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80/25

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www.rfberlin.com OCTOBER 2025

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Reference

JEL Codes: J13, J24

Keywords: Knowledge Spillovers, Peer Effects, Competition

Recommended Citation: Thomas Cornelissen, Christian Dustmann, Uta Schönberg (2025): Knowledge Spillovers, Competition, and Individual Careers. RFBerlin Discussion Paper No. 80/25

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Knowledge Spillovers, Competition, and Individual Careers *

Thomas Cornelissen
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Abstract

Exposure to better peers in the workplace can influence career trajectories through two opposing channels: positively, via knowledge spillovers, and negatively, through competition for advancement. We disentangle these effects by studying untrained labor market entrants and distinguishing between coworkers in the same occupation with whom they are likely to compete versus those with whom they are unlikely to compete. We find robust evidence of persistent knowledge spillovers but also identify countervailing competition effects of comparable magnitude. Both effects are more pronounced for men than for women.

Keywords: Knowledge Spillovers, Peer Effects, Competition

JEL: J13, J24

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1 Introduction

A substantial body of economic literature attributes productivity gains in the workplace to human capital accumulation (see, for example, Becker, 1994; Mincer, 1974; Ben-Porath, 1967; Killingsworth, 1982). However, the mechanisms of skill acquisition within firms remain relatively underexplored. Beyond individual learning, productive skills may also be transmitted through coworker interactions. If so, worker education and training investments could generate externalities and multiplier effects (Glaeser et al., 2003; Becker and Murphy, 2000). While the notion that skills diffuse among workers is not new—Marshall (1890), Lucas (1988), Jovanovic and Rob (1989), and Glaeser (1999), among others, have articulated this idea—the empirical evidence on knowledge spillovers remains mixed. ¹

In this paper, we revisit the question of how exposure to high-quality coworkers in one's first job affects long-term career outcomes for young labor market entrants. We argue that, even in studies employing clean identification strategies, the existing literature on coworker peer effects often overlooks a crucial countervailing mechanism: competition. Specifically, assigning a focal worker to high-quality peers may increase the likelihood that they lose out in intra-firm competition for career opportunities. Such competition may arise over promotions (Lazear and Rosen, 1981; Baker et al., 1988; DeVaro, 2006; DeVaro and Kauhanen, 2016), retention, bonuses, wage increases based on relative performance, or access to learning

¹ Workplace-level studies generally find limited evidence of knowledge spillover effects (Cornelissen et al., 2017; Bentsen et al., 2019). These effects tend to appear more strongly in settings where shared background characteristics are less tightly controlled (Battisti, 2017; Battu et al., 2003; Martins and Jin, 2010; Wirz, 2008; Nix, 2020). Some workplace studies focused on high-skilled occupations have documented spillovers—for example, among scientific co-authors (Azoulay et al., 2010), teachers (Jackson and Bruegmann, 2009), and patent examiners (Frakes and Wasserman, 2021). However, evidence is more mixed in academic settings, where Waldinger (2012) finds no spillover effects among university faculty. Research on knowledge spillovers in lower-skilled environments is scarce, with notable exceptions including studies on call center workers by Sandvik, Seegert, and Stanton (2020) and De Grip and Sauermann (2012). For a broader synthesis of findings across occupational field studies, see the meta-analysis by Herbst and Mas (2015).

opportunities.² Whenever career rewards are allocated based on comparative performance and are in fixed supply, peer quality can generate negative externalities through competitive pressure. This negative spillover may attenuate or even mask positive knowledge spillover effects in empirical analyses. Consequently, studies that do not account for within-firm competition may underestimate the true extent of knowledge spillover from higher-quality peers. Our first and most important contribution is, therefore, to explicitly address the bias.³

To disentangle the effects of peer group quality via knowledge spillovers from those driven by competition, we exploit a unique institutional feature of the German labor market: young individuals can either enter the labor market directly or first complete a 2–3-year firm-based apprenticeship program before obtaining a regular job. We refer to the former group as "untrained" and the latter as "trained" workers. Both types often work in the same occupations, and untrained entrants may learn from trained and untrained coworkers. However, untrained entrants are unlikely to compete with trained incumbents, as they typically follow different career trajectories within the firm—an observation we confirm in our data.⁴ This distinction allows us to estimate a lower bound of knowledge spillover effects by focusing on spillovers from trained incumbents. In contrast, the quality of untrained peers may generate competition effects that could offset or even outweigh the benefits of knowledge spillovers.

Our empirical strategy draws on rich German social security data, which enables us to control for the non-random sorting of workers into peer groups and adjust for unobserved factors affecting the future careers of labor market entrants and the quality composition of their

 $^{^2}$ Examples include Amazon's promotion policy, where only the top-ranked get promoted, and lower-performing workers are encouraged to leave the firm (e.g., The New York Times, 2021).

³ Experimental designs that induce knowledge flows without altering coworker quality, thereby holding competitive dynamics constant, as in Sandvik, Saouma, Seegert, and Stanton (2020), are less susceptible to bias from intra-firm competition, but are difficult to scale and are not easily implemented in a representative manner across firms and occupations.

⁴ This interpretation aligns with findings in the literature showing larger spillover effects from coworkers at higher hierarchical levels (Espinosa and Stanton, 2022; Hoffman and Tadelis, 2021; Lazear, Shaw, and Stanton, 2015; Englmaier et al., 2021; Chen et al., 2025), where competition is likewise an unlikely confounding factor.

initial coworkers. Identification comes from comparing individuals who entered the same firm and occupation but in different years and who were therefore exposed to different peer groups upon entry. We further control flexibly for occupation-specific time trends and key observable characteristics of both focal workers and their peers.

We find strong evidence for both knowledge spillover and competition effects. In a baseline analysis that does not distinguish peers by training status, average peer quality, measured by the average worker fixed effect from an AKM-style wage regression incorporating both firm and worker fixed effects, shows no systematic impact on entrants' future career outcomes. However, once we differentiate between trained and untrained peers, a clearer picture emerges. High-quality trained coworkers generate long-lasting career benefits for untrained entrants, boosting their earnings and wages even ten years later, an effect we attribute to knowledge spillover. In contrast, higher-quality untrained peers lead to persistent career disadvantages, which we interpret as evidence of increased competition. Overall, our findings suggest that the knowledge and competition effects roughly offset each other. We also find that a greater *share* of trained coworkers in the initial peer group improves entrants' career prospects, consistent with the idea that untrained labor market entrants learn from, but do not compete with, their trained coworkers.

The positive spillover effects from trained peers are most pronounced in occupations with more complex tasks, where learning opportunities are likely more important. A one-standard-deviation increase in the quality of trained peers raises earnings five years later by 3.7 percent, driven by both employment and wage gains. This effect persists over the ten-year follow-up period and remains significant even after conditioning on future peer quality. It also holds for individuals who switch employers, consistent with the acquisition of transferable knowledge and skills.

Negative spillovers from untrained peers also tend to be more pronounced in complex occupations, suggesting that the returns to promotion and retention are greater in these settings. The most substantial negative earnings effects originate from untrained peers early in their careers and thus at a similar career stage as the entrants. In contrast, we find no significant effects on earnings from untrained peers who are either further along in their careers or working in different occupational contexts where direct competition is less likely. High-quality untrained peers also increase the likelihood of focal workers switching jobs or occupations.

Our results also uncover important gender differences. While competition effects are present for both men and women, they are significantly larger for men. This is consistent with prior research highlighting men's greater career orientation or higher willingness to compete (e.g., Azmat and Petrongolo, 2014; Niederle and Vesterlund, 2011), as well as with findings that women may face lower returns from participating in promotion contests (e.g., Benson, Li, and Shue, 2022; Blackaby, Booth, and Frank, 2005). Similarly, knowledge spillover effects are also more pronounced for men. Women tend to benefit from high-quality trained peers primarily when they remain with their initial employer. In contrast, for men, such peers create opportunities beyond the initial firm, increasing the likelihood of employment in larger, higher-paying firms. This pattern aligns with evidence that job and occupational mobility play a more central role in men's wage growth than in women's (e.g., Loprest, 1992; Fitzenberger and Kunze, 2005; Hirsch, Schank, and Schnabel, 2010).

As an alternative strategy to identify knowledge spillovers, we implement an approach that does not distinguish between workers by training status but instead conditions on both the average peer group quality and the worker's rank within the group. We argue that a worker's ordinal position can capture competition effects, while learning depends on the absolute level of peers' knowledge and skills. Thus, we identify knowledge spillovers through measures of absolute peer quality and competition through relative rank. Unlike our primary approach, this

method requires additional identification assumptions and parametric restrictions, which we discuss in Section 3.2.

Our estimates from the rank-based approach corroborate the findings from our primary strategy. We observe similarly positive effects of peer quality in the first job on earnings and wages five years later, once we control for ordinal rank. Additionally, relative rank positively influences future earnings and wages, consistent with the idea that a stronger relative position within the peer group confers an advantage in internal competition for career advancement.

We further apply the rank-based strategy to two additional groups: trained labor market entrants who have completed a 2–3-year apprenticeship training and entrants with a college degree. We find that exposure to high-quality peers during the apprenticeship generates particularly pronounced knowledge spillover and competition effects, possibly due to the formal and structured nature of such programs. While we also detect knowledge spillover and competition effects among college graduates in their first jobs, their magnitudes are much smaller.

These findings are consistent with insights from the education literature, which has highlighted the importance of rank effects among classmates or schoolmates (Murphy and Weinhardt, 2020; Denning, Murphy, and Weinhardt, 2021; Elsner et al., 2021) and their potential to confound peer effects if not properly accounted for (Bertoni and Nisticò, 2023). As in the workplace, rank effects in educational settings likely reflect competitive dynamics, whether explicit, for instance, when top-performing students are granted admission to elite universities under policies like Texas's Top 10% rule, or implicit, such as through increased attention or support from teachers for higher-ranked students.

Our paper contributes to a growing literature on within-firm competition among coworkers. In line with evidence from the Norwegian labor market, Johnsen, Ku, and Salvanes (2020) show that the departure of coworkers can advance a worker's career. Similarly, Bianchi,

Bovini, Li, Paradisi, and Powell (2022) find that the delayed retirement of older workers in Italy can negatively affect the career progression of their younger colleagues.⁵ We add to this literature by demonstrating that competition effects can confound positive spillovers, such as those from peer learning, and by documenting the pervasiveness of such competition effects. We show how these effects vary with the degree of substitutability between coworkers and how workers mitigate them through job and occupational mobility.

Beyond our central contribution—identifying coworker competition as a key confounding factor in estimating knowledge spillover—we also extend the empirical literature on workplace peer effects in several important ways. Prior labor market—wide studies of coworker spillovers, including our own earlier work (Cornelissen et al., 2017), typically examine contemporaneous effects aggregated across worker skill groups (e.g., Bentsen at al., 2019, Battisti, 2017; Battu et al., 2003; Martins and Jin, 2010; Moretti, 2004; Wirz, 2008). In contrast, we focus explicitly on young workers with low initial formal qualifications and analyze the impact of the peer quality they are exposed to in their first year in the labor market, a period when on-the-job skill acquisition is likely to be most formative. We further examine long-term outcomes, allowing us to distinguish knowledge spillovers from other types of coworker peer effects, such as social pressure (Kandel and Lazear, 1992; Mas and Moretti, 2009; Cornelissen et al., 2017), or complementarities in production (e.g., teamwork). In addition, we broaden the scope of the

⁵ Related work on external labor market competition highlights similar dynamics. Lazear, Shaw, and Stanton (2018) examine the implications of competition among external job applicants for a fixed number of job slots. Borjas and Doran (2015) document adverse career effects among U.S. academic mathematicians following the influx of Soviet mathematicians, illustrating competition from a sudden supply shock of high-quality peers. The effects of competing against superstars have also been studied in other high-skill domains, such as golf (Brown, 2011) and chess (Bilen and Matros, 2021), where the presence of top performers can discourage or crowd out others.

⁶ Some papers that look at longer-run outcomes and past peer exposure are Jarosch et al. (2021), Nix (2020) and Hong and Lattanzio (2022).

⁷ By examining early exposure to coworkers, we also contribute to the broader literature on how initial labor market conditions shape long-term career outcomes for young workers (e.g., Arellano-Bover, 2024; Arellano-Bover and Saltiel, 2025; Kahn, 2010; Oreopoulos, von Wachter, and Heisz, 2012).

⁸ Social pressure and production complementarities are mechanisms that operate only through current peers, whereas knowledge spillovers are likely to persist over time and can originate from past peers. This is because

literature that has primarily focused on aggregate spillovers from average educational attainment (Acemoglu and Angrist, 1999; Battu et al., 2003; Martins and Jin, 2010; Wirz, 2008) or college-educated peers specifically (Bentsen et al., 2019; Moretti, 2004; Nix, 2020). Instead, we examine spillover effects from peers with firm-provided apprenticeship training, which imparts practical, occupation-specific skills that may be more easily transmitted to coworkers than the abstract knowledge acquired through university education.⁹

Finally, our alternative identification strategy, based on conditioning on a worker's ordinal rank within the peer group, complements our main approach and provides the first direct evidence that a worker's relative position among peers in their first job has significant and lasting career effects. The consistency between the results of our rank-based and training-based identification strategies suggests that conditioning on ordinal rank, under suitable identification assumptions, may offer a feasible and informative approach to estimating knowledge spillovers in institutional contexts where more detailed training-based classifications are unavailable.

2 Theoretical Framework: Coworker Competition with Knowledge Spillover

To motivate our empirical analysis, we extend a standard promotion tournament model (Lazear and Rosen, 1981) by incorporating knowledge spillovers and distinguishing between coworkers who do and do not compete for promotion. Such competition naturally arises in settings where fixed job hierarchies are combined with internal hiring policies (DeVaro, 2006; Lazear, Shaw, and Stanton, 2018), and promotion tournaments are commonly used to incentivize effort (Lazear and Rosen, 1981; Prendergast, 1999). While promotion is a central example, the mechanism we emphasize here is more general: any career opportunity within the

knowledge, once acquired, remains with the worker even if either the coworkers or the worker herself leave the firm.

