The value of complementary co-workers

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As individuals specialize in specific knowledge areas, a society’s know-how becomes distributed across different workers. To use this distributed know-how, workers must be coordinated into teams that, collectively, can cover a wide range of expertise. This paper studies the interdependencies among co-workers that result from this process in a population-wide dataset covering educational specializations of millions of workers and their co-workers in Sweden over a 10-year period. The analysis shows that the value of what a person knows depends on whom that person works with. Whereas having co-workers with qualifications similar to one’s own is costly, having co-workers with complementary qualifications is beneficial. This co-worker complementarity increases over a worker’s career and offers a unifying framework to explain seemingly disparate observations, answering questions such as “Why do returns to education differ so widely?” “Why do workers earn higher wages in large establishments?” “Why are wages so high in large cities?”

INTRODUCTION

The accumulated technological, cultural, and scientific knowledge of modern societies has expanded far beyond what an individual can master. To resolve the implicit tension contained in an inexorably expanding body of knowledge and individuals’ limited capacity to store and comprehend it, societies have relied on the division of labor (1–3). Division of labor allows a society to keep its collectively accumulated knowledge in working memory, as it were, by having its members specialize in different areas of expertise. To mobilize this distributed knowledge, individuals must pool their know-how and collaborate in teams. This necessity is manifested in the growth of teams across a range of human endeavors, from patenting (4, 5) to art and science (6), as well as in notions of intelligence as an attribute of collectives (7) in addition to of individuals.

This narrative challenges our traditional understanding of human capital. When the notion of human capital, essentially the quality of labor, was introduced in economics [e.g., (8, 9)], it expanded the list of conventional factors of production from land, labor, and physical capital to include a worker’s skills and know-how. This offered a rigorous way to think about investments in human beings. The original studies successfully applied the concept of human capital to shed light on the role of education for economic growth [for an overview of the impact of human capital theory in economics, see (10)].

To measure human capital, these early studies typically used years of schooling or work experience. Later, work went beyond such unidimensional metrics and described human capital in terms of the skills of a worker (11) or the task requirements of a job (12). Most recently, researchers have started to map the relations among skills using network analysis. For example, Anderson (13) examines what skills appear to be “synergistic” by observing how often pairs of skills are required in the same job, and Alabdulkareem et al. (14) argue that skills are “complementary” when they are used in the same occupations. Similar analyses have probed into complementarities between technology fields by observing what fields are jointly assigned to the same patent applications (15). Collectively, these studies emphasize that skills and technological expertise are inherently multidimensional concepts that are best described by networks to capture their inner structure as interdependencies among skill or knowledge elements.

While these past studies have firmly established that a skill’s usefulness depends on which other skills a person commands, their analyses focus on relationships between skills rather than between individuals. These studies are, therewith, anchored in an individualistic understanding of human capital. However, as knowledge becomes distributed, human capital acquires a distinct relational dimension: Each worker packages a specific set of skills, and, as a consequence, a worker’s productivity will depend on the skills of the people he or she works with. For instance, an anesthesiologist’s skills are of little value without a surgical team, and a mason cannot erect a functional building without the help of plumbers, electricians, and other skilled construction workers. Not unlike evolutionary biologists’ contention that an organism’s fitness should always be seen in the context of its relations to other organisms within its ecosystem [e.g., (16)], many of the highly specialized skills that we nowadays acquire would be meaningless—or at least devoid of value—if they were not accompanied by other people’s specializing in complementary skills.

The relational aspect of human capital has received attention in prior work on the assortativity of worker-worker (17) or worker-firm matches (18), as well as in the literature on macrolevel matching functions between workers and jobs [e.g., (19)]. In this type of research, skills and matches are either ranked along a single dimension (low to high) or understood as connecting workers to jobs. In contrast, the current paper proposes that there is a social dimension to human capital, rooted in a deepening division of labor that progressively distributes collective know-how. It focuses on the relation between a worker and his or her team of co-workers, is decidedly multidimensional, and emerges from the distribution and coordination of expertise across workers.

