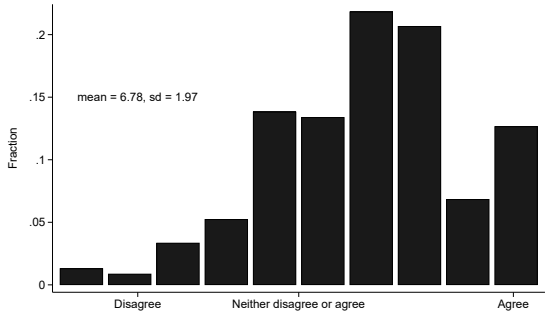

*Notes:* Figure A.9 presents histograms of worker responses in the auxiliary survey regarding their perceptions of firm investments, informal learning, motivation, and outside opportunities, in developing human capital. These data are from a survey fielded by Norstat to 1,026 workers.

Figure A.10: Managers, perspectives

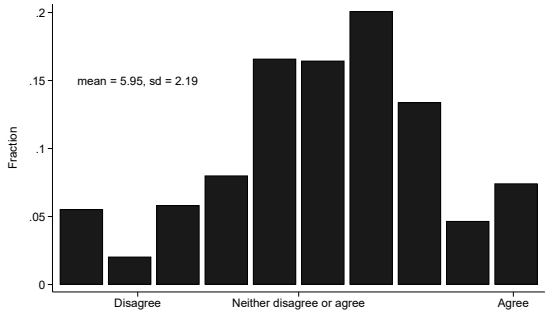
(a) "Investments in training by firms play an important role in improving worker productivity."



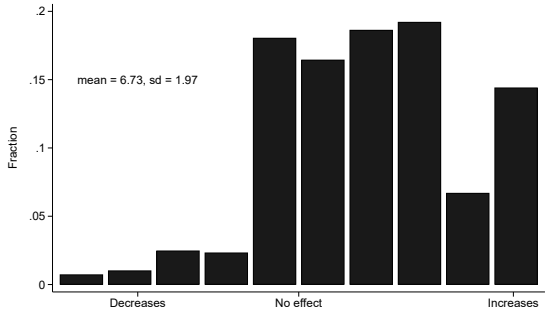

(b) "How effective is training provided by people at your firm (ex. internal workshops or presentations) for improving worker productivity?"



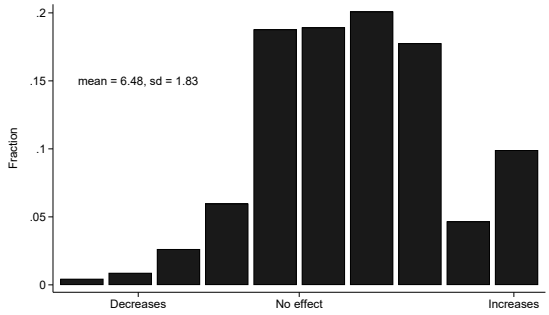

(c) "How effective is training provided by people outside your firm (ex. bringing in outside speakers, attending firm-sponsored workshops) for improving worker productivity?"




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



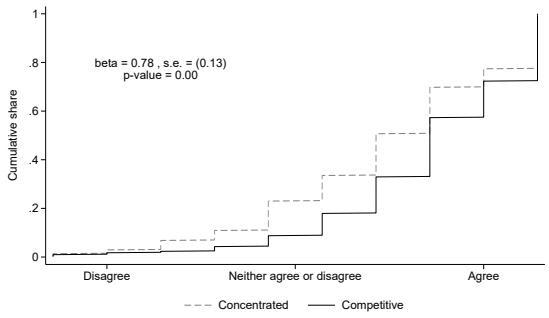

(e) "The level of competition between firms influences the effort and incentives of workers to take up training such as those described above."