⁹ Empirical evidence on whether practical skills acquired through firm-provided training generate spillovers remains limited. One of the few studies to provide convincing evidence is De Grip and Sauermann (2012), who exploit a field experiment in a call center and show that increasing the share of trained coworkers improves the productivity of untrained workers.

firm that is limited in supply and allocated based on relative performance can generate similar competitive dynamics. These opportunities may include retention, bonuses, wage increases, or access to senior coworkers and task assignments that facilitate learning. We focus on "competition for promotion" throughout the model discussion for expositional clarity. Full details are provided in Online Appendix A.

2.1 Set-Up

Consider a setting with three workers: an untrained job starter i, an untrained incumbent j, and a trained incumbent k. There are two periods, t = 1,2. In period 1, knowledge spillover may occur, and there is competition for promotion between the two untrained workers, i and j. In period 2, the more productive of the two is promoted to a higher position.

The trained worker k does not participate in this promotion tournament, as she follows a distinct career path—an assumption we relax in Online Appendix Section A.2. This reflects the idea that tournaments between workers with systematically different skill levels are inefficient and fail to provide optimal incentive structures (Lazear and Rosen, 1981; Brown, 2011; Bilen and Matros, 2022; Xiao, 2020).

Individual output q_w for worker w (at the end of period 1) has three components:

$$q_w = s_w + \omega_w + \epsilon_w, \quad w \in \{i, j, k\},$$

where s_w denotes the skill level of worker w, ω_w their effort, and ϵ_w an idiosyncratic productivity shock. The skill component s_w is composed of the worker's initial ability μ_w and a knowledge spillover component derived from the ability μ of more senior or more highly trained incumbent coworkers:

$$s_i = \mu_i + \lambda_j \mu_j + \lambda_k \mu_k,$$

$$s_j = \mu_j + \lambda_k \mu_k,$$

$$s_k = \mu_k$$
.

Here, $\lambda_w > 0$ (for $w \in \{j, k\}$) denotes the knowledge spillover coefficient. This formulation reflects the simplifying assumption that untrained workers i, j do not generate knowledge spillovers for trained coworkers k. Knowledge spillovers are modeled as exogenous, arising through informal channels such as day-to-day social interactions and observational learning in the workplace.

2.2 Workers' Maximization Problem

In period 1, untrained workers exert effort ω to increase their probability of winning the promotion in period 2. Untrained workers have no incentive to exert effort in period 2; trained workers do not exert any effort in either period 1 or 2. Untrained workers choose their optimal effort levels in period 1 to maximize their expected wages in period 2. The expected period-2 wages of the untrained job starter and the untrained incumbent are given by:

$$E[W_i] = f(s_i) + \alpha P(q_i > q_i), \text{ and}$$
 (1)

$$E[W_j] = f(s_j) + a(1 - P(q_i > q_j)).$$

Here, $f(s_w)$ is a positive monotone function, with f' > 0, that forms part of the wage contract. The probability that the job starter i is promoted rather than the incumbent j is given by $P(q_i > q_j)$, and a denotes the wage spread associated with the promotion (the promotion prize). Thus, the period 2 wage consists of two components: the skill-based wage $f(s_w)$, and the expected return from promotion.

The probability that the job starter wins the promotion tournament is:

 $^{^{10}}$ Since outside firms can observe s_w , for example, through skills and knowledge demonstrated in job interviews, skills form part of the workers' outside options. As a result, the current employer must compensate workers for their higher skills.

$$P(q_i > q_j) = G(\mu_i - (1 - \lambda_j)\mu_j + \omega_i - \omega_j),$$

where $G(\cdot)$ is the cumulative distribution function (CDF) of $\epsilon_j - \epsilon_i$, with probability density function (PDF) g(.).

The job starter chooses effort ω_i to maximize expected wages in period 2:

$$\max_{\omega_i} f(s_i) + G(\mu_i - (1 - \lambda_j)\mu_j + \omega_i - \omega_j)a - C(\omega_i),$$

yielding the first-order condition (F.O.C.):

$$g(\mu_i - (1 - \lambda_i)\mu_i + \omega_i - \omega_i)a - C'(\omega_i) = 0.$$
 (2)

Assuming the second-order condition is satisfied, this condition implicitly defines the optimal effort level ω_i^* . The optimal effort level of the untrained incumbent ω_j^* is derived analogously; see Online Appendix A.1.

The untrained job starter's expected wage at equilibrium effort level is (see Online Appendix A.1 for details):

$$E[W_i] = f(\mu_i + \lambda_j \mu_j + \lambda_k \mu_k) + G(\mu_i - (1 - \lambda_j)\mu_j)a.$$
(3)

2.3 Comparative Statics and Empirical Implications

Untrained Incumbent Worker Quality. Totally differentiating equation (3) with respect to the quality of untrained incumbent workers and rearranging terms yields:

$$\frac{dE[W_i]}{d\mu_j} = \underbrace{\lambda_j f'(\mu_i + \lambda_j \mu_j + \lambda_k \mu_k)}_{\text{knowledge spillover}} - \underbrace{(1 - \lambda_j)g(\mu_i - (1 - \lambda_j)\mu_j)a}_{\text{competition}}$$
(4)

The knowledge spillover effect and the competition effect operate in opposite directions. The positive knowledge spillover effect increases with the knowledge spillover parameter λ_j and the marginal return to skills f'(.). The negative competition effect depends on the promotion

prize a. If the competition effect dominates, the term $\frac{dE[W_i]}{d\mu_i}$ will be negative, thus providing a lower bound on the competition effect (i.e., the true competition effect is more negative than the estimate suggests).

Trained Incumbent Worker Quality. By contrast, the effect of an increase in the trained incumbent's quality μ_k on the job starter's wage does not include a competition component, since the trained worker is not part of the promotion tournament:

$$\frac{dE[W_i]}{d\mu_k} = \lambda_k f'(\mu_i + \lambda_j \mu_j + \lambda_j \mu_k). \tag{5}$$

This derivative is unambiguously positive, reflecting a pure knowledge spillover effect. If we relax the assumption that the trained worker is not a competitor in the promotion tournament, the impact of the incumbent's quality on the entrant's wage can be interpreted as a lower bound on the knowledge spillover effect; that is, the true spillover effect may be even larger. Our baseline identification strategy exploits this distinction by comparing the impact of trained and untrained incumbent quality on the wages of untrained job starters, thereby disentangling the roles of knowledge spillover and competition.¹¹

As an alternative identification approach, we infer the knowledge spillover effect from untrained incumbent coworkers by conditioning on the worker's relative rank in the promotion tournament. Define $rank_i = 1$ if $q_i > q_j$ and $rank_i = 0$ otherwise. Then expected wages conditional on rank are $E[W_i|rank_i] = f(s_i) + rank_i a$. Differentiating with respect to μ_i yields:

¹¹ Even when accounting for competition, the model predicts a clear ranking in the magnitude of effects: $\frac{dE[W_i]}{d\mu_k} > \frac{dE[W_i]}{d\mu_j}$, provided that the untrained job starter competes less with the trained incumbent than the untrained incumbent and learns more from the trained incumbent (i.e., $\lambda_k > \lambda_j$). This ordering would hold in the absence of competition effects, assuming that $\lambda_k > \lambda_j$. However, in the absence of competition, $\frac{dE[W_l]}{d\mu_j}$ could not turn negative.

$$\frac{dE[W_i|rank_i]}{d\mu_i} = \lambda_j f' (\mu_i + \lambda_j \mu_j + \lambda_k \mu_k),$$

which isolates the pure knowledge spillover effect from the untrained incumbent's quality, net of competition. We discuss this approach in more detail in Section 3.2.

3 Empirical Approach

3.1 Distinguishing Peers by Training Status

Our primary identification strategy for estimating knowledge spillover effects leverages a key institutional feature of the German labor market. Within the same firms and occupations, some workers are graduates of the German apprenticeship training system ("trained"), while others enter directly without such training ("untrained"). Because completing an apprenticeship typically takes two to three years, trained workers in our data have already spent time in the labor market. Despite this, trained and untrained workers frequently work side by side in the same occupations and workplaces, providing opportunities for interaction and thus facilitating knowledge spillovers. At the same time, because trained and untrained workers, as we show in Section 4.2, are on different career tracks, direct competition between the two groups is likely to be minimal. This institutional setup allows us to identify knowledge spillovers from trained workers to untrained job starters with limited confounding from competition effects.

Our empirical model relates the outcomes of an untrained worker i, who enters occupation o in firm j in year t, to the quality of trained and untrained coworkers in their first job:

$$y_{i,t+\tau} = \mu + \gamma^u u_{jot} + \gamma^s s_{jot} + x'_{ijot} \beta + \omega_{ot} + \delta_{jo} + v_{i,t+\tau}.$$
 (6)

Here, $y_{i,t+\tau}$ is a labour market outcome measured τ years after entry, and $v_{i,t+\tau}$ is an idiosyncratic error term. The variables u_{iot} and s_{iot} capture the peer quality of untrained and

¹² See Online Appendix B for further details on the apprenticeship system.

trained coworkers, respectively, in the same firm and occupation ("peer group"), excluding focal labor market entrants. These are averages of individual wage fixed effects from an AKM-style wage regression, normalized to mean zero and unit variance (see Section 4.1). The parameter γ^u reflects a combination of knowledge spillovers and competition from untrained coworkers, as in equation (4). Assuming no competition between trained and untrained workers, γ^s captures the knowledge spillover effect in equation (5).

To interpret γ^u and γ^s as causal, we need to account for the endogenous sorting of workers into peer groups and for shared background characteristics. To address worker sorting based on their own quality, we include the focal worker's age at labor market entry and the initial wage during the first year on the job in the control variable vector x'_{ijot} .¹³

To adjust for shared background characteristics of focal workers and their peers, we build on Cornelissen et al. (2017) and include initial-firm-by-initial-occupation fixed effects (δ_{jo}) and initial-occupation-by-year-of-entry fixed effects (ω_{ot}). By conditioning on occupation-by-entry-year fixed effects ω_{ot} , we allow the selection of workers into occupations to change over time. By controlling for firm-occupation fixed effects δ_{jo} , we absorb time-constant unobserved peer group characteristics that might influence worker sorting and exploit variation in peer quality across cohorts within the same firm and occupation, driven by turnover in coworkers. Such turnover could reflect either coworker entry and exit due to job creation and destruction (expanding or shrinking peer groups) or churn (worker reallocation across stable peer groups). These flows may result from factors such as firms' responses to market conditions, workers' job search decisions, or retirements. The key identification assumption is that untrained

 $[\]chi'_{ijot}$ further includes the average age of the peer group, the share of trained workers in the peer group, as well as own and average peer gender. We further control for the share of college graduates in the peer group and their average quality, but do not focus on these variables, as the exposure of untrained labor market entrants to college graduates is small (1-2 percent). If a particular education group is absent in the peer group, we impute their average peer quality by the sample mean and include a dummy variable to indicate these cases. In practice, the inclusion of these additional controls has little impact on our estimates.

entrants do not systematically sort into peer groups based on year-to-year changes in peer quality—an assumption we view as plausible given that such workers are unlikely to observe or respond to coworker turnover.

We probe this specification by implementing a range of robustness checks. For instance, we use past coworkers who left before the focal worker joined as placebo peers; we allow firm-occupation fixed effects to vary across three-year intervals; or we include firm-class-by-year-of-entry fixed effects to account for broader time-varying firm heterogeneity.¹⁴

3.2 Alternative approach: Controlling for Rank

In an alternative strategy, we identify knowledge spillover effects from measures of absolute peer quality and competition effects from measures of a worker's ordinal rank within the peer group, while controlling for workers' own quality. This strategy is motivated by the following insights. First, workers compete for career opportunities with their immediate peer group rather than the broader population. Second, success in such competitions depends on relative performance, specifically, a worker's rank, rather than the magnitude by which they outperform others. Thus, the competition effect is primarily driven by a worker's ordinal position within the group, while knowledge spillovers depend on peers' absolute skill and knowledge levels. We estimate the following alternative regression:

$$y_{i,t+\tau} = \mu + \gamma p_{jot} + \theta r_{jot} + \chi'_{ijot} \beta + \widetilde{\omega}_{ot} + \widetilde{\delta}_{jo} + \vartheta_{i,t+\tau}. \tag{7}$$

Here, p_{jot} denotes the average wage fixed effect ('peer quality') of all coworkers in the same occupation (excluding focal labor market entrants), irrespective of their training status, and γ captures knowledge spillover. In turn, r_{jot} represents the ordinal rank of the focal worker

¹⁴ While including firm-by-year-of-entry fixed effects is feasible in principle, it severely limits identifying variation, as it requires firms to hire untrained labor market entrants into at least two occupations in the same year—a condition met by only a small number of firms in our sample.

among her peers, with θ capturing competition effects. As in equation (6), we include initial occupation-by-year of entry and initial firm-by-initial occupation fixed effects ($\widetilde{\omega}_{ot}$ and $\widetilde{\delta}_{jo}$), and control for the same observables. Rank is based on wage residuals during the worker's first year on the job, net of experience to better isolate effort and ability.^{15, 16}

Average peer quality, conditional on rank, identifies the full knowledge spillover effect only if rank perfectly captures within-firm competition, an assumption difficult to satisfy in practice. The econometrician typically lacks information on the exact performance metrics used for pay, promotion, and retention decisions, as well as on the timing and scope of competitive interactions. As a result, rank is an imperfect proxy for within-firm competition, and the estimated effect of peer quality, conditional on rank, may not accurately capture knowledge spillovers.

Even with perfect performance data, separating the effects of rank, peer quality, and own ability presents econometric challenges. Identifying these effects relies on functional form assumptions about how they influence outcomes. The specification in equation (7) assumes that average peer quality, rank, and own peer quality affect outcomes linearly. Under this (or any other) parameterization, ambiguity may remain as to whether the rank effect captures non-linearities in peer quality, or vice versa. For these reasons, we treat this strategy primarily as

¹⁵ An alternative would be to base rank on worker fixed effects from a wage regression. However, using wages offers several advantages. First, wages capture time-varying productivity relevant for promotion, whereas fixed effects reflect average, long-term productivity—more suited to measuring spillovers. Second, wages reflect information observable to the employer at the time, while fixed effects may include future or unobservable components. Third, fixed effects are estimated over the worker's career and may themselves be affected by knowledge spillovers, making them unsuitable for constructing an exogenous rank measure.

¹⁶ Consider two workers earning the same wage. One is more experienced but underperforms relative to their seniority, while the other is less experienced but performs strongly for their level. Firms are more likely to promote the latter, as higher performance conditional on experience signals greater potential.