Exploring the merits of such an approach requires that we do not just observe a worker’s own skills but also the full set of skills he or she can mobilize through his or her co-workers. To do so, this paper exploits data from administrative records of Sweden. These records contain detailed information on the education and work histories for the entire Swedish population. Because of this, they do not only provide a high-resolution depiction of the know-how of a single individual but also allow describing how this know-how relates to the immediate knowledge ecosystem that is constituted by the skills of the team of co-workers in which he or she is embedded.

As in (13) and (14), this paper considers skills synergistic if they are often co-used. However, co-use of skills is now recorded at the
level of economic establishments: The appearance of multiple educational tracks among workers of the same establishment suggests that these educational tracks are synergic, just as multiple skills held by the same individual may be. This shifts the focus from synergies that occur between skills contained within the same worker to skills spread across different workers. Note, however, that in many establishments, several workers may have the same or similar skill profiles. Such co-workers may rather substitute than complement one another. To capture this, we will construct two separate networks. In the first, we will map what pairs of educational tracks suggest strong synergy by frequently co-appearing in the same establishments. In the second, we will map which educational tracks are substitutes, by observing which educational tracks allow a worker to do the same jobs, as expressed in the extent to which these educations give access to similar occupations. These networks allow us to observe and distinguish groups of skills that are synergistic and groups of skills that are substitutes. The complementarity to co-workers is now defined as the component of a worker’s synergy with co-workers that cannot be explained by his or her substitutability by co-workers.

This notion of co-worker complementarity proves to be a strong predictor of wages and career paths: The networks of educational synergy and substitutability predict what a worker will earn, based on whom he or she works with. In particular, workers with many synergistic co-workers but few substitutes earn higher wages. In addition, workers change jobs in ways that increase their complementarity to co-workers over the course of multidecadal careers. What is more, co-worker complementarity connects—and suggests a unified mechanism behind—a number of well-known, yet seemingly disparate, stylized facts: (i) Returns to the same education can vary widely across individuals, (ii) larger establishments typically pay higher wages to observationally similar workers, and (iii) wages are particularly high in big cities. These stylized facts describe different types of wage premiums that are typically analyzed in separate subfields of economics. However, the notion of human capital as distributed expertise suggests that these premiums may have a common origin: They do not reward an individual’s private human capital, but rather the context in which he or she operates. That is, these premiums would, respectively, reward the opportunities educated workers have to complement their co-workers, a deep division of labor in large establishments, and an easy formation of complementary teams in large cities. This claim resonates with prior work that has put forward matching as an explanation for these observations [see, e.g., (20) regarding urban wage premiums (UWPs) and (21) regarding returning to schooling]. In that context, the current paper can be regarded as substantiating this matching hypothesis. However, whereas matches often remained amorphous in this prior work (as in assortative matches or in worker-job or worker-firm matches of an abstract quality), the current paper pinpoints matches in the relation between the skills of workers and their co-workers, provides a unified explanation for why this particular match would give rise to various wage premiums, develops an empirical framework for quantifying this type of match, and tests its explanatory force across different phenomena within a single estimation framework.

Synergy, substitutability, and complementarity
To measure educational synergy, we will exploit the fact that some educational tracks are more often co-used in the same establishments than others. To quantify this co-use, we must first define what it means that an educational track is “present” in an establishment. Because certain educations are more ubiquitous than others, we follow (14) and say that education e is present in establishment (“plant”) p, \( P_{ep} = 1 \), if e is overrepresented in the workforce of p

\[
P_{ep} = \begin{cases} 1 & \text{if } \frac{E_{ep}}{E_p} > 1 \\ 0 & \text{elsewhere} \end{cases}
\]

where \( E_{ep} \) is the number of employees with education e in establishment p, and the omission of subscripts denotes a summation over the

MATERIALS AND METHODS
Data
Studying the complementarity between the skills of a worker and those of his or her co-workers requires data that not only describe skills of individuals in great detail but also record with whom each individual
omitted dimension (e.g., \( E = \Sigma_{e,p} E_{ep} \)). The quantity \( \sum_{\mathbb{E}/\mathbb{E}} E_{ep} \) is known as revealed comparative advantage in trade (23), the location quotient in geography and as lift or the (exponentiated) point-wise mutual information in machine learning. It compares the actual number of employees with education \( e \) in establishment \( p \) with the expected number of such employees, had employees chosen establishments at random in proportion to an establishment’s size.