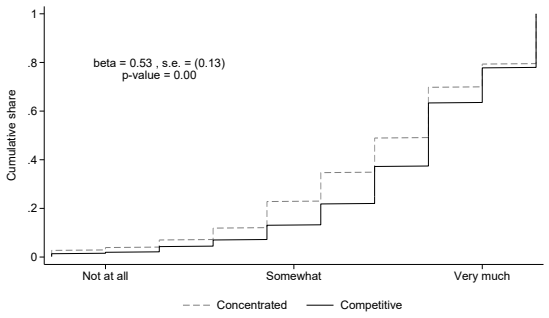

*Notes:* Figure A.10 presents histograms of manager responses in private sector firms in the auxiliary survey regarding their perceptions of firm investments, informal learning, motivation, and outside opportunities in developing human capital. These data are from a survey fielded by Norstat to 1,001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

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

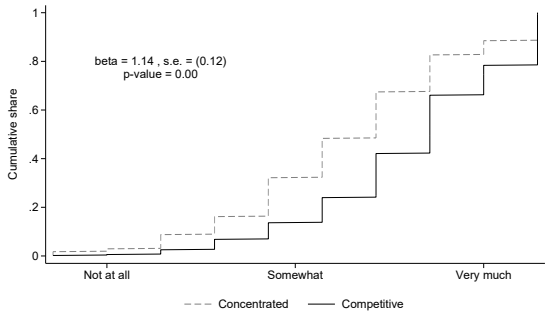
(a) "Skills are critical for my firm's success."



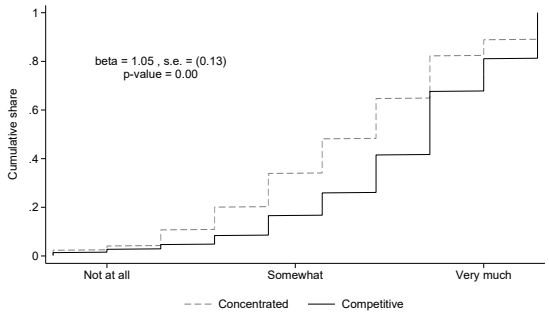

(b) "How motivated will you be to take up firm-provided training?"




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



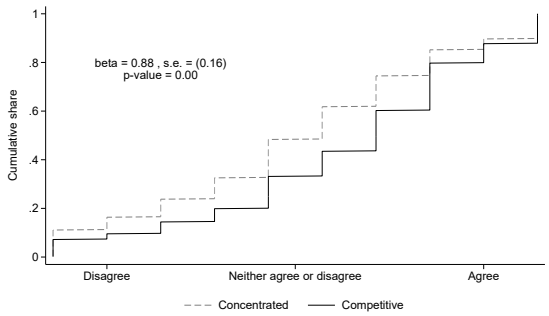

(d) "How motivated will you be to improve higher-order skills?"



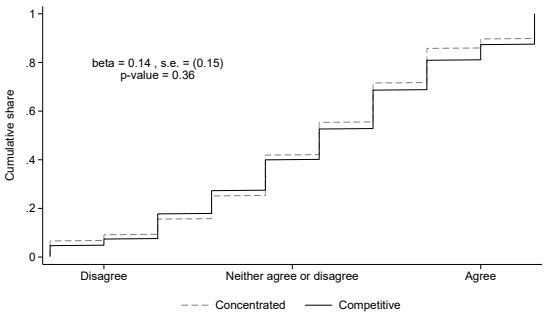

*Notes:* This figure presents cumulative density distributions of worker responses in the auxiliary survey, by randomized treatment condition – whether they are in a competitive or concentrated market. These data are from a survey fielded by Norstat to 1,026 workers.

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

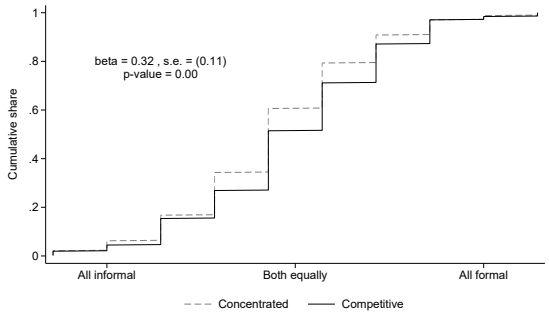
(a) "Improving my ability to do my job improves my outside options."