¹⁷ Rank is defined as the percentile of the peer quality distribution corresponding to the focal worker's own quality. Given the distribution and a fixed level of own quality, rank is fully determined, leaving no independent variation. As a result, conditional on all features of the peer quality distribution, own ability fully determines rank, making it impossible to non-parametrically identify the separate effects of own ability, rank, and peer quality.

a robustness check and continue to rely on our main approach, which distinguishes between trained and untrained coworkers.

4 Data

4.1 Data Description and Sample Selection

We use German social security records provided by the Institute of Employment Research (IAB), which cover the universe of employees in regular employment (excluding civil servants, the self-employed, and military personnel) observed every year on June 30. These data are well-suited to our analysis, as they contain workplace-level identifiers ("firms" for simplicity) and detailed occupational codes that distinguish over 300 occupations. This granularity allows us to define peer groups by occupation within firms, settings where coworkers are likely to interact. The dataset also includes the whole workforce within each firm, enabling precise measurement of peer group characteristics and ensuring representativeness for both firms and workers. Crucially, it distinguishes between workers who have and have not completed apprenticeship training before entering the labor market—our 'trained' and 'untrained' groups. The longitudinal structure further allows us to track workers, their coworkers, and firms over time.

Our baseline sample includes all untrained labor market entrants aged 15–25—defined as those holding neither a vocational nor university degree—who began their first full-time job in West Germany between 1984 and 1998. We follow these workers for up to 10 years to assess whether the quality of their initial coworkers influences long-term outcomes. Table 1, Panel A, summarizes the sample: 774,701 untrained job starters across 206,861 firms and 329 occupations.

We also construct a subsample of untrained entrants who start in occupations with more complex tasks, where knowledge spillovers are likely to be more relevant. This is based on the

1991/92 wave of the Qualification and Career Survey (see Gathmann and Schönberg, 2010), which includes detailed data on task frequency. We classify occupations as "complex" if they fall within the 25% of workers reporting the lowest incidence of predefined tasks. This yields a subsample of 172,242 focal workers in 33,023 firms across 63 occupations. Our main results are robust to alternative cutoffs for defining task complexity (see Appendix Table D.7).

As is common in administrative data, wages are top-coded at the social security contribution ceiling. Since we focus on untrained entrants, only about 1% of wage observations are affected. We address this censoring using the imputation procedure described in Cornelissen et al. (2017).

4.2 Peer Group Definition and Measures of Peer Group Quality

We define peer groups as all workers employed in the same firm and 3-digit occupation—the most granular occupational classification available in the social security data. Since we focus on untrained job starters, the sample is concentrated in predominantly low-skilled occupations such as warehouse workers, gardeners, salespeople, assembly workers, construction workers, and office assistants (see Online Appendix Table D.1 for the 20 most common occupations). Consequently, the share of college graduates in peer groups is negligible (2%). Instead, coworkers are almost exclusively either untrained peers with no formal qualification (35%) or trained peers with an apprenticeship degree (63%)—see Table 1, Panel D. These two groups correspond to the untrained and trained incumbents in our theoretical model.

To construct measures of worker quality, we use a sample of all full-time, regularly employed workers in West Germany from 1984 to 1998—comprising 260 million observations

on 33 million workers across 2.6 million firms. We estimate an AKM-style wage regression with worker (a_i) and firm (θ_i) fixed effects: ¹⁸

$$ln(w)_{it} = a_i + \theta_i + \theta_t + \varepsilon_{it}$$
(8)

We then retain the estimated worker fixed effects, \hat{a}_i , and use them to compute the average peer quality of untrained, trained, and all peers, u_{jot} , s_{jot} and p_{jot} in equations (6) and (7). These peer quality measures are standardized to have a mean of zero and a standard deviation of one. As a result, estimated coefficients represent the effect of a one standard deviation increase in peer quality. In our sample, the standard deviation of peer quality is approximately 0.2 for both untrained and trained workers, so the estimated effects can also be interpreted as reflecting a 20 percent increase in peer quality.

Since peer quality is based on pre-estimated worker fixed effects, the spillover parameters γ^u and γ^s in equation (6) could potentially be biased due to sampling error or a reflection problem. In Section 5.1, we present several pieces of evidence suggesting that any such bias is likely small.

Table 1 presents descriptive statistics for our estimation sample. As shown in Panel B, focal workers are on average 21 years old, and just over 40% are female. Roughly 40–50% remain employed five years after labor market entry, and among those, about half have switched firms during that period. ¹⁹ Conditional on being employed, about half of the focal workers have switched firms within the first five years.

 $^{^{18}}$ We purge ln(w) of age effects using a cross-sectional OLS regression and use the residual as the dependent variable in the AKM model. Since our main specification includes average peer age as a control, removing age effects from the fixed effects allows for a cleaner interpretation. Specifically, the coefficient on average peer age captures spillovers from older, more experienced coworkers, while the coefficient on the average peer wage fixed effect (net of age) captures spillovers from peer quality, adjusted for age.

¹⁹ The relatively low employment rate may reflect several factors. First, our focus on low-skilled workers, who tend to have weaker labor market attachment, makes unemployment spells more likely. Second, the sample consists of young workers who may transition in and out of employment due to job shopping, search unemployment, or life events such as childbearing (for women) or military service (for men).

Panel C reports information on career progression during the first five years for workers who remain with their initial employer. Although we do not observe promotions directly, we proxy career advancement using movements within the firm's wage distribution and changes in occupational status. In complex occupations, 29% of untrained labor market entrants have reached at least the 5th decile of the firm's wage distribution of trained and untrained workers after five years, and 6% have transitioned into a higher-paying occupation within the firm. Additionally, 20% have experienced at least one instance of unusually high wage growth, exceeding that of their coworkers by at least 15 percentage points—a proxy for promotion proposed by Bronson and Skogman Toursie (2021).

Panel D of Table 1 shows that the initial firms of untrained entrants are roughly evenly split between manufacturing (40%) and services (44%). In the sample of complex occupations, the share of manufacturing rises to 80%. The median peer group size is 10 in the full sample and 23 in complex occupations. Peer groups in complex occupations are in firms that pay higher wages on average, with AKM firm fixed effects about 5% higher, likely reflecting their concentration in manufacturing.

Our identification strategy rests on the assumption that untrained job starters are more likely to compete for career opportunities with untrained peers than with trained peers, who typically follow a different career path within the firm. Figure 1 provides empirical support for this assumption. It compares the career progression of trained and untrained workers who begin their first job in the same firm, occupation, and year, by tracking their positions in the firm's wage distribution, divided into deciles. Trained entrants start about one decile higher than untrained ones; after 10 years, this gap widens to nearly three deciles, consistent with the view that trained and untrained workers follow distinct advancement paths within the firm.

5 Results

5.1 Identifying Knowledge Spillover and Competition Effects

Baseline Results. Table 2 presents our baseline results, focusing on labor market earnings and daily wages (in logs) five years after labor market entry. We impute zero earnings for non-employed individuals, so the earnings measure captures both wage and employment effects. To ease interpretation, we normalize earnings by their sample mean.

In Panel A, we pool trained and untrained peers, reflecting the typical specification in studies that ignore competition effects. We find no clear evidence of positive spillovers from higher-quality peers encountered in the first job. Average peer quality has a negative effect on earnings and no effect on wages five years later. When restricting the sample to complex occupations in columns (3) and (4), where the learning potential should be greater, peer quality positively affects wages but still has no effect on earnings. Taken at face value, these results suggest no consistent evidence of positive spillovers from peer quality among untrained young workers.

However, we observe positive spillover effects stemming from observed characteristics that are linked to the overall quality of the peer group. A 10-percentage-point rise in the share of trained peers in the initial job results in a 1.6% increase in earnings five years later across all occupations, and a 1% increase in earnings for complex occupations. Similarly, a one-year increase in the average age of peers leads to a 0.4% increase in earnings in both samples. These positive effects are indicative of knowledge spillover and are unlikely to be contaminated by a competition effect, as inexperienced, untrained labor market entrants are not expected to compete with trained and older coworkers for career advancement.

In Panel B, we distinguish peer quality by training status, as in equation (6). The effects now diverge clearly: in the overall sample, peer quality among untrained workers has a negative impact on both earnings and wages, while peer quality among trained workers has a positive

effect on wages (though not on earnings). As shown in equation (4), the impact of untrained peer quality combines knowledge spillovers and competition. The negative overall effect implies that competition outweighs any positive spillovers. We refer to the effect of untrained peer quality as the competition effect for simplicity, even though it represents a lower bound. Similarly, we refer to the positive impact of trained peers as a knowledge spillover effect, though it may also include a (likely smaller) competition component.

Both patterns, and specifically knowledge spillover, become stronger when we focus on complex occupations.²⁰ For instance, while a one-standard-deviation increase in trained peer quality has little effect on earnings in the full sample, it raises earnings by 3.7% in complex occupations. This is consistent with the idea that learning opportunities and skill requirements are more pronounced in such settings. For these reasons, we focus the remainder of the paper on complex occupations.

Figure 2 shows how the positive spillover from trained peers and the negative spillover from untrained peers in complex occupations evolve. Both effects are persistent. If anything, the positive impact from trained peers (which primarily captures knowledge spillover) increases slightly over time, consistent with the idea that skills build on each other.

The figure also includes placebo estimates based on "non-interacting" peers: trained and untrained workers who were employed in the same firm and occupation but had already left before the focal worker joined. Reassuringly, the quality of these placebo peers does not significantly affect earnings, with estimates close to zero.²¹

To further investigate whether the negative effect of untrained peer quality reflects competition, we decompose peer quality by experience level for both trained and untrained

²¹ Confidence intervals for placebo peer quality are omitted from the figure for clarity. All placebo effects are statistically insignificant.

²⁰ As shown in Appendix Table D.7, this conclusion is robust to alternative definitions of complex occupations.

peers (Table 3). We hypothesize that job starters are more likely to compete with similarly inexperienced coworkers than with more senior peers. The estimates confirm this for earnings: the negative effect is most substantial from untrained peers with up to three years of experience—a one-standard-deviation increase in their quality reduces earnings by 7.1%. In contrast, the reduction is only 1.8%, and is statistically insignificant for untrained peers with at least nine years of experience.

Spillover effects from trained peers are relatively stable across experience levels, suggesting largely homogeneous knowledge spillovers. No clear pattern is expected for these peers: while job starters may find learning easier from younger peers, more experienced workers may possess greater knowledge.

Robustness Checks. The pattern of negative spillovers from untrained peers and positive spillovers from trained peers is highly robust, as shown in Table 4. For reference, row (i) presents our baseline estimates. In row (ii), we flexibly control for initial firm size. Row (iii) adds initial firm-class-by-year-of-entry fixed effects, where firm classes are defined by the ventiles of the pre-estimated firm fixed effect distribution, interacted with entry-year dummies, capturing time-varying shocks at the firm-class level. In row (iv), we allow the initial firm-by-occupation fixed effect (δ_{jo}) to vary across three-year intervals—a demanding specification that restricts identification to comparisons among job starters entering the same firm-occupation within a short window. In row (v), we exclude peer groups with more than 50 members, where knowledge sharing or competition may be less well-defined.²² Across these specifications, estimates remain very similar.

²² Results continue to hold when further restricting to smaller peer groups.

Row (vi) excludes job starters under age 20, who may be students in temporary jobs. While these jobs can offer learning opportunities, competition is likely weaker since these workers have not yet begun full labor market careers. Consistent with this, negative spillovers from untrained peers become slightly stronger, while positive spillovers from trained peers remain essentially unchanged.

Because peer quality is constructed from pre-estimated worker fixed effects, measurement error could attenuate estimated coefficients. This concern is greater when fixed effects are based on short work histories. In row (vii), we drop coworkers whose fixed effects are based on three or fewer observations; estimates remain nearly identical, suggesting that this does not drive our results.

In row (viii), we remove excess sampling variation from the worker fixed effects by shrinking them toward their sample mean in proportion to the signal-noise ratio implied by the sampling error in the first-step AKM regression of equation (8).²³ Estimates using these shrunk fixed effects are virtually unchanged.

In principle, the quality of untrained focal workers could affect their coworkers' estimated wage fixed effects through reverse peer effects—a potential reflection problem. However, this concern is unlikely in our setting, as focal workers are untrained job starters with no prior work experience. To further assess this, we restrict the sample to untrained entrants from the last three years of the observation period (1996–1998). Since worker fixed effects are estimated over 1984–1998, these later cohorts could influence peer fixed effects for at most three years, compared to up to 15 years for 1984 entrants. If our estimates were driven by reflection, we

²³ We run 200 bootstrap iterations of the first-step AKM model (equation 8), clustering at the firm level, to obtain standard errors for the worker fixed effects. Using these, we shrink the fixed effects following equation (15) in Walters (2024). To generate the estimates in row (viii), we recompute peer quality using the shrunk fixed effects and re-estimate our baseline regression.

would expect substantially smaller effects in these cohorts. As shown in row (ix), this is not the case.

Alternative rank strategy. As an alternative approach, we estimate spillover effects from combined trained and untrained peers, conditioning on the focal worker's rank within the peer group, as in equation (7). Columns (1) and (3) of Table 5 replicate the findings from Panel A of Table 2. As before, we find no consistent pattern: peer quality has a mildly negative effect on future earnings and a mildly positive effect on wages. However, once we condition on rank, the effects of peer quality become substantially stronger. A one-standard-deviation increase in peer quality raises earnings and wages five years after entry by 7% and 2.6%, respectively. These results underscore the importance of conditioning on rank in uncovering knowledge spillover effects that may otherwise be overshadowed by competition. The estimates derived from the rank strategy are stronger than the positive spillovers from trained peers in our baseline strategy, possibly indicating that the latter underestimates the true knowledge spillover.

We also find that rank in the first job has a strong and lasting impact on labor market outcomes. A one-standard-deviation increase in rank, equivalent to moving roughly 30 percentiles up in the peer group's wage distribution, increases earnings by 15.7% and wages by 1.7% after five years. This aligns with the view that a better relative position among peers confers an advantage in within-firm competition for promotion and retention, improving long-term outcomes. ²⁴ As we show in Section 5.4 (Table 8), this pattern also holds across all occupations.