Next, two educational tracks are said to co-occur if they are simultaneously present in the same establishment. To avoid that large establishments dominate co-occurrence counts, co-occurrences are not on a notonous transformation of the count. Therefore, educational synergy is quantified using the following monotonic transformation:

\[
\begin{align*}
\tilde{e}_{ce} &= \frac{N_{e'c}}{N_{ac}N_{e'c}} \\
\end{align*}
\]

\( \tilde{e}_{ce} \) is calculated by performing essentially the same operation as in Eq. 1: It takes the ratio of observed to expected co-occurrences, had co-occurrences formed at random. Note that \( \tilde{e}_{ce} \) is by construction distributed with a heavy right skew: for overexpressed pairs \( 1 < \tilde{e}_{ce} < \infty \), for underexpressed pairs \( 0 < \tilde{e}_{ce} \). At the same time, \( \tilde{e}_{ce} \) cannot be log transformed because it may evaluate to zero. Therefore, educational synergy is quantified using the following monotonic transformation of \( \tilde{e}_{ce} \):

\[
\begin{align*}
\epsilon_{ce} &= \frac{\tilde{e}_{ce}'}{\tilde{e}_{ce}} \left( e^{\tilde{e}_{ce}} + 1 \right) \\
\end{align*}
\]

which maps \( \tilde{e}_{ce} \) onto the interval \([0,1)\).

Note that not all skills that are co-used complement one another: Certain tasks are so common that they require establishments to hire several workers with the same skills. Therefore, some skills that are designated as synergistic may instead substitute each other. To quantify the latter, a second network is created to capture educational substitutability. Later, we will use this to define the complementarity of a worker to his or her co-workers as the synergy to co-workers that cannot be explained by his or her substitutability by co-workers.

The substitutability network aims to capture the fact that certain educations teach skills that are similar in the sense that they allow workers to carry out the same tasks. Taking occupations as bundles of tasks, the substitutability between educational tracks \( e \) and \( e' \) will be reflected in the occupational choices of workers with either education, i.e., by the similarity of the educations’ occupational employment vectors.

\[
\begin{align*}
s_{ce'} &= \text{corr}(E_{oce}, E_{oce'}) \\
\end{align*}
\]

where \( E_{oe} \) is the number of workers in the measurement sample with education \( e \) who work in occupation \( o \). The measurement of educational synergy and substitutability is summarized graphically in Fig. 1 (C and D).

**RESULTS**

**Educational networks**

The quantities \( c_{ce} \) and \( s_{ce'} \) form the basis of the educational synergy graph, \( G_{\text{syn}} = (\mathbb{V}, L_{\text{syn}}) \), and of the educational substitutability graph, \( G_{\text{sub}} = (\mathbb{V}, L_{\text{sub}}) \), where \( \mathbb{V} = \{e_1, \ldots, e_n\} \) is a collection of nodes (educations), and \( L_{\text{syn}} \) and \( L_{\text{sub}} \) are edge lists consisting of triplets \( (e, e', s_{ce'}) \), respectively \( (e, e', c_{ce}) \). Figure 1 (A and B) depicts these graphs using force-directed network representations, where node colors represent broad educational content areas, and node shapes represent educational levels. Edges are colored by their strength, ranging from blue to red.

A challenge in visualizing the co-use–based educational synergy network is that some edge estimates are based on very few observations. This happens when educations are found in only a handful of establishments. The consequent measurement error (section SD.3.1) will result in spurious edges, which clutter the graph’s layout and obscure its community structure. Therefore, the graph only shows statistically significant edges, using 99% Bonferroni-adjusted confidence intervals based on (24). To keep both networks comparable, the same number of edges is displayed in the substitutability network. Last, to ensure that the networks are fully connected, their maximum spanning trees are retained as well. The resulting networks consist of 491 nodes and 3283 edges.