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



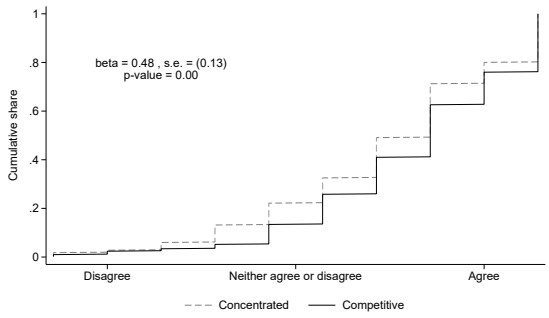

(c) "What share of improvements in skills will come from formal training versus informal learning?"



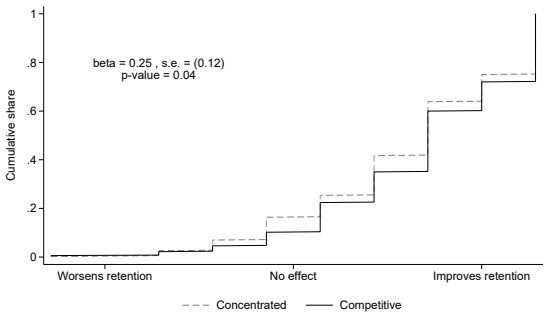

*Notes:* This figure presents cumulative density distributions of worker responses in the auxiliary survey, by randomized treatment condition – whether they are in a competitive or concentrated market. These data are from a survey fielded by Norstat to 1,026 workers.

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

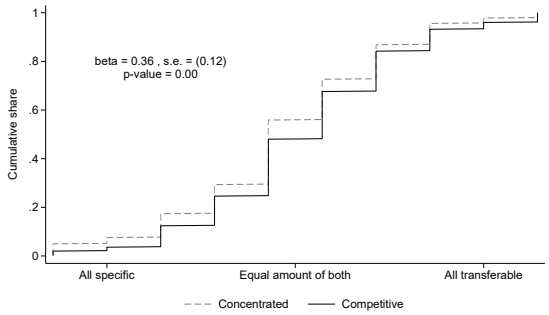
(a) "Investing in training improves my firm's ability to hire workers."



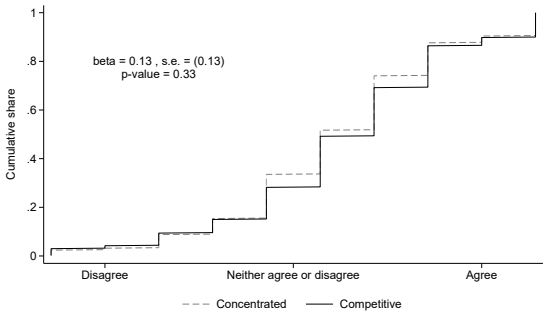

(b) "Investing in training improves my firm's ability to retain workers."




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



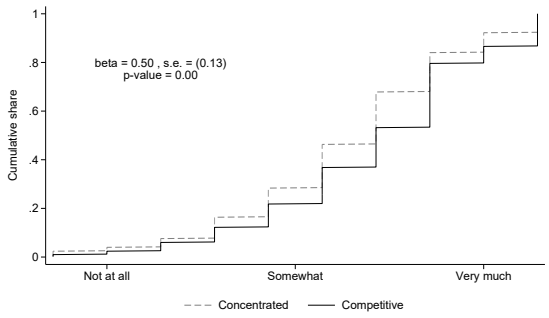

(d) "After these training investments, would you increase wages for workers?"



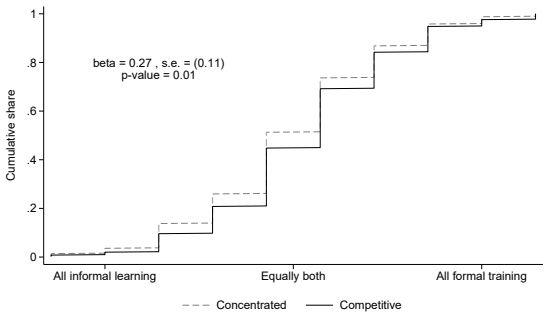

*Notes:* This figure presents cumulative density distributions of manager responses in the auxiliary survey, by randomized treatment condition – whether they are in a competitive or concentrated market. These data are from a survey fielded by Norstat to 1,001 managers.