²⁴ Interestingly, the rank effect on earnings is substantially larger than the effect on wages. In additional results (not shown in the table), we find that a one-standard-deviation increase in rank raises the probability of employment five years after entry by six percentage points, which helps explain the stronger effect on earnings. Since separation from the initial firm is a key reason for non-employment, this suggests that the competition effect may be driven, at least in part, by competition for retention.

5.2 Anatomy of the Competition Effect

To better understand the mechanisms behind the competition effect, we examine how the quality of untrained incumbents affects employment and job mobility among untrained labor market entrants (Panel A, Table 6). A one-standard-deviation increase in untrained peer quality reduces the probability of employment five years later by 2.1 percentage points, suggesting that part of the earnings effect in Table 2 operates through the extensive employment margin. Moreover, workers exposed to higher-quality untrained peers are more likely to be employed in a different firm or occupation after five years, consistent with the idea that competition raises the likelihood of non-retention or voluntary exit due to limited advancement prospects. Our alternative rank strategy corroborates these findings (Panel A, Online Appendix Table D.2), where the rank coefficient, interpreted as an inverse competition effect, shows similar patterns.

In Panel B, we further investigate the effects of the quality of untrained peers on wages separately for workers who remain employed at their initial firm (stayers) and workers who have moved to another firm (movers). We find similar (and statistically insignificant) effects for both groups.

Panel C examines whether exposure to high-quality, untrained peers affects the promotion chances of those still employed at their initial firm after five years. We use several proxies for promotion: reaching at least the 5th decile of the firm's wage distribution (achieved by 29% of workers); moving to a higher-ranked occupation based on a time-constant wage-based occupation ranking; changes in the average occupational wage; and having experienced at least one instance of unusually high wage growth, exceeding that of their coworkers by at least 15 percentage points. Except for the latter proxy, the results generally show that a higher quality of untrained peers reduces the probability of promotion. In terms of magnitude, a one-standard-deviation increase in the quality of untrained peers leads to a reduction in the rungs of the

occupational ladder of approximately two, which reduces average occupational wages by 0.4 percent, accounting for half of the negative wage effect for stayers of 0.8 percent in Panel B.

In Panel D, we test for spillovers from untrained coworkers in other occupations within the same firm. We find no evidence of such effects, reinforcing the idea that competition is localized within occupations.

Finally, Panel E provides suggestive evidence that the intensity of the competition effect increases with the size of the "promotion prize," as predicted by our model (equation 4). Using the wage gap between the 90th and 10th percentiles of untrained workers in the firm-occupation cell as a proxy for the promotion prize, we find that the negative effect of untrained peer quality on earnings and (to a lesser extent) wages is stronger in cells with above-median wage spreads.

5.3 Knowledge Spillover and Its Mechanisms

We next examine in more detail how exposure to high-quality, trained peers shapes the careers of untrained labor market entrants. Panel A of Table 7 shows that a higher quality of trained peers in the initial job increases the likelihood of being employed five years later, indicating that part of the earnings effect observed in Table 2 operates through the employment margin. However, trained peer quality does not significantly affect the probability of switching firms or occupations.

Turning to wage effects (Panel B), we find that trained peer quality raises wages five years later even when controlling for trained peer quality at t+5 (column 2). This suggests the effect is not purely driven by mechanical correlation with current peer quality. Columns (3) and (4) further split the sample into stayers (those still at the initial firm) and movers. While both groups benefit, the effect itends to be larger for movers. This indicates that much of the benefit reflects a long-lasting advantage realized in other firms, consistent with transferable knowledge spillovers. Results from our alternative rank strategy (Online Appendix Table D.3) support this conclusion.

In Panel C, we investigate a range of additional outcomes that could mediate the effect of initial peer quality on future wages. Exposure to higher-quality trained peers increases subsequent peer quality by 4.5% of a standard deviation, the employing firm fixed effects by 0.7%, and firm size by 4.4%.²⁵ These findings suggest that exposure to high-quality, trained peers facilitates the transition of untrained workers into larger, better-paying firms with higher-quality coworkers. We find no effect on the probability of referral, measured as joining a firm where an initial coworker previously moved, suggesting that network-based job searching is not a key driver of the mover advantage.

We report a tentative mediation analysis in the Online Appendix C, estimating the extent to which the wage effect (from column 1, Panel B) can be explained by these mediators. Together, they account for 65% of the effect, with future firm and peer quality being the main channels. We interpret this descriptively, as the causal interpretation depends on strong assumptions.

Panel D explores whether knowledge spills over from trained peers in different occupations. Our findings indicate no evidence of such effects, thus reinforcing the idea that knowledge spillovers are confined within three-digit occupations.

Panel E examines whether the positive spillover from trained peers is stronger in peer groups with greater "learning opportunities." We classify peer groups based on the ratio of experienced trained workers (with at least three years of experience) to untrained workers: groups above one are considered high-opportunity (42% of complex occupation peer groups), and those below one are considered low-opportunity. In low-opportunity groups, competition for learning opportunities may be greater, potentially limiting knowledge spillovers. We find suggestive evidence consistent with this: a one-standard-deviation increase in the quality of

²⁵ As the regression conditions on the initial firm-by-initial occupation fixed effect, the effect on future firm fixed effect is driven entirely by workers who move to another firm.

trained peers raises wages by 4.1% in high-opportunity groups, compared to 1.6% in low-opportunity groups. Similar differences between high- and low-learning groups arise when we focus on workers who have moved to a new firm, suggesting that the skills learned through knowledge spillover are transferable across firms.

5.4 Other Labor Market Entrants

So far, our analysis has focused on untrained workers without postsecondary education. In Table 8, we extend the investigation to trained labor market entrants who completed an apprenticeship (focusing on peer exposure during firm-based apprenticeship training) and to entrants with a college degree (focusing on peer exposure during their first job after graduation from college). We employ the alternative rank strategy and a sample that covers all apprenticeship and entry occupations. For untrained workers, results across all occupations closely mirror those for complex occupations in Table 5: peer quality in the first job negatively affects earnings (and does not affect wages) five years later when rank is not controlled for. However, once we condition on rank, positive spillovers emerge, and rank itself has a strong positive effect on both earnings and wages (Panel A).

The patterns are similar for both trained and college-educated entrants, though the magnitudes differ. Exposure to high-quality peers during apprenticeship training yields notably positive effects, pointing toward the effectiveness of Germany's structured formal apprenticeship system in facilitating knowledge transfer (Panel B). Rank effects are also more pronounced, indicating that an apprentice's relative position among coworkers plays an important role in their career advancement. Both effects are more minor in magnitude for entrants with a college degree (Panel C).

These findings highlight that knowledge spillovers may be obscured if the counteracting effects of competition are ignored. They also suggest that trained and untrained workers benefit more from peer learning than college graduates, and that peer learning is particularly important

when enrolled in apprenticeship programs. Finally, since untrained and trained workers rarely work alongside college-educated peers in their first job, the results imply that spillovers primarily stem from trained coworkers with apprenticeship backgrounds, rather than those with university degrees.²⁶

5.5 Distinguishing Effects by Gender

Both competition and knowledge spillover effects may vary by gender. A large body of lab and field evidence suggests that women are generally less willing to compete or to sort into competitive environments (Gneezy, Niederle, and Rustichini, 2003; Niederle and Vesterlund, 2011; Flory, Leibbrandt, and List, 2015). Men and women also differ in promotion aspirations (Azmat, Cunat, and Henry, 2020), negotiation behavior (Azmat and Petrongolo, 2014), and exposure to gender-based biases in promotion processes (Benson, Li, and Shue, 2022; Sarsons et al., 2021; Blackaby, Booth, and Frank, 2005; Haegele, 2022, 2023). Collectively, this literature suggests that women are less likely to enter promotion contests and face lower expected returns. Accordingly, an increase in the quality of potential competitors should affect women's career progression less than men's.

Consistent with this hypothesis, Table 9 shows that untrained peer quality has a more negative effect on male than female job starters (Panels A and B, column 1). A one-standard-deviation increase in the quality of untrained peers reduces men's earnings five years later by 6.4%, compared to 2.5% for women—a statistically significant difference at the 10% level. These differences are not explained by occupational sorting: they persist when regressions for

²⁶ For untrained workers, only 2% of coworkers in their first job hold a college degree. The share is also low for apprentices in training (5%). This contrasts with the experience of labor market entrants with a college degree: 45% of coworkers in their first job hold a college degree. These statistics highlight the limited exposure of trained and untrained labor market entrants to university-educated coworkers at the beginning of their careers.

men (women) are reweighted to match the occupational distribution of women (men) (column 2).²⁷

Interestingly, the negative competition effect for both genders appears driven primarily by same-gender peers (columns 3 and 4). One possible interpretation is that employers view same-gender peers as closer substitutes; alternatively, firms may apply explicit or implicit gender quotas in promotion or retention decisions.²⁸

As with competition effects, knowledge spillovers may also differ between male and female labor market entrants, potentially due to differences in workplace interactions. Women are more likely than men to take career breaks following childbirth, contributing to well-documented child penalties in earnings (Adda, Dustmann, and Stevens, 2017; Kleven et al., 2019). These career "resets" may reduce the persistence of benefits from early knowledge spillovers for women. Additionally, if workplace interactions are shaped by homophily—where same-gender coworkers are more likely to engage with one another due to gender-based segregation in occupations, teams, mentoring, or social networks—then knowledge spillovers may be more substantial among same-gender peers than between opposite-gender peers.

The findings in Table 9 show that positive spillover effects from trained peers are concentrated among men. For women, these effects are small and statistically insignificant (Panel B, column 1), suggesting that men benefit more from knowledge spillovers. These differences are not primarily due to differential occupational sorting between mean and women, as they persist when controlling for the occupational structure of men and women (column 2).

²⁷ The respective regression weight for a worker of a given sex in occupation j is the sample share of occupation j in the opposite-sex sample divided by the corresponding share in the own-sex sample.

²⁸ Existing research suggests that men and women may not be perfect substitutes in the workplace (De Giorgi, Paccagnella, and Pellizzari, 2015). This imperfect substitutability may stem from gender differences in task preferences (Gelblum, 2020) or aptitudes (Baker and Cornelson, 2018). Relatedly, the presence of explicit or implicit gender quotas may influence the dynamics of promotions. Azmat and Boring (2020, Table 2) report that among large firms in Germany, 84% implement basic gender diversity policies, and 33% set quantitative gender targets.

There is also evidence that spillovers are stronger among same-gender peers for both sexes, consistent with Messina et al. (2024), who find much stronger same-gender than oppositegender spillovers in the Brazilian labor market.

Table 10 explores potential mechanisms behind the stronger spillovers for men. For male entrants, the quality of trained peers in the first job has a positive impact on employment, experience, peer and firm quality (measured via firm fixed effects), and firm size five years later. These effects are largely absent for women. Strikingly, both men and women benefit similarly from high-quality trained peers if they remain with their initial firm. However, among workers who switch firms, only men experience gains from initial peer quality. This suggests that women primarily benefit from trained peers when staying in the same firm, while men also gain through mobility to larger, better-paying firms.

This finding aligns with prior research showing that job and occupational mobility contribute more to men's wage growth than to women's (e.g., Loprest, 1992; Fitzenberger and Kunze, 2005; Hirsch, Schank, and Schnabel, 2010; Petrongolo and Ronchi, 2020). Our alternative rank strategy supports this interpretation, revealing more substantial competition effects for men (Online Appendix Table D.2, Panel B) and greater spillover-driven mobility to better-paying firms (Online Appendix Table D.4).

6 Discussion and Conclusions

In this paper, we argue that workplace knowledge spillovers may go undetected if one ignores the counteracting effects of workplace competition from high-productivity peers. We address this challenge with an identification strategy based on the premise that competition is most intense among coworkers with similar qualifications and career stages, but unlikely between those on different career paths. We leverage an institutional feature of the German labor market, where trained (apprenticeship-completers) and untrained workers frequently work side by side in the same occupations but are likely on distinct career trajectories.

We find robust evidence of persistent knowledge spillovers, alongside competition effects of similar magnitude. Exposure to high-quality untrained peers significantly reduces the future earnings and wages of untrained labor market entrants, consistent with competition among peers on similar career paths. These effects are strongest among workers at similar career stages and more pronounced for men, aligning with evidence that men are more willing to engage in and benefit from workplace competition.

In contrast, consistent with knowledge spillovers, early exposure to high-quality trained peers increases future wages and earnings, especially in complex occupations. Spillover effects are also stronger for men than for women. Women benefit primarily when they remain with their initial firm. At the same time, men also gain through job mobility, suggesting that men more fully capitalize on the transferable human capital they acquire from trained peers. We corroborate these findings using an alternative identification strategy that conditions on both absolute peer quality (to capture knowledge spillovers) and ordinal rank (to capture competition).

Applying this rank-based strategy, we further show that knowledge spillover and competition effects are particularly pronounced for trained workers during apprenticeship training, consistent with such programs being conducive to knowledge spillover but also increasing competition. For college graduates, the same patterns hold but are smaller in magnitude.

Our findings carry important implications for research and policy. We document significant knowledge spillovers that stem largely from trained peers with apprenticeship backgrounds. If the higher quality of trained peers reflects productivity increases due to training (as opposed to positive selection into training programs), our results suggest that vocational and apprenticeship programs generate positive externalities, implying that the social return to apprenticeship training likely exceeds the private return. This also suggests that studies using

untrained workers as a comparison group may underestimate the true private returns to such training (see Wolter and Ryan, 2011, for a summary of the returns to apprenticeship training found in the literature).

Finally, our analysis provides new insights into gender differences in competition. While existing studies typically rely on lab settings or specific contexts such as sports or individual firms, we demonstrate in a broader labor market context that men experience more substantial competition effects than women. This supports the view that women are less inclined to enter competitive environments and gain less from within-firm competition for promotions.

References

Acemoglu, D., & Angrist, J. (1999). How Large are the Social Returns to Education? Evidence from Compulsory Schooling Laws (Working Paper No. 7444). National Bureau of Economic Research.

Adda, J., Dustmann, C., & Stevens, K. (2017). The career costs of children. *Journal of Political Economy*, 125(2), 293-337.

Arellano-Bover, J. (2024). Career consequences of firm heterogeneity for young workers: First job and firm size. *Journal of Labor Economics*, 42(2), 549-589.