Both networks tend to link nodes of the same color: Workers educated in the same broad field often work together and can also often substitute one another. The same holds for node shapes: Educations taught at the same or similar levels are relatively often connected. Section SB.4 analyzes this formally by studying the networks’ community structure. In both networks, communities are more homogeneous in terms of educational levels than what we would expect, had communities formed at random (Fig. 1E). However, this pattern is more salient in substitutability communities than in synergy communities. Apparently, having similar amounts of education is more important for workers to be substitutes, than for them to be synergistic. In contrast, no such difference between substitutability and synergy communities exists when it comes to homogeneity in educational content (Fig. 1F). Apparently, workers often work with others who are schooled in the same area of expertise, but at different levels. In contrast, to substitute one another, workers must have educations with, both, similar contents and similar levels. For instance, car mechanics may work with automotive engineers, but they cannot easily replace them. These nuances highlight the shortcomings of conceiving matches as being assortative or not: In reality, co-worker matchings occur in more complex spaces than along a unidimensional axis.

Communities also tend to be more tightly defined in the substitutability network than in the synergy network. Moreover, substitutability communities are often nested within synergy communities. Take, for instance, the community that is highlighted in the synergy network. This community is composed mostly of dark blue health care educations, but it also contains nodes with other colors, associated with administrative work (orange) and psychiatry (pink). In the substitutability network, this community becomes spread out across several smaller substitutability communities that are more homogeneous in colors. The interpretation of this is that, although it may be fruitful to combine expertise in psychiatry or health care administration with medical expertise, it is hard to substitute one for the other. Further examples are provided in section SB.4.

**Co-worker relations**

To assess the relation between a worker’s skills and the skills he or she can access in his or her work environment, we need to describe the relation between a worker and a set of co-workers, not between...
Co-worker synergy and co-worker substitutability are defined as the average educational synergies and substitutabilities of a worker to each of his or her co-workers:

\[ C_{w_{pt}} = \frac{1}{E_{p_{wt}}} \sum_{w \in P_w} C_{e_w} \]

\[ S_{w_{pt}} = \frac{1}{E_{p_{wt}}} \sum_{w \in P_w} S_{e_w} \]

where \( P_w \) denotes the set of workers in \( w \)’s establishment, \( p_{wt} \) \( E_{p_{wt}} \) is the number of workers in this establishment, and \( e_w \) is the education of \( w \). Note that, by definition, an educational track is a perfect substitute for itself: \( s_{e_e} = 1 \). For reasons of symmetry, the calculations above use \( c_{e_e} = 1 \) to quantify an educational track’s synergy with itself.

Co-worker synergy and substitutability are strongly and positively correlated (\( r = 0.69, N = 2,576,964 \)), supporting the idea that some co-workers who we determined to be synergistic may also easily substitute one another. The following ordinary least squares (OLS) regression Fig. 1. Educational synergy and substitutability networks. Who works with whom? Who can substitute whom? Educational tracks are connected if they often co-occur in economic establishments (A) or give access to the same occupations (B). In both cases, connections predominantly form between educational tracks with similar content areas (colors) or, albeit less so, similar levels (shapes). The highlighted community in the synergy network consists of health care–related educations. In the substitutability network, this community is distributed across several tighter substitutability communities, showing how both networks differ: Although medical secretaries and doctors complement each other, they cannot replace one another. Definition of metrics. (C) Synergy: Educations \( e, e', \) and \( e'' \) are overrepresented in establishment \( p \), creating co-occurrences \( e-e', e-e'', \) and \( e'-e'' \) that are scaled by the total number of co-occurrences (here, three) in \( p \). The synergy between \( e \) and \( e' \) is defined as the pairs’ overrepresentation in these co-occurrences across establishments. Last, the homogeneous transformation from \( e' \) to \( c \) reduces distributional skew. (D) Substitutability: Workers with educations \( e \) and \( e' \) choose different occupations. The substitutability between these educations is defined as the correlation between their occupational profiles. Heterogeneity in levels (E) and content areas (F) of educational tracks in synergy (blue) and substitutability (red) communities. Vertical lines: Average effective number of educational tracks per community in units of SDs of a simulated benchmark (shown in kernel density plots, details are provided in section SB.4). Synergy communities are less homogeneous in educational levels than substitutability communities, but both are similarly heterogeneous in content.
isolates the component of co-worker synergy that is orthogonal to co-worker substitutability

\[ C_{wp,t} = \alpha^c + \beta^c S_{wp,t} + m_{wp,t} \]  