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

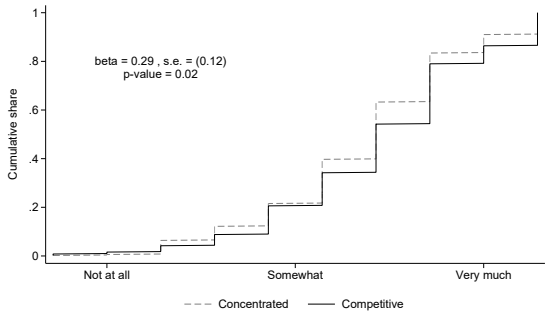
(a) "How much will your workers invest in informal learning?"



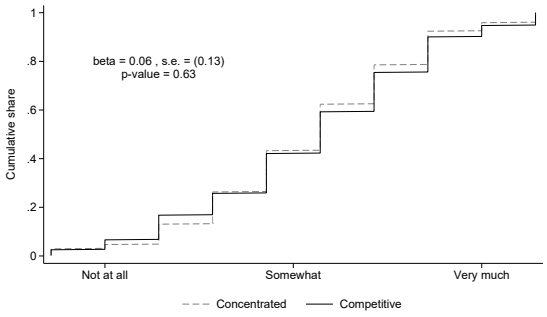

(b) "What share of improvements in worker skills will come from formal training versus informal learning?"




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



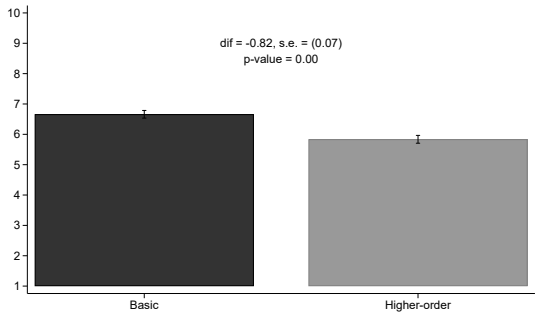

(d) "How motivated will your workers be to improve higher-order skills?"



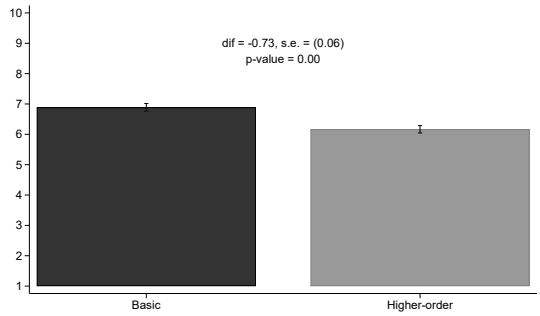

*Notes:* This figure presents cumulative density distributions of manager responses in the auxiliary survey, by randomized treatment condition – whether they are in a competitive or concentrated market. These data are from a survey fielded by Norstat to 1,001 managers.

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

(a) Workers



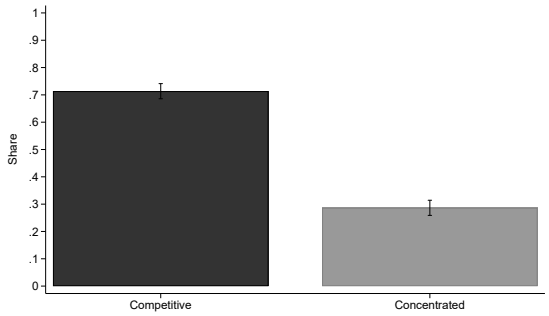

(b) Managers



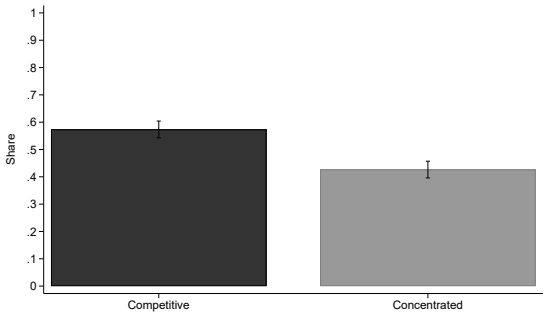

*Notes:* This figure reports worker and manager perceptions of how easy they perceive it to be to develop basic versus higher order skills. These data are from surveys fielded by Norstat to 1,036 workers and 1,001 managers.