Arellano-Bover, J., & Saltiel, F. (2025). Differences in on-the-job learning across firms. *Journal of Labor Economics*, forthcoming.

Azmat, G., & Boring, A. (2020). Gender diversity in firms. *Oxford Review of Economic Policy*, 36(4), 760-782.

Azmat, G., Cuñat, V., & Henry, E. (2020). Gender promotion gaps: Career aspirations and workplace discrimination. Available at SSRN 3518420.

Azmat, G., & Petrongolo, B. (2014). Gender and the labor market: What have we learned from field and lab experiments? *Labour Economics*, 30, 32-40.

Azoulay, P., Graff Zivin, J. S., & Wang, J. (2010). Superstar extinction. *The Quarterly Journal of Economics*, 125(2), 549-589.

Baker, G. P., Jensen, M. C., & Murphy, K. J. (1988). Compensation and incentives: Practice vs. theory. *The Journal of Finance*, 43(3), 593-616.

Baker, M., & Cornelson, K. (2018). Gender-based occupational segregation and sex differences in sensory, motor, and spatial aptitudes. Demography, 55(5), 1749-1775.

Battisti, M. (2017). High wage workers and high wage peers. Labour Economics, 46, 47-63.

Battu, H., Belfield, C. R., & Sloane, P. J. (2003). Human capital spillovers within the workplace: Evidence for Great Britain. *Oxford Bulletin of Economics and Statistics*, 65(5), 575-594.

Becker, G. S. (1994). Human Capital (3rd ed.), University of Chicago Press, Chicago.

Becker, G. S., & Murphy, K. M. (2000). Social economics: Market behavior in a social environment. Harvard University Press.

Ben-Porath, Y. (1967). The production of human capital and the life cycle of earnings. *Journal of Political Economy*, 75(4, Part 1), 352-365.

Benson, A., Li, D., & Shue, K. (2021). "Potential" and the gender promotion gap. Working paper.

Bentsen, K. H., Munch, J. R., & Schaur, G. (2019). Education spillovers within the workplace. *Economics Letters*, 175, 57-59.

Bertoni, M., & Nisticò, R. (2023). Ordinal rank and the structure of ability peer effects. *Journal of Public Economics*, 217, 104797.

Bianchi, N., Bovini, G., Li, J., Paradisi, M., & Powell, M. (2022). Career Spillovers in Internal Labor Markets. *The Review of Economic Studies*, in press.

Bilen, E., & Matros, A. (2022). The Queen's Gambit: Explaining the Superstar Effect Using Evidence from Chess. Available at SSRN. https://dx.doi.org/10.2139/ssrn.4045910

Blackaby, D., Booth, A. L., & Frank, J. (2005). Outside offers and the gender pay gap: Empirical evidence from the UK academic labour market. *The Economic Journal*, 115(501), F81-F107.

Borjas, G. J., & Doran, K. B. (2015). Which peers matter? The relative impacts of collaborators, colleagues, and competitors. *Review of economics and statistics*, 97(5), 1104-1117.

Bronson, M. A., & Skogman Thoursie, P. (2021). The wage growth and within-firm mobility of men and women: New evidence and theory. Unpublished Manuscript.

Brown, J. (2011). Quitters never win: The (adverse) incentive effects of competing with superstars. *Journal of Political Economy*, 119(5), 982-1013.

Chen, Y., Hensel, L., & Yao, X. (2025). From Followers to Leaders: The Career Impact of High-Quality Managers. IZA Discussion Paper No. 17848.

Cornelissen, T., Dustmann, C., & Schönberg, U. (2017). Peer effects in the workplace. *American Economic Review*, 107(2), 425–56.

De Giorgi, G., Paccagnella, M. and Pellizzari, M. (2015) Gender complementarities in the labor market. In Polachek, S. W., Tatsiramos, K. and Zimmermann, K. F. (eds.), *Gender Convergence in the Labor Market* (Research in Labor Economics, Volume 41), pp. 277–298. Bingley, UK: Emerald Group Publishing Limited.

De Grip, A., & Sauermann, J. (2012). The effects of training on own and co-worker productivity: Evidence from a field experiment. *The Economic Journal*, 122(560), 376-399.

Denning, J. T., Murphy, R., & Weinhardt, F. (2021). Class rank and long-run outcomes. *The Review of Economics and Statistics*, doi: https://doi.org/10.1162/rest_a_01125.

DeVaro, J. (2006). Internal promotion competitions in firms. *The Rand Journal of Economics*, 37(3), 521-542.

DeVaro, J., & Kauhanen, A. (2016). An "opposing responses" test of classic versus market-based promotion tournaments. *Journal of Labor Economics*, 34(3), 747-779.

Elsner, B., Isphording, I. E., & Zölitz, U. (2021). Achievement rank affects performance and major choices in college. *The Economic Journal*, 131(640), 3182-3206.

Englmaier, F., Grimm, S., Grothe, D., Schindler, D., & Schudy, S. (2021). The Value of Leadership: Evidence from a Large-Scale Field Experiment. CESifo Working Paper No. 9273.

Espinosa, M., & Stanton, C. T. (2022). Training, Communications Patterns, and Spillovers Inside Organizations. *NBER Working Paper No. w30224*. National Bureau of Economic Research.

Fairburn, J. A., & Malcomson, J. M. (2001). Performance, promotion, and the Peter Principle. *The Review of Economic Studies*, 68(1), 45-66.

Fitzenberger, B., & Kunze, A. (2005). Vocational training and gender: Wages and occupational mobility among young workers. *Oxford review of Economic policy*, 21(3), 392-415.

Flory, J. A., Leibbrandt, A., & List, J. A. (2015). Do competitive workplaces deter female workers? A large-scale natural field experiment on job entry decisions. *The Review of Economic Studies*, 82(1), 122-155.

Frakes, M. D., & Wasserman, M. F. (2021). Knowledge spillovers, peer effects, and telecommuting: Evidence from the US Patent Office. *Journal of Public Economics*, 198, 104425.

Gathmann, C., & Schönberg, U. (2010). How general is human capital? A task-based approach. Journal of Labor Economics, 28(1), 1-49.

Gelblum, M. (2020). Preferences for job tasks and gender gaps in the labor market. Unpublished Manuscript, Harvard University.

Glaeser, E. L. (1999). Learning in Cities. *Journal of Urban Economics*, 46(2), 254–277.

Glaeser, E. L., Scheinkman, J. A., & Sacerdote, B. I. (2003). The Social Multiplier. *Journal of the European Economic Association*, 1(2/3), 345–353.

Gneezy, U., Niederle, M., & Rustichini, A. (2003). Performance in competitive environments: Gender differences. *The Quarterly Journal of Economics*, 118(3), 1049-1074.

Haegele, I. (2022). Talent hoarding in organizations. arXiv preprint arXiv:2206.15098.

Haegele, I. (2023). The Broken Rung: Gender and the Leadership Gap. Working Paper.

Herbst, D., & Mas, A. (2015). Peer effects on worker output in the laboratory generalize to the field. *Science*, 350(6260), 545-549.

Hirsch, B., Schank, T., & Schnabel, C. (2010). Differences in labor supply to monopsonistic firms and the gender pay gap: An empirical analysis using linked employer-employee data from Germany. *Journal of Labor Economics*, 28(2), 291-330.

Hoffman, M., & Tadelis, S. (2021). People management skills, employee attrition, and manager rewards: An empirical analysis. *Journal of Political Economy*, 129(1), 243-285.

Hong, L., & Lattanzio, S. (2025). The peer effect on future wages in the workplace. *Journal of Applied Econometrics*.

Jackson, C. K., & Bruegmann, E. (2009). Teaching students and teaching each other: The importance of peer learning for teachers. *American Economic Journal: Applied Economics*, 1(4), 85-108.

Jarosch, G., Oberfield, E., & Rossi-Hansberg, E. (2021). Learning from coworkers. *Econometrica*, 89(2), 647-676.

Johnsen, J., Ku, H., & Salvanes, K. G. (2020). Competition and Career Advancement: The Hidden Costs of Paid Leave. *CreAM Discussion Paper* 17/20.

Jovanovic, B., & Rob, R. (1989). The Growth and Diffusion of Knowledge. *The Review of Economic Studies*, 56(4), 569–582.

Kahn, L. B. (2010). The long-term labor market consequences of graduating from college in a bad economy. *Labour Economics*, 17(2), 303-316.

Kandel, E., & Lazear, E. P. (1992). Peer pressure and partnerships. *Journal of Political Economy*, 100(4), 801-817.

Killingsworth, M. R. (1982). "Learning by doing" and "investment in training": A synthesis of two "rival" models of the life cycle. *The Review of Economic Studies*, 49(2), 263-271.

Kleven, H., Landais, C., Posch, J., Steinhauer, A., & Zweimuller, J. (2019). Child penalties across countries: Evidence and explanations. *AEA Papers and Proceedings*, 109, 122-26.

Lazear, E. P., & Rosen, S. (1981). Rank-order tournaments as optimum labor contracts. *Journal of Political Economy*, 89(5), 841-864.

Lazear, E. P., Shaw, K. L., & Stanton, C. T. (2015). The value of bosses. *Journal of Labor Economics*, 33(4), 823-861.

Lazear, E. P., Shaw, K. L., & Stanton, C. T. (2018). Who gets hired? The importance of competition among applicants. *Journal of Labor Economics*, 36(S1), S133-S181.

Loprest, P. J. (1992). Gender differences in wage growth and job mobility. *The American Economic Review*, 82(2), 526-532.

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, 22(1), 3–42.

Marshall, A. (1890). Principles of political economy. Macmillan, New York.

Martins, P. S., & Jin, J. Y. (2010). Firm-level social returns to education. *Journal of Population Economics*, 23, 539-558.

Mas, A., & Moretti, E. (2009). Peers at work. American Economic Review, 99(1), 112-145.

Messina, J., Sanz-de-Galdeano, A., & Terskaya, A. (2024). Birds of a Feather Earn Together. Gender and Peer Effects at the Workplace, IZA Discussion Paper No. 16721.

Mincer, J. A. (1974). The human capital earnings function. In Schooling, Experience, and Earnings (pp. 83-96). NBER.

Moretti, E. (2004). Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data. *Journal of Econometrics*, 121(1), 175–212.

Murphy, R., & Weinhardt, F. (2020). Top of the class: The importance of ordinal rank. *The Review of Economic Studies*, 87(6), 2777-2826.

Niederle, M., & Vesterlund, L. (2011). Gender and competition. Annual Review of Economics, 3(1), 601-630.

Nix, E. (2020). Learning spillovers in the firm, *Working Paper, No. 2020:14*, Institute for Evaluation of Labour Market and Education Policy (IFAU), Uppsala.

Oreopoulos, P., Von Wachter, T., & Heisz, A. (2012). The short-and long-term career effects of graduating in a recession. *American Economic Journal: Applied Economics*, 4(1), 1-29.

Petrongolo, B., & Ronchi, M. (2020). Gender gaps and the structure of local labor markets. *Labour Economics*, 64, 101819.

Prendergast, C. (1999). The provision of incentives in firms. *Journal of Economic Literature*, 37(1), 7-63.

Prendergast, C. (1999). The provision of incentives in firms. *Journal of economic literature*, 37(1), 7-63.

Sandvik, J. J., Saouma, R. E., Seegert, N. T., & Stanton, C. T. (2020). Workplace knowledge flows. *The Quarterly Journal of Economics*, 135(3), 1635-1680.

Sarsons, H., Gërxhani, K., Reuben, E., & Schram, A. (2021). Gender differences in recognition for group work. *Journal of Political Economy*, 129(1), 101-147.

The New York Times (2021). *The morning newsletter: The Amazon Customers Don't See*. https://www.nytimes.com/2021/06/15/briefing/amazon-warehouse-investigation.html [accessed 11th April 2023].

Waldinger, F. (2012). Peer effects in science: Evidence from the dismissal of scientists in Nazi Germany. *The Review of Economic Studies*, 79(2), 838-861.

Walters, C. (2024). Empirical Bayes methods in labor economics. In Handbook of Labor Economics (Vol. 5, pp. 183-260). Elsevier.

Wirz, A. M. (2008). Private returns to education versus education spill-over effects. *Empirical Economics*, 34(2), 315-342.

Wolter, S. C., & Ryan, P. (2011). Apprenticeship. In *Handbook of the Economics of Education* (Vol. 3, pp. 521–576). Elsevier.

Xiao, J. (2020). Whether to hire a(nother) superstar. Available at SSRN. https://dx.doi.org/10.2139/ssrn.3520962

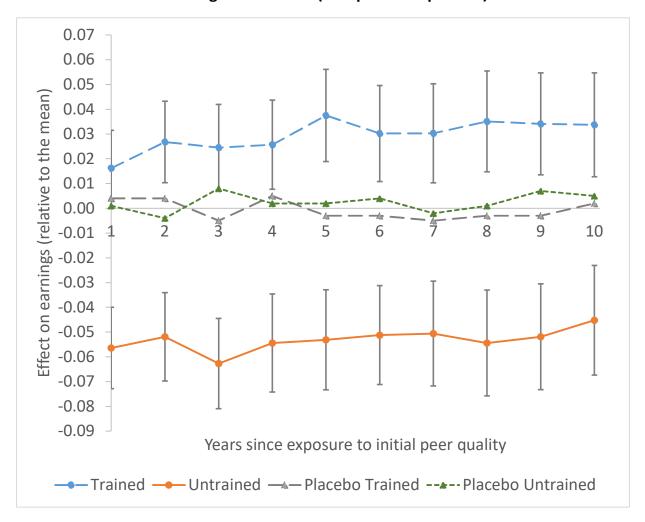
Figures and Tables

5.0 Decile within the firm-wage distribution 4.0 3.0 2.0 1.0 0.0 1 2 0 3 4 5 6 8 9 10 Years of tenure at the initial firm Trained — Untrained

Figure 1: Career Progression of Untrained and Trained Workers in the Initial Firm (Stayers)

Notes: The figure plots the evolution of workers' positions within the deciles of the firm-specific wage distribution, relative to the starting decile of untrained workers. For all firms in our sample, we partition the within-firm wage distribution (excluding college graduates) each year into deciles and compute each worker's decile position. The starting difference (at 0 years of tenure) between trained and untrained workers is derived from a regression (reported in Appendix Table D.6) of the decile position at labor market entry on an indicator variable for whether a worker is trained versus untrained, controlling for firm-by-occupation-by-year effects. Using the sample of stayers at their initial firm, the slopes of the tenure profiles are then derived from a regression of the decile position on interactions of the trained dummy with dummy variables indicating the years of tenure from 1 to 10, conditional on worker fixed effects.