(6)

where \( \alpha^c \) and \( \beta^c \) are intercept and slope parameters that may vary freely by year and by educational level. Note that by virtue of the OLS regression, the estimated residual, \( m_{wp,t} \), will be orthogonal to \( S_{wp,t} \).

It therewith represents the component of a worker’s co-worker synergy that cannot be attributed to his or her co-worker substitutability.

The next section shows that this component can be interpreted as the worker’s complementarity to his or her co-workers.

Note that the effect of co-worker complementarity on an outcome of interest can be assessed in two ways. We can either run a univariate regression of the outcome variable on co-worker complementarity or a multivariate regression of the outcome variable on co-worker synergy and co-worker substitutability. The partial regression coefficient for co-worker synergy in the latter type of model can also be interpreted as the effect of co-worker complementarity. According to the Frisch-Waugh-Lovell theorem, either approach yields the same result (albeit for this to hold exactly, any further control variables would need to be added to both equations).

Figure 2A plots average co-worker synergy against average co-worker substitutability by occupation for workers in the estimation sample. In this graph, co-worker complementarity, i.e., the residual of the regression fit, is expressed in the distance to the regression line. The regression line itself divides the plot into occupations that tend to work with complementary co-workers and those that tend to work with potential substitutes.

Complementarity is high in many knowledge-intensive jobs, such as in health care, engineering, and professional occupations (e.g., lawyers), but low in the lower-skilled work of elementary occupations (e.g., cleaners), machine operators, and services and sales jobs, all of which exhibit high levels of substitutability. Yet, not all low-skilled jobs have low co-worker complementarity. For instance, workers with lower-level educations in construction, such as carpentry, painting, and masonry, tend to be organized in teams of highly complementary co-workers. This shows that co-worker complementarity quantifies an aspect of human capital that is not easily captured by traditional, individual-centric, job categories such as those versus low-skill jobs or blue versus white collar jobs.

Similar patterns emerge when analyzing industries (Fig. 2B). Low-skill sectors like restaurants and hotels tend to hire mostly homogeneous workforces in which workers can easily substitute but not complement one another. However, among the economic activities with a high co-worker complementarity, we also find low-tech construction industries. Similarly, there is no strong connection between co-worker relations and the services-manufacturing dichotomy. Both manufacturing industries (blue squares) and business services (orange triangles) are found across a wide range of synergy and substitutability levels. Moreover, some low-tech manufacturing industries, like structural metal production, exhibit higher, not lower, levels of co-worker complementarity than, for instance, the pharmaceuticals industry, which is typically considered part of the so-called knowledge economy. Again, these examples show that traditional classification schemes, such as low versus high-tech industries and services versus manufacturing have no straightforward mapping to the co-worker quantities that are central to this paper. This shows that these co-worker quantities capture a different aspect of work and human capital.

**Wages**

How important are co-worker synergy and substitutability for workers? To explore this, Table 1 regresses the logarithm of a worker’s wage on his or her co-worker synergy and co-worker substitutability. Columns 1 and 2 show that, whereas co-worker synergy is positively associated with wages, the association of co-worker substitutability with wages is negative. Column 3 estimates the effects of co-worker synergy and substitutability simultaneously. Note that by doing so, this specification partials out the co-worker substitutability effect from the co-worker synergy effect. The co-worker synergy effect, therefore, now corresponds to the effect of what we labeled...
co-worker complementarity. The positive association of co-worker synergy with wages strengthens in this column, as does the negative association of co-worker substitutability with wages. This shows once more that the two concepts are related. Column 4 additionally controls for the size of the establishment and the worker’s age and level of education. Also with these controls, the associations between co-worker variables and wages remain strong.