Figure A.16: Location choice: Workers and managers

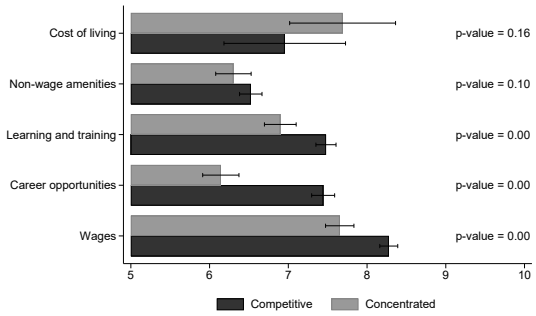
(a) Worker early career preferences



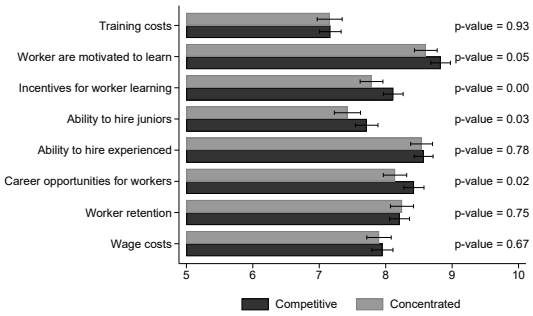

(b) Manager choice of where to start business




(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

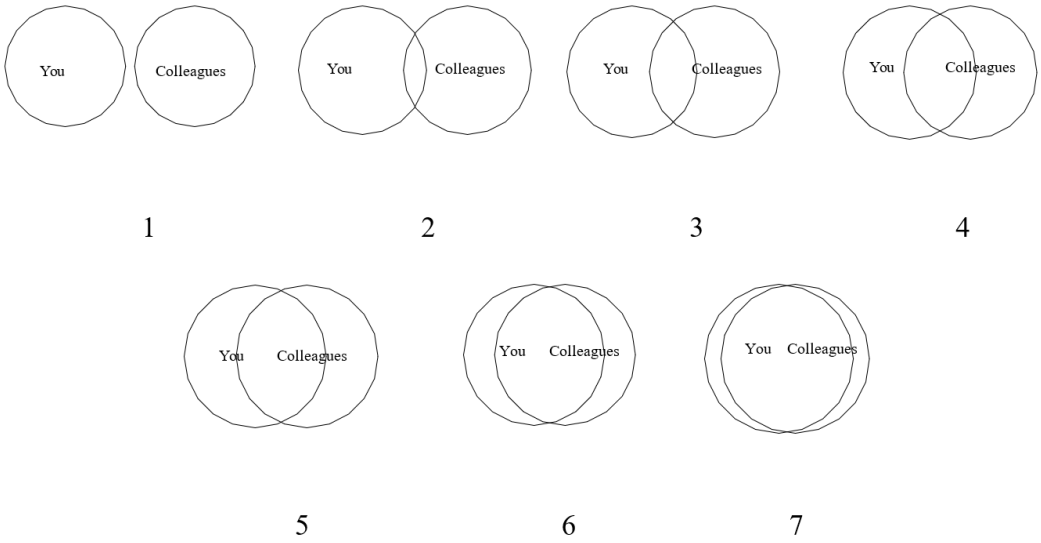
1. I am given opportunities to try new roles and/or tasks.
2. I am given opportunities to take on increasing responsibilities.
3. I am given access to attractive work assignments.
4. I am assigned to take care of "office housework".
5. My workplace rewards new ideas.
6. I have incentives to learn skills 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.