Figure 2: The Effects of the Quality of Trained and Untrained Peers in the First Job on Earnings Over Time (Complex Occupations)



Notes: The figure plots the effects of (standardized) initial peer quality (at labor market entry) of actual and placebo coworkers on earnings in complex occupations over time, up to 10 years after labor market entry, distinguishing between peer quality of trained and untrained coworkers. Peers are coworkers in the same initial firm and occupation. Placebo peers are made up of workers who were in the same peer group two years before the focal worker joined but left the peer group the year before the focal worker joined, precluding any overlap with the focal worker. Average peer quality is standardized and measured by the average AKM wage fixed effects of coworkers; a one-unit increase in standardized average peer quality corresponds to an increase in average peer quality of approximately 20%. The regressions control for initial occupation × cohort effects, initial firm × occupation effects, the coworker shares of trained and college-educated workers, the average quality of college-educated coworkers, the coworker share of females, the wage in the initial job, age at labor market entry, and sex. Earnings are set to zero for the non-employed and are divided by mean earnings. Confidence intervals are based on standard errors clustered at the firm level. Confidence intervals for the placebo peer quality are not shown to keep the figure clearly legible. All placebo effects are statistically insignificant.

Table 1: Descriptive statistics

	(1)	(2)
	Overall	Complex
Panel A: Sample characteristics	sample	occupations
Number of unskilled focal workers	774,701	172,242
Number of firms	206,861	33,023
Number of occupations	329	63
Number of firm-occupation cells	275,862	37,455
Panel B: Untrained job starters		
Average age at initial job	21	20
Female	0.41	0.44
Employed in t+5	0.43	0.50
Daily earnings in EUR in t+5 (if not employed =0)	25	30
Same firm in t+5 (conditional on employment)	0.49	0.55
Same occupation in t+5 (conditional on employment)	0.55	0.58
Panel C: Career progression of firm stayers:		
Share moved >= 5th percentile of firm's wage distribution by t+5	0.28	0.29
Move to higher-paying occupations	0.06	0.06
Exceeded coworkers' annual wage growth by 15pp at least once by t+5	0.22	0.20
Panel D: Peer group characteristics		
Standard deviation of peer quality, trained peers	0.19	0.16
Standard deviation of peer quality, untrained peers	0.20	0.14
Manufacturing	0.40	0.80
Construction	0.09	0.02
Services	0.44	0.15
Other	0.08	0.03
Median peer group size	10	23
AKM log wage establishment fixed effect in t+5	1.12	1.17
Coworker share of untrained	0.35	0.44
Coworker share of trained	0.63	0.55
Coworker share of university graduates	0.02	0.01
Share with ratio of experienced trained to untrained workers < 1	0.46	0.58
Coworker share of females Notes: The table reports descriptive statistics for the overall sample of all init	0.37	0.39

Notes: The table reports descriptive statistics for the overall sample of all initial occupations of untrained labor market entrants (column 1), and for a subsample of initial occupations with more complex tasks (column 2).

Table 2: The Effects of Peer Characteristics in the First Job on Future Earnings and Wages

	Overall	sample	Complex o	ccupations
-	(1)	(2)	(3)	(4)
	Earnings, rel.	Log wage,	Earnings, rel.	Log wage,
_	to mean, t+5	t+5	to mean, t+5	t+5
Panel A: Overall peer quality				
Average quality of peers	-0.032	0.001	-0.015	0.016
	(0.005)	(0.004)	(0.014)	(0.007)
Average peer age	0.004	-0.001	0.004	-0.0002
	(0.001)	(0.0003)	(0.002)	(0.001)
Share of trained workers	0.164	0.019	0.101	0.028
	(0.014)	(0.007)	(0.036)	(0.015)
Panel B: Quality of untrained vs	trained peers			
Quality of untrained peers	-0.036	-0.007	-0.053	-0.013
	(0.004)	(0.002)	(0.010)	(0.005)
Quality of trained peers	0.0005	0.007	0.037	0.019
	(0.004)	(0.002)	(0.010)	(0.005)
Average peer age	0.004	-0.001	0.003	-0.0002
	(0.001)	(0.0003)	(0.002)	(0.001)
Share of trained workers	0.174	0.029	0.088	0.036
	(0.020)	(0.009)	(0.044)	(0.017)
No. of observations	774,701	329,649	172,242	85,963

Notes: The table shows the effects of various characteristics of initial peers (i.e., coworkers in the same firm and occupation at labor market entry) on the earnings and wages of untrained workers five years after labor market entry. Average peer quality is standardized and measured by the average AKM wage fixed effects of coworkers. In Panel A, peer quality is averaged over all peers; in Panel B, we distinguish between untrained and trained peers. Earnings are set to zero for the non-employed and are divided by mean earnings. All specifications control for initial occupation × cohort effects, initial firm × occupation effects, the coworker share of college-educated workers, the average quality of college-educated coworkers (in Panel B), the coworker share of females, the wage in the initial job, age at labor market entry, and sex. Standard errors are clustered at the firm level.

Table 3: The Effects of the Quality of Untrained and Trained Peers Broken Down by Peer Experience (Complex Occupations)

_	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	E	arnings, rel. 1	to mean, t+5			Log wa	ges, t+5	
	Pacolino	By peers	s' years of ex	perience	Pacolino	By peers	s' years of ex	perience
	Baseline	<=3 yrs	4-9 yrs	>9 yrs	Baseline	<=3 yrs	4-9 yrs	>9 yrs
Quality of untrained peers	-0.058	-0.071	-0.032	-0.018	-0.012	-0.015	-0.011	-0.012
	(0.010)	(0.011)	(0.013)	(0.013)	(0.005)	(0.006)	(0.006)	(0.006)
Quality of trained peers	0.03	0.027	0.035	0.036	0.019	0.017	0.02	0.02
	(0.009)	(0.010)	(0.011)	(0.011)	(0.005)	(0.005)	(0.005)	(0.005)
No. of observations	172,242		172,242		85,963		85,963	

Notes: The table shows the effects of the (standardized) quality of initial peers (i.e., untrained and trained coworkers in the same firm and occupation at labor market entry) on untrained job starters' earnings and wages five years after labor market entry. Peer quality is measured by the average AKM wage fixed effects of coworkers, broken down by the training status and labor market experience of the peers. All specifications control for initial occupation × cohort effects, initial firm × occupation effects, the average coworker age, the coworker shares of trained and college-educated workers, the average quality of college-educated coworkers, the coworker share of females, the wage in the initial job, age at labor market entry, sex. Earnings are set to zero for the non-employed and are divided by mean earnings. Standard errors are clustered at the firm level.

Table 4: Robustness of the Effects of the Quality of Untrained and Trained Peers in the First Job (Complex Occupations)

	Earnings, rel. to mean, t+5		Log wa	age, t+5	
	Untrained	Trained	Untrained	Trained	
_	Peers	Peers	Peers	Peers	
(i) Baseline	-0.053	0.037	-0.013	0.019	
	(0.010)	(0.010)	(0.005)	(0.005)	
(ii) Control for eight firm size	-0.054	0.037	-0.013	0.018	
categories of intial firm	(0.010)	(0.010)	(0.005)	(0.005)	
(iii) Add firm-class by	-0.056	0.034	-0.017	0.016	
cohort FE	(0.010)	(0.010)	(0.005)	(0.005)	
(iv) Add triannual	-0.05	0.018	-0.028	0.017	
peer group FE	(0.017)	(0.015)	(0.011)	(0.009)	
(v) Drop large groups	-0.053	0.029	-0.02	0.012	
with > 50 peers	(0.011)	(0.010)	(0.006)	(0.005)	
(vi) Starting age >=20	-0.081	0.033	-0.026	0.021	
	(0.016)	(0.014)	(0.009)	(800.0)	
(vii) Peers with FE estimated	-0.05	0.041	-0.012	0.019	
on 4 or more observations	(0.010)	(0.010)	(0.005)	(0.005)	
(viii) Fixed effects	-0.05	0.039	-0.01	0.018	
shrunk	(0.011)	(0.010)	(0.005)	(0.004)	
(ix) Over last 3 cohorts	-0.095	0.034	-0.039	0.009	
(1996-1998)	(0.051)	(0.043)	(0.028)	(0.040)	

Notes: The table reports several robustness checks for the baseline effects of the (standardized) quality of initial peers (i.e., untrained and trained coworkers in the same firm and occupation at labor market entry) on the earnings and wages of untrained workers five years after labor market entry. Earnings are set to zero for the non-employed and are divided by mean earnings. All specifications control for initial occupation × cohort effects, initial firm × occupation effects, the average coworker age, the coworker shares of trained and college-educated workers, the average quality of college-educated coworkers, the coworker share of females, the wage in the initial job, age at labor market entry, and sex. Earnings are set to zero for the non-employed and are divided by mean earnings. Standard errors are clustered at the firm level.

 $Source: German\ Social\ Security\ Records\ from\ the\ \textit{Besch\"{a}ftigtenhistorik}\ \ (BEH).$

Table 5: The Effects of Peer Quality in the First Job on Future Labor Market Outcomes When Controlling for Rank (Complex Occupations)

	(1)	(2)	(3)	(4)
	Earnings, mear		Log wag	ges, t+5
Average peer quality	-0.015 (0.014)	0.07 (0.014)	0.016 (0.007)	0.026 (0.008)
Rank in peer group		0.157 (0.007)		0.017 (0.003)
No. of observations	172,242	172,242	85,963	85,963

Notes: The table shows the effect of the (standardized) quality of initial peers (i.e., coworkers in the same firm and occupation at labor market entry) on the earnings and wages of untrained workers five years after labor market entry, with and without controlling for the rank of untrained workers among their initial peers. Average peer quality is measured as the average AKM wage fixed effect. Average peer quality is standardized; a one-unit increase in standardized peer quality corresponds to an increase of approximately 20%. The untrained worker's rank among their initial peers is based on residualized wages net of experience to capture current performance relative to expectations based on seniority. Rank is standardized; a one-unit increase in standardized rank corresponds to an increase in rank of about 30 percentiles. Earnings are set to zero for the non-employed and are divided by mean earnings. All specifications control for initial occupation × cohort effects, initial firm × occupation effects, the average coworker age, the coworker shares of trained and college-educated workers, the coworker share of females, the wage in the initial job, age at labor market entry, and sex. Standard errors are clustered at the firm level.

Table 6: The Effects of the Quality of Untrained Peers in the First Job: Mechanisms (Complex Occupations)

Panel A: Mobility, t+5	(1) Employed	(2) Moved Firm	Moved ((3) Occupation	
— Quality of Untrained Peers	-0.021	0.028		.029	
,	(0.005)	(0.009)	(0	.009)	
No. of obs	172,242	85,963	8!	5,963	
Panel B: Log Wages, t+5, Movers vs Stayers					
	All	Stayers	M	overs	
Quality of Untrained Peers	-0.013	-0.008	-0.007		
	(0.005)	(0.006)	(0.008)		
No. of obs	85,963	47,003	38	3,960	
Panel C: Promotion outcomes (Stayer	rs)				
	(1)	(2)	(3)	(4)	
	Move to	Change in the	Change in	Wage growth rel.	
	>=5th	occupational	occupational log	to coworkers	
_	decile	hierarchy	mean wage	>= 15pp	
Quality of Untrained Peers	-0.024	-2.201	-0.004 0.007		
	(0.014)	(1.038)	(0.002)	(0.015)	
No. of obs.	47,003	46,984	46,984	47,003	

Panel D: Earnings, t+5, Peers in the same vs different occupations

 (1)
 (2)

 Peers in own occupation
 Peers in other occupations

 Quality of Untrained Peers
 -0.053
 0.005

 (0.010)
 (0.007)

 No. of obs.
 172,242
 172,242

Panel E: Earnings, t+5, High vs Low "Promotion" Prize (wage spread in firm-occupation)

	Earnings, t+5	Log Wages, t+5
Quality of Untrained Peers	-0.019	-0.009
x below-median promotion prize	(0.013)	(0.006)
Quality of Untrained Peers x above-median promotion prize	-0.074 (0.011)	-0.015 (0.006)
No. of obs.	172,242	85,963

Notes: The table shows the effects of the (standardized) quality of initial untrained peers (i.e., untrained coworkers in the same firm and occupation at labor market entry) on various career outcomes of untrained workers five years after labor market entry. Peer quality of untrained peers is measured by the average AKM wage fixed effects of untrained coworkers. Earnings are set to zero for the non-employed and are divided by mean earnings. All specifications control for initial occupation × cohort effects, initial firm × occupation effects, the average coworker age, the coworker shares of trained and college-educated workers, the average quality of trained and college-educated coworkers, the coworker share of females, the wage in the initial job, age at labor market entry, and sex. Column (1) in Panel C additionally controls for the worker's starting decile in the firm wage distribution. Promotions in Panel C are proxied as follows: A dummy variable for whether the worker has moved to at least the 5th decline in the firm's wage distribution (calculated excluding college graduates) by the 5th year since labor market entry (column 1); the absolute change in the worker's occupational ranking between year 5 and labor market entry, where occupations are ranked by the average occupational wage in a reference year (column 2); the worker's change in the occupational log mean wage measured in a reference year between year 5 and labor market entry (column 3); a dummy variable for whether the worker has experienced annual wage growth exceeding the average wage growth of coworkers in the firm by at least 15 percentage points at least once over the five years since labor market entry (column 4). The sample in Panel C is restricted to untrained workers who have remained employed in their initial firm for at least five years. Standard errors are clustered at the firm level.In Panel E, the promotion prize is proxied by the 90th-10th percentile wage gap of untrained workers in the firm-occupation cell.