How should we interpret these results? In economics, two production factors are formally defined to be substitutes [more accurately, q-substitutes (25)] if a relative increase in the supply of one coincides with a decrease in the marginal productivity (and, hence, the price, or here the wage) of the other. In the opposite case, the production factors are said to be q-complements. The negative association of what we have called co-worker substitutability with wages means that this variable behaves like a measure of q-substitutability, justifying its label. Likewise, the positive sign of the estimated parameter for co-worker synergy confirms that co-worker synergy (or better, its component orthogonal to co-worker substitutability) can indeed be interpreted as a measure of q-complementarity.

These estimated signs are highly robust. They neither change when adding further control variables nor when adding worker, establishment-year, or worker-establishment fixed effects, i.e., when controlling for a fourth-order polynomial of age, educational levels, and log_{10} (establishment size). All models contain year dummies. Model (4) implies that an increase from the 10th to 90th synergy percentile—a shift comparable to the shift in the educational distribution from primary school to college education—is associated with an increase in wages of 18.1%, whereas the same increase in co-worker substitutability is associated with a decrease in wages of 4.8%.

Table 1. Wage effects. Models (1) to (3) show regression analyses of log10 (wage) on co-worker synergy and substitutability, and model (4) also controls for a fourth-order polynomial of age, educational levels, and log10 (establishment size). All models contain year dummies. Model (4) implies that an increase from the 10th to 90th synergy percentile—a shift comparable to the shift in the educational distribution from primary school to college education—is associated with an increase in wages of 18.1%, whereas the same increase in co-worker substitutability is associated with a decrease in wages of 4.8%.

<table>
<thead>
<tr>
<th>Dependent variable: log(wage)</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Co-worker synergy</td>
<td>0.126*** (0.0025)</td>
<td>0.371*** (0.0036)</td>
<td>0.274*** (0.0030)</td>
<td></td>
</tr>
<tr>
<td>Co-worker substitutability</td>
<td>-0.061*** (0.0015)</td>
<td>-0.211*** (0.0021)</td>
<td>-0.044*** (0.0018)</td>
<td></td>
</tr>
<tr>
<td>Log(establishment size)</td>
<td>0.044*** (0.0003)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fourth polynomial of age?</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Educational level dummies?</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R^2</td>
<td>0.040</td>
<td>0.038</td>
<td>0.060</td>
<td>0.300</td>
</tr>
<tr>
<td># Observations</td>
<td>2,144,965 2,144,965 2,144,965 2,144,965</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># Clusters</td>
<td>364,642 364,642 364,642 364,642</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

***P < 0.01; **P < 0.05; *P < 0.1, SEs clustered at worker level.

Causal interpretation of these effects would require that workers were randomly assigned to co-workers. However, workers choose their jobs—and therewith their co-workers—purposively, and firms choose their workers deliberately, not at random. In section SD.2, the issue of causality is addressed by means of instrumental variable (IV) estimation. The effects in these IV models are substantially larger than those in Table 1 and similar in magnitude to the aforementioned noise-corrected effects. This suggests that the causal effects of having complementary co-workers substantially exceed the correlational estimates reported above.

**Careers**

If the wage effects in Table 1 truly are causal, workers should try to find work environments with high co-worker synergy and low co-worker substitutability. The table in Fig. 3 confirms that this is what workers do. It analyzes the likelihood that a worker switches establishments (column 1) or remains with one and the same establishment for a longer period (columns 2 to 4).

An increase in co-worker synergy is associated with a decrease in the likelihood that a worker switches establishments and with an increase in his or her likelihood of reaching long tenures. The implied effects are sizable: Moving from the 10th to the 90th synergy percentile coincides with a 2.5–percentage point (pp) lower switching rate, against an average ("base") switching probability of 13.7% (column 1) and with a between 9.2 and 12.0 pp higher likelihood of long tenures (over base probabilities of between 72.6 and 45.8%, columns 2 to 4). Substitutability, in contrast, is associated with higher switching rates and a lower likelihood of reaching long tenures. When comparing the 10th to the 90th substitutability percentile, expected switching rates increase by 1.3 pp and the likelihood of achieving long tenures decreases by between 3.5 and 5.8 pp.