Table 7: The Effects of the Quality of Trained Peers in the First Job: Mechanisms (Complex Occupations)

Panel A: Mobility, t+5	(1)	(2)	(3)
_	Employed	Moved Firm	Moved O	ccupation
Quality of Trained Peers	0.011	-0.01	-0.	013
	(0.005)	(0.009)	(0.	009)
No. of obs.	172,242	85,963	85,	.963
Panel B: Log Wages, t+5, Movers vs Stayers				
	(1)	(2)	(3)	(4)
_	Baseline	Controlling for quality of peers in t+5	Stayer	Mover
Quality of Trained Peers	0.019	0.013	0.016	0.03
	(0.005)	(0.004)	(0.006)	(0.007)
No. of obs.	85,963	85,963	47,003	38,960
Panel C: Mediating outcomes				
	(1)	(2)	(3)	(4)
	Peer quality,		Log firm size,	Ever referred
_	t+5	Firm Fixed Effect, t+5	t+5	by t+5
Quality of Trained Peers	0.045	0.007	0.044	0.002
	(0.013)	(0.003)	(0.027)	(0.002)
No. of obs.	85,963	85,607	85,963	172,242

Panel D: Earnings, t+5, peers in the same vs different occupations

	(1)	(2)
_	Peers in own occupation	Peers in other occupations
Quality of Trained Peers	0.037	-0.002
	(0.010)	(0.009)
No. of obs.	172,242	172,242

Panel E: High vs Low "Learning Opportunities"

	(1)	(2)	(3)
	Earnings, t+5	Log Wages, t+5	Log Wages, t+5, Movers
Quality of Trained Peers	0.048	0.041	0.054
x high learning opportunities	(0.019)	(0.009)	(0.015)
Quality of Trained Peers	0.035	0.016	0.026
x low learning opportunities	(0.010)	(0.005)	(800.0)
No. of obs.	172,242	85,963	38,960

Notes: The table shows the effects of the (standardized) quality of initial trained peers (i.e., trained coworkers in the same firm and occupation at labor market entry) on various career outcomes of untrained workers five years after labor market entry. The quality of trained peers is measured by the average AKM wage fixed effects of trained coworkers. All specifications control for initial occupation × cohort effects, initial firm × occupation effects, average coworker age, the coworker shares of trained and college-educated workers, the average quality of untrained and college-educated coworkers, the coworker share of females, the wage in the initial job, age at labor market entry, and sex. Earnings are set to zero for the non-employed and are divided by mean earnings. In Panel E, learning opportunities are defined as low or high depending on whether the ratio of the number of experienced trained workers to the number of untrained workers in the peer group is smaller or greater than 1. Here, a dummy variable indicating a peer group with low learning opportunities is added as a control variable. Standard errors are clustered at the firm level.

Table 8: The Effects of Peer Quality in the First Job on Future Labor Market Outcomes When Controlling for Rank: Three Groups of Labor Market Entrants (All Occupations)

	(1)	(2)	(3)	(4)
	Earnings, rel. to mean, t+5		Log wage, t+5	
Panel A: Untrained				
Average peer quality	-0.032 (0.005)	0.027 (0.005)	0.001 (0.004)	0.01 (0.004)
Rank in peer group		0.131 (0.003)		0.017 (0.002)
No. of observations	774,701	774,701	329,649	329,649
Panel B: Trained				
Average peer quality	-0.008 (0.002)	0.061 (0.002)	-0.004 (0.001)	0.036 (0.001)
Rank in peer group		0.196 (0.001)		0.105 (0.000)
No. of observations	2,211,011	2,211,011	1,552,053	1,552,053
Panel C: College graduates				
Average peer quality	-0.011 (0.006)	0.012 (0.006)	-0.007 (0.003)	0.008 (0.003)
Rank in peer group		0.044 (0.002)		0.028 (0.001)
No. of observations	1,265,753	1,265,753	777,948	777,948

Notes: The table shows the effects of (standardized) initial peer quality (at labor market entry) on earnings and wages five years after labor market entry (completion of the apprenticeship program) for three groups of labor market entrants: untrained workers (in all occupations; Panel A), trained workers who completed an apprenticeship program (Panel B), and college-educated workers (Panel C). Results are reported with and without controlling for the entrant's standardized rank within the initial peer group (to capture competition effects). For untrained and college-educated workers, initial peers are coworkers in the same firm and occupation in their first job at labor market entry. For trained workers, initial peers refer to their coworkers during apprenticeship training. Average peer quality is standardized and measured by the average AKM wage fixed effects of coworkers. For untrained and college-educated workers, their rank among initial peers is based on residualized wages net of experience to capture current performance relative to expectations based on seniority. Since the wages of apprentices in training are not comparable to the wages of regularly employed coworkers, we compute the rank of apprentices based on AKM wage fixed effects rather than current wages. Earnings are set to zero for the non-employed, and are divided by mean earnings. All specifications control for initial occupation × cohort effects, initial firm × occupation effects, average coworker age, coworker shares of trained and college-educated workers, the coworker share of females, the wage in the initial job, age at labor market entry, and sex. Standard errors are clustered at the firm level.

Table 9: The Effects of the Quality of Untrained and Trained Peers in the First Job on Future Earnings: Men vs Women (Complex Occupations)

Panel A: Male Untrained Labor Market Entrants						
	(1)	(2)	(3)	(4)		
	all peers	weighted for female occupations	male peers	female peers		
Quality Untrained Peers	-0.064 (0.015)	-0.041 (0.030)	-0.065 (0.015)	-0.019 (0.027)		
Quality Trained Peers	0.063 (0.015)	0.073 (0.025)	0.06 (0.015)	0.039 (0.026)		
-		95,707				
Panel B: Female Untrained Labor Mar	ket Entrants					
	(1)	(2)	(3)	(4)		
	all peers	weighted for male occupations	male peers	female peers		
Quality Untrained Peers	-0.025 (0.014)	-0.028 (0.024)	0.008 (0.021)	-0.041 (0.016)		
Quality Trained Peers	0.011 (0.013)	-0.022 (0.019)	0.012 (0.014)	0.028 (0.015)		
		76,535	5			

Notes: The table shows the effects of the quality of initial peers (i.e., untrained and trained coworkers in the same firm and occupation at labor market entry) on the earnings of untrained workers five years after labor market entry. Results are shown separately for male (Panel A) and female (Panel B) untrained workers. Columns (3) and (4) additionally break down peer quality by the gender of the peers. Average peer quality is standardized and measured by the average AKM wage fixed effects of coworkers. Earnings are set to zero for the non-employed and are divided by mean earnings. All specifications control for initial occupation × cohort effects, initial firm × occupation effects, average coworker age, the coworker shares of trained and college-educated workers, the average quality of college-educated coworkers, the coworker share of females, the wage in the initial job, and age at labor market entry. Standard errors are clustered at the firm level.

Table 10: The Effects of the Quality of Trained Peers in the First Job on Future Labor Market Outcomes by Gender: Mechanisms (Complex Occupations)

(1)	(2)
Male	Female
0.018	0.003
(0.007)	(0.008)
0.074	-0.014
(0.027)	(0.030)
0.063	0.04
(0.017)	(0.021)
0.013	0.0003
(0.004)	(0.004)
0.065	-0.016
(0.038)	(0.044)
0.029	0.013
(0.006)	(800.0)
0.018	0.024
(0.008)	(0.009)
0.046	0.002
	(0.015)
	Male 0.018 (0.007) 0.074 (0.027) 0.063 (0.017) 0.013 (0.004) 0.065 (0.038) 0.029 (0.006) 0.018

Notes: The table shows the effects of (standardized) quality of trained initial peers (i.e., trained coworkers in the same firm and occupation at labor market entry) on the career outcomes of untrained workers five years after labor market entry. Results are shown separately for male and female untrained workers. Average peer quality is standardized and measured by the average AKM wage fixed effects of coworkers. All specifications control for initial occupation × cohort effects, initial firm × occupation effects, the average coworker age, the coworker shares of trained and college-educated workers, the average quality of untrained and college-educated coworkers, the coworker share of females, and the wage in the initial job. Standard errors are clustered at the firm level.

APPENDIX

Knowledge Spillovers, Competition, and Individual Careers

Thomas Cornelissen Christian Dustmann Uta Schönberg

APPENDIX A: Model details

A.1 Optimization problem of untrained job starter

Untrained job starters choose effort ω_i to maximize:

$$\max_{\omega_i} f(s_i) + G(\mu_i - (1 - \lambda_j)\mu_j + \omega_i - \omega_j)a - C(\omega_i)$$

The first order condition (FOC) is given by equation (2) in the main text, where g is the pdf related to G. Also, the second order condition needs to hold:

$$g'(\mu_i - (1 - \lambda_j)\mu_j + \omega_i - \omega_j)a - C''(\omega_i) < 0$$

Since g is a density function, g' can be positive. For the objective function to be concave, we require g' < C'' in the relevant range. Lazear and Rosen (1981) discuss that this condition holds provided that σ^2 is sufficiently large and assume this to be the case (see their footnote 2). This will yield an optimal effort level ω_i^* .

How then does ω_i^* depend on the quality of the untrained incumbent worker, μ_j ?

$$\frac{d\omega_i^*}{d\mu_j} = -\frac{dFOC/d\mu_j}{dFOC/d\omega_i^*} = \frac{-(1-\lambda_j)g'(\mu_i - (1-\lambda_j)\mu_j + \omega_i^* - \omega_j^*)a}{g'(\mu_i - (1-\lambda_j)\mu_j + \omega_i^* - \omega_j^*)a - C''(\omega_i^*)}$$

Note that g' will tend to be small if the distribution has fat tails. For a symmetric distribution function, g' is positive on the left tail and negative on right tail. The denominator will be positive if the second order condition holds. Better peer quality may increase or decrease own effort, depending on which tail of the distribution we are.

Similarly, the untrained incumbent chooses effort to maximize:

$$\max_{\omega_i} f(s_i) + \left[1 - G(\mu_i - (1 - \lambda_j)\mu_j + \omega_i - \omega_j)\right] a - C'(\omega_j)$$

The first and second order conditions, determining the untrained incumbent's effort choice, are:

F.O.C.:

$$g(\mu_i - (1 - \lambda_i)\mu_i + \omega_i - \omega_i)\alpha - C'(\omega_i) = 0$$

S.O.C.:

$$g'(\mu_i - (1 - \lambda_j)\mu_j + \omega_i - \omega_j)a - C''(\omega_j) < 0$$

Their optimal effort then depends on their quality as follows:

$$\frac{d\omega_j^*}{d\mu_j} = -\frac{-(1-\lambda_j)g'(\mu_i - (1-\lambda_j)\mu_j + \omega_i^* - \omega_j^*)a}{g'(\mu_i - (1-\lambda_j)\mu_j + \omega_i^* - \omega_i^*)a - C''(\omega_i)}$$

Hence, $\frac{d\omega_i^*}{d\mu_j} = \frac{d\omega_j^*}{d\mu_j}$ and the untrained job starter and incumbent will both choose the same effort level, $\omega_i^* = \omega_j^*$, provided that their cost functions are the same. In consequence, the expected untrained job starter's expected wage at equilibrium effort level, reduces to equation (3) in the main text:

$$E[W_i] = f(\mu_i + \lambda_j \mu_j + \lambda_k \mu_k) + G(\mu_i - (1 - \lambda_j)\mu_j +)a.$$

A.2 Allowing for some competition between the untrained job starter and the trained incumbent

We have set up the model under the assumption that the untrained job starter competes only with the untrained incumbent but not with the trained incumbent. We can relax this assumption by allowing for competition with both types of workers, but to different degrees. For this we define:

 P_i : probability that the untrained incumbent competes with the job starter

 P_k : probability that the trained incumbent competes with the job starter

Equations (4) and (5) in the main text then modify to:

$$\frac{dE[W_i]}{d\mu_j} = \underbrace{\lambda_j f'(\mu_i + \lambda_j \mu_j + \lambda_k \mu_k)}_{\text{knowledge spillover}} \underbrace{-P_j(1 - \lambda_j)g(\cdot)a}_{\text{competition}}$$
(A. 1)

$$\frac{dE[W_i]}{d\mu_k} = \underbrace{\lambda_k f'(\mu_i + \lambda_j \mu_j + \lambda_k \mu_k)}_{\text{knowledge spillover}} \underbrace{-P_k(1 - \lambda_k)g(\cdot)a}_{\text{competition}}$$
(A. 2)

Hence, differently from equation (5) in the main text, the spillover from the trained incumbent (equation A.2) is now a composite of a knowledge spillover effect and a competition effect and needs to be interpreted as a lower bound of the knowledge spillover effect. Moreover, under the assumptions $\lambda_k > \lambda_j$ (there is more to learn from the trained than untrained incumbent) and $P_k < P_j$ (there is less likely to be competition with the trained than the untrained incumbent), spillover effects from trained and untrained co-workers can be clearly ranked: $\frac{dE[W_i]}{dE[W_i]} > \frac{dE[W_i]}{dE[W_i]}$

ranked:
$$\frac{dE[W_i]}{d\mu_k} > \frac{dE[W_i]}{d\mu_j}$$

APPENDIX B: The German Apprenticeship System

The German Apprenticeship System is a vocational training program which combines practical firm provided on-the-job training, with state-provided classroom instruction. It is an important pillar of the German education system, with about 500,000 young people starting an apprenticeship contract in Germany each year (BMBF 2022, section 2.3 and Figure 3). Training typically starts after secondary school from the age of around 16. There are no formal entry requirements into an apprenticeship, but an apprenticeship contract must be concluded between the apprentice and the training firm, meaning that firms effectively screen applicants.

There are over 300 recognized occupations that offer apprenticeships, covering a wide range of blue-collar (e.g., craft, industrial, and technical) and white-collar (e.g., administrative and service) professions. The program usually lasts between two to three years. The classroom-based component at a vocational school makes up one third of the training time (1-2 days per week), leaving most of the time (3-4 days per week) spent learning in a work environment at the training firm under the instruction of a skilled supervisor. Firms pay the cost for the on-the-job training and pay the apprentice a renumeration, typically lower than what is obtainable for unskilled work.

The apprenticeship training system is strongly regulated. The standards for the training content are set by occupational profiles defined in training ordinances for each occupation. Qualification certificates are awarded through final examinations by the relevant competent bodies for each occupation (chambers of commerce, chambers of craft trades, etc.).

While completing an apprenticeship within a recognized occupation greatly facilitates labor market entry and career development, many occupations can also be entered without a

¹ See Franz and Soskice (1995), Hoeckel and Schwartz (2010), and Solga et al. (2014) for additional details on the apprenticeship system.

formal vocational qualification. For example, a salesperson in a retail shop can be untrained, or can hold an apprenticeship degree as a retail salesperson. This is the feature we exploit in the present paper, where we observe in many occupations trained and untrained workers working alongside each other.

References:

BMBF - Bundesministerium für Bildung und Forschung (2022). Berufsbildungsbericht 2022, available at https://www.bmbf.de/SharedDocs/Publikationen/de/bmbf/3/31749 Berufsbildungsbericht 2022.pdf

Franz, W., & Soskice, D. (1995). The German apprenticeship system. Institutional frameworks and labor market performance: comparative views on the US and German economies, 208-234.

Solga, Heike, Paula Protsch, Christian Ebner, and Christian Brzinsky-Fay (2014). The German vocational education and training system: Its institutional configuration, strengths, and challenges. WZB Discussion Paper No. SP I 2014-502.

Hoeckel, K., & Schwartz, R. (2010). A learning for jobs review of Germany. OECD Reviews of vocational education and training.

APPENDIX C: Details on the mediation analysis

In this section we discuss the mediation analysis reported in Table D.5.

Framework:

To explain the mediation analysis, we first re-write our baseline equation (6) using simplified notation as

$$y_i = a + bPEER_i + cX_i + \epsilon_{1i}. \tag{B.1}$$

For simplicity we have suppressed all subscripts other than i, we have renamed the treatment variable of interest as $PEER_i$ (the quality of trained peers), and we subsume all other right-hand side variables and fixed effects into X_i . Using the wage five years after exposure as an outcome, this equation measures the total spillover effect from trained peers, i.e., b=0.019 (see Table 2, Panel B, column 4). Now consider a set of P mediators M_i^p , for p = 1, ..., P. These are intermediate outcomes that can drive the wage effect, such as job tenure, or the quality of the firm a worker is employed at five years after exposure. Adding these mediators as control variables to equation (B.1) yields

$$y_i = d + ePEER_i + \sum_{p=1}^{P} f^p M_i^p + gX_i + \epsilon_{2i}.$$
 (B.2)

The coefficient e captures the direct effect of treatment on the outcome, conditional on mediators. Thus, e is the part of the effect of treatment that cannot be explained by the mediators. To complete the mediation model, consider a set of P regressions to capture the treatment effect on each of the mediators:

$$M_i^p = h^p + k^p P E E R_i + l^p X_i + \epsilon_{3i}^p, \qquad p = 1, ..., P.$$
 (B.3)

Each mediator's contribution to the treatment effect can be computed as $k^p f^p$, which is the product of how much the treatment shifts the mediator (k^p) , and how much the mediator affects the outcome (f^p) . Consequently, the total indirect effect that can be explained by the mediators is $\sum_{p=1}^{p} k^p f^p$.

To yield a decomposition that captures the true causal relationships, the mediation model would need to fulfil the following assumptions:

- (i) $PEER_i$ is exogenous in equations (B.1) and (B.3),
- (ii) $Cov(\epsilon_{2i}, \epsilon_{3i}^p) = 0$ for p = 1, ..., P (the mediators are exogenous),
- (iii) Any unobserved mediators are orthogonal to the observed mediators.

While assumption (i) is the same assumption on which our baseline empirical approach of equation (6) is based, assumptions (ii) and (iii) are strong additional assumptions. Assumption (ii) in principle requires an identification strategy for each of the mediator, while assumption (iii) requires that we observe all relevant mediators that are correlated with the included mediators. We therefore prefer to interpret the mediation analysis as a descriptive decomposition rather than giving it a causal interpretation.

Results:

In Table D.5 we present the results from the mediation analysis. Column (1) reports effects of a one-standard deviation increase in the peer quality of trained peers in the initial job on the mediators five years after exposure (k^p in equation B.3). In column (2) we show partial regression coefficients from our baseline regression equation (5) on wages 5 years after exposure, adding all the mediators as right-hand side variable (f^p in equation B.2). In column (3) we calculate for each mediator the part of the total treatment effect that runs through this mediator ($k^p f^p$, obtained as the product of the coefficients in columns 1 and 2). In the last column, we then express these indirect effects due to each mediator in percent of the total wage effect. We find that the mediators taken together explain 65% of the total effect, with by far the largest contribution coming from a better firm fixed effect (36%), followed by better peer quality (19%), having more labor market experience (5%), and being in a larger firm (3%). The contributions of all other variables are negligible.

APPENDIX D: Additional Tables

Table D.1: Top 20 occupations of unskilled job starters

Panel A: Overall Sample	
Occupation	Sample share
Cooks	6.6%
Warehouse transport workers	5.1%
Metal workers	4.8%
Packagers, goods receivers, despatchers	4.5%
Salespersons	4.4%
Construction worker	4.0%
Cleaners	3.5%
Gardeners, garden workers	3.4%
Plastics processors	3.2%
Waiters, stewards	2.6%
Office assistant	2.4%
Warehouse logistics worker	2.2%
Electrical appliance, electrical parts assemblers	2.2%
Housekeeping attendants	1.9%
Guest attendant, concierge	1.8%
Assembly worker	1.7%
Motor vehicle drivers	1.4%
Chemical plant operatives	1.3%
Laundry workers	1.1%
Meat, sausage goods makers	1.1%

Panel B: Sample of complex occupations

Occupation	Sample share
Metal workers	21.5%
Electrical appliance, electrical parts assemblers	9.8%
Assembly worker	7.8%
Chemical plant operatives	6.0%
Meat, sausage goods makers	4.8%
Clothing sewers	3.8%
Sugar, sweets, ice-cream makers	3.6%
Rubber makers, processors	3.1%
Machinery, container cleaners and related occupations	2.2%
Concrete workers	2.2%
Ceramics workers	2.1%
Sheet metal pressers, drawers, stampers	2.1%
Street cleaners, refuse disposers	1.9%
Sewer, seamstress	1.7%
Printer's assistants	1.7%
Food preparer	1.7%
Footwear makers	1.6%
Agricultural workers	1.5%
Vehicle cleaners, servicers	1.5%
Spinners, fibre preparers	1.3%

Notes: The table shows the twenty most frequent occupations for the sample of all occupations of untrained labor market entrants (Panel A), and for a subsample of occupations with more complex tasks (Panel B).

Table D.2: The Effects of Rank (Inverse Competition Effect, Complex Occupations)

Panel A: Mobility					
		Employed,	Move by	t+5 to new	
	_	t+5	Firm	Occupation	
	Rank	0.066	-0.035	-0.041	

No. of obs. 172,242 85,963 85,963

(0.003)

Panel B: Men vs Women

No

	Earnings, rel. to mean, t+5		Log Wa	ges, t+5
_	Men	Women	Men	Women
Rank	0.18	0.122	0.019	0.008
	(0.009)	(0.009)	(0.004)	(0.005)
o. of obs.	95,707	76,535	54,987	30,976

(0.005)

(0.005)

Notes: The table shows the effects of (standardized) rank of untrained labor market entrants among their initial peers (i.e., coworkers in the same firm and occupation at labor market entry) on career outcomes five years after labor market entry. Rank is based on residualized wages net of experience to capture current performance relative to expectations based on seniority. Rank is standardized; a one-unit increase in standardized rank corresponds to an increase in rank of about 30 percentiles. Earnings are set to zero for the non-employed and are divided by mean earnings. All specifications control for initial occupation × cohort effects, initial firm × occupation effects, average peer quality, average coworker age, the coworker shares of trained and college-educated workers, the coworker share of females, the wage in the initial job, age at labor market entry, and sex. Standard errors are clustered at the firm level.

 $Source: German\ Social\ Security\ Records\ from\ the\ \textit{Beschäftigtenhistorik}\ \ (BEH).$

Table D.3: The Effects of Average Peer Quality When Controlling for Rank (Knowledge Spillover, Complex Occupations)

	(1)	(2)	(3)	(4)	(5)		
	_		Log Wages, t+5				
	Employment,		Controlling for				
	t+5	Baseline	quality of peers in	Stayer	Mover		
			t+5				
Average peer quality	0.018	0.026	0.016	0.016	0.035		
	(0.007)	(0.008)	(0.007)	(0.010)	(0.011)		
No. of observations	172,242	85,963	85,963	47,003	38,960		

Notes: The table shows the effects of standardized quality of initial peers (i.e., coworkers in the same firm and occupation at labor market entry) on various career outcomes of untrained workers five years after labor market entry, controlling for the untrained worker's rank in the initial peer group (to capture competition effects). Average peer quality is standardized and measured by the average AKM wage fixed effects of coworkers. Rank among initial peers is based on residualized wages net of experience to capture current performance relative to expectations based on seniority. Earnings are set to zero for the non-employed and are divided by mean earnings. All specifications control for initial occupation × cohort effects, initial firm × occupation effects, the average coworker age, the coworker shares of trained and college-educated workers, the coworker share of females, the wage in the initial job, age at labor market entry, and sex. Standard errors are clustered at the firm level.

Table D.4: The Effects of Average Peer Quality When Controlling for Rank (Knowledge Spillover): Men vs Women (Complex Occupations)

	(1)	(2)
	Male	Female
Employment, t+5	0.036 (0.010)	0.025 (0.012)
Actual experience, t+5	0.166 (0.036)	0.083 (0.047)
Firm fixed effect, t+5	0.021 (0.006)	-0.004 (0.007)
Peer quality, t+5	0.111 (0.025)	0.059 (0.037)
Log firm size, t+5	0.133 (0.057)	0.023 (0.073)

Notes: The table shows the effect of the (standardized) quality of initial peers (i.e., coworkers in the same firm and occupation at labor market entry) on various career outcomes of untrained workers five years after labor market entry, controlling for the untrained worker's rank in the initial peer group (to capture competition effects). Results are reported separately for male and female untrained workers. Average peer quality is standardized and measured by the average AKM wage fixed effects of coworkers. Rank is based on residualized wages net of experience to capture current performance relative to expectations based on seniority. Earnings are set to zero for the non-employed and are divided by mean earnings. All specifications control for initial occupation × cohort effects, initial firm × occupation effects, the average coworker age, the coworker shares of trained and college-educated workers, the coworker share of females, the wage in the initial job, age at labor market entry, and sex. Standard errors are clustered at the firm level.

Table D.5: The Effects of the Quality of Trained Peers in First Job on Future Wages:

Mediation Analysis (Complex Occupations)

	Effect of	Dependent variable: Log wage in t+5			
	quality of trained peers on mediator	Coefficient of mediator on wages	Indirect effect due to mediator	Percent of total effect of 0.019	
	(1)	(2)	(1)×(2)		
Mediators					
Peer quality, t+5	0.042 (0.013)	0.086 (0.002)	0.0036 (0.0002)	19%	
Firm Fixed Effect, t+5	0.007 (0.003)	0.971 (0.012)	0.0068 (0.012)	36%	
Log firm size, t+5	0.044 (0.027)	0.012 (0.001)	0.0005 (0.0016)	3%	
Ever referred	0.002 (0.002)	-0.005 (0.002)	-0.00001 (0.00001)	0%	
Mean occupational log wage, t+5	0.004 (0.002)	0.027 (0.008)	0.00011 (0.0002)	1%	
Actual experience, t+5	0.029 (0.019)	0.033 (0.001)	0.0010 (0.00034)	5%	
Switching firm, t+5	-0.01 (0.009)	-0.007 (0.003)	0.00007 (0.0001)	0%	
Switching occupation, t+5	-0.013 (0.009)	-0.017 (0.002)	0.00022 (0.00004)	1%	
Total explained via mediators			0.012	65%	

Notes: The table shows results for a mediation analysis of the effect of the quality of the initial trained peers (i.e., trained coworkers in the same firm and occupation at labor market entry) on the wages of untrained workers five years after labor market entry; see Appendix C for details. The total wage effect to be decomposed is 0.019 (see column 4, Panel B of Table 2). Column (1) reports the effects of the quality of the initial trained peers on a range of mediators, using our baseline specification from Table 2 (Panel B). In Column (2), the dependent variable is the wage, and the baseline specification is extended by jointly including the mediators, the effects of which are reported in the column. Column (3) reports the product of columns (1) and (2), representing each mediator's contribution to the total wage effect. Column (4) reports the contributions in relative terms. Standard errors are clustered at the firm level.

Table D.6: The Position of Untrained and Trained Workers in the Firm
Hierarchy at Labor Market Entry

		<u> </u>		
	Firm wage decile			
_	(1)	(2)		
Trained	1.035	1.025		
	(0.006)	(0.011)		
Cohort effects	Yes			
Firm effects	Yes			
Occupation effects	Yes			
Age effects	Yes	Yes		
Cohort-firm-occupation effec	ct	Yes		
No. of observations	2,443	3,691		

Notes: The table reports the coefficient of a dummy variable for being a trained rather than an untrained labor market entrant on a worker's decile position in the firm-wage distribution (calculated excluding college graduates) in the first year of labor market entry.

Table D.7: The Effects of the Quality of Trained and Untrained Peers in the First Job on Future Earnings: Varying the Threshold Defining Complex Occupations

	Share of workers in complex occupations							
	10%	20%	25%	30%	40%	50%	60%	70%
Quality of untrained peers	-0.055	-0.056	-0.053	-0.052	-0.045	-0.045	-0.038	-0.035
	(0.017)	(0.011)	(0.010)	(0.010)	(0.007)	(0.007)	(0.006)	(0.005)
Quality of trained peers	0.042	0.035	0.037	0.03	0.021	0.018	0.012	0.008
	(0.014)	(0.010)	(0.010)	(0.009)	(0.007)	(0.007)	(0.005)	(0.005)
No. of observations	68,964	146,426	172,242	215,928	290,794	358,784	434,868	497,200

Notes: The table reports results for the effects of the quality of initial peers (i.e., coworkers in the same firm and occupation at labor market entry) on the earnings of untrained workers five years after labor market entry when varying the threshold used to define complex occupations. The column labeled "25%" corresponds to our baseline definition of complex occupations (i.e., occupations that fall within the 25% of workers reporting the lowest incidence of predefined tasks). Column titles indicate the alternative cut-off used to define complex occupations, varying between 10% and 70%. Earnings are set to zero for the non-employed and are divided by mean earnings. All specifications control for initial occupation × cohort effects, initial firm × occupation effects, the average coworker age, the coworker shares of trained and college-educated workers, the average quality of college-educated peers, the coworker share of females, the wage in the initial job, age at labor market entry, and sex. Standard errors are clustered at the firm level.