A consequence of these job switching patterns is that a worker’s complementarity to co-workers rises over time. Figure 3A compares the rise in co-worker complementarity to a worker’s wage development, as depicted by a Mincerian wage curve (9). This curve shows the component of wages that cannot be explained by a worker’s level of education, \( \delta_{wp,t} \), as derived from the following regression

\[
\log_{10}(\text{wage}_{wp,t}) = \alpha_{lt} + \omega_{wp,t}
\]
The paper has focused on an inherently social aspect of human capital. Workers are more productive when they can specialize, but this requires that others "co-specialize" such that workers can complement one another. If this is true, the reward for labor will depend not just on a worker's own characteristics but also on the characteristics of the context in which he or she works. There are two well-known wage premiums that fit this description and that have attracted attention from economists. First, labor economists have shown that larger establishments pay higher wages to observationally similar workers. Second, urban economists have noted a strong positive relation between wages and the size of a city. This section shows that both premiums are related to—and dependent on—co-worker complementarities. Moreover, the same holds for a third well-known premium: The fact that workers with higher levels of education tend to earn higher wages.

**Education**

To start with the last premium, note that if societies use education to distribute knowledge across their members, more education should coincide with deeper specialization. This in turn would mean that, the higher educated workers are, the more dependent they will be on co-workers to complement their skills.

The table in Fig. 4 supports this conjecture. It shows that the estimated returns to co-worker complementarity rise with a worker's level of education. The exception are workers with postgraduate degrees. However, the sample of postgraduates is small and includes many workers with PhD degrees, who might be willing to trade higher wages for intellectual achievement in research careers.

Returns to complementarity vary substantially across educational levels. The increase in wages associated with a move from the 10th to the 90th percentile in co-worker synergy ranges from 5.8% for workers with upper secondary degrees to 47.7% for college-educated workers. The latter is almost on par with the 54% average (private) returns to a college degree itself (see section SF.1). Given that, due to measurement error, these parameter estimates represent lower bounds, the true complementarity premium is likely to surpass the private returns to college education.

The returns to co-worker complementarity exhibit a notable asymmetry. Whereas synergy and substitutability links between educations are, by construction, symmetric, their effects are not. Take, for instance, two workers who are highly synergistic. Assume now that one worker has a college degree, whereas the other only completed upper secondary education. Because the estimated synergies are the same in either direction, we would expect both workers to benefit from working together. However, the table in Fig. 4 suggests that these benefits are not divided equally but in favor of the college-educated worker. A possible explanation for this asymmetry is that higher-educated workers have a stronger bargaining position because their skills are less ubiquitous. Therefore, it may take an employer longer to find adequate replacements for them, allowing higher-educated workers to claim a larger share of the productivity gains.

As the returns to complementarity rise with the level of educational attainment, so do the returns to education rise with the complementarity to co-workers. Figure 4 (A and B) illustrates this by first splitting workers into quintiles of co-worker complementarity and then plotting how the returns to a given education vary across these quintiles.

In absolute terms, returns to skills in Sweden have been shown to be the lowest among a sample of 22 industrialized countries.

**Wage premiums**

where $\alpha_{lt}$ represents year-specific effects of educational-level dummies and $\delta_{wp,t}$ the regression's residual.

The graph shows that educational choices cast long shadows. For at least 20 years into their working lives, the average complementarity between the educational backgrounds of workers and their co-workers keeps improving. This does not only happen because workers tend to leave low-complementarity jobs (see table in Fig. 3), but also because they move to jobs with higher complementarity when changing employers. Figure 3B shows that the most pronounced complementarity-improving switches occur early in a worker’s career. Consequently, most improvements in complementarity happen within the first 5 to 10 years of a worker’s professional life. Taking both effects together, co-worker complementarity rises for about 20 years after a worker finishes his or her education and starts working (Fig. 3A). This is remarkable, given that complementarity is solely based on this educational attainment. Moreover, the concave curvature of the complementarity graph is remarkably similar to the one that describes the evolution of wage residuals, $\delta_{wp,t}$, corroborating the link between co-worker complementarity and wages. Section SF.2 shows that these patterns are highly robust across educational levels.

The returns to co-worker complementarity exhibit a notable asymmetry. Whereas synergy and substitutability links between educations are, by construction, symmetric, their effects are not. Take, for instance, two workers who are highly synergistic. Assume now that one worker has a college degree, whereas the other only completed upper secondary education. Because the estimated synergies are the same in either direction, we would expect both workers to benefit from working together. However, the table in Fig. 4 suggests that these benefits are not divided equally but in favor of the college-educated worker. A possible explanation for this asymmetry is that higher-educated workers have a stronger bargaining position because their skills are less ubiquitous. Therefore, it may take an employer longer to find adequate replacements for them, allowing higher-educated workers to claim a larger share of the productivity gains.

As the returns to complementarity rise with the level of educational attainment, so do the returns to education rise with the complementarity to co-workers. Figure 4 (A and B) illustrates this by first splitting workers into quintiles of co-worker complementarity and then plotting how the returns to a given education vary across these quintiles.

In absolute terms, returns to skills in Sweden have been shown to be the lowest among a sample of 22 industrialized countries.

**Fig. 3. Career paths.** Table: Linear probability models of workers’ switching establishments in a given year (column 1) or remaining for at least 2, 3, or 4 years with the same establishment (columns 2 to 4). The units of observation are worker-year combinations in column (1) and worker-establishment combinations in columns (2) to (4). “Base probability” provides estimated probabilities of switching or reaching long tenures for the average worker. SEs, clustered at the worker level (column 1) or at the establishment level (columns 2 to 4), in parentheses. The estimates show strong positive associations of employee retention rates with having synergistic co-workers and negative associations with having substitutable co-workers. Strong positive associations of employee retention rates with having synergistic co-workers and negative associations with having substitutable co-workers.
...there are clear positive gradients in the returns to education across complementarity quintiles.

**Large-plant premium**

The second wage premium we explore is the so-called large-plant premium (LPP): Workers in large establishments tend to earn higher wages than similar workers in smaller establishments. The premium is defined as the elasticity of wages with respect to the size of a worker’s establishment (i.e., the effect of the logarithm of the number of employees in an establishment on the logarithm of wages), or, equivalently, as the scaling coefficient of an establishment’s wage sum with its size minus 1. In the overall sample, the LPP is around 4%: For each doubling of the establishment size, wages go up by 4%.

Various mechanisms have been proposed to explain the LPP, ranging from rent sharing, to efficiency wages (i.e., high wages that prevent shirking because they make workers careful not to lose their jobs), to large plants’ greater capital intensity, and to assortative matching between workers and entrepreneurs [for an overview, see (29)]. However, could the LPP also depend on co-worker complementarities, just like the returns to education did? After all, large establishments allow for deep divisions of labor, which should allow workers to specialize more in the tasks they excel at. This increased specialization would make them more reliant on co-workers to complement their skills and, thus, provide a premium to working in complementarity-rich environments. Note that if this is true, workers in larger establishments should benefit more from co-worker complementarities.

Figure 5A shows that benefits of co-worker complementarity indeed rise with establishment size. To create these figures, workers were split into quintiles of establishment size. Interacting these establishment-size-quintile dummies with co-worker complementarity allows estimating quintile-specific returns to co-worker complementarity. The pattern that returns to complementarity rise as establishments become larger is even more pronounced in Fig. 5B, which compares wages of the same worker across different years in worker fixed effects models.

Figure 5C asks a related question: To what extent can co-worker complementarity account for the LPP? It shows how the estimated LPP changes once we control for synergy and substitutability among co-workers. When using the average co-worker synergy and substitutability variables, the estimated LPP remains unchanged: Co-worker relations cannot account for any of the observed LPP. This is to be expected: Co-worker synergy and substitutability are all but uncorrelated with establishment size. However, if we replace the average synergy and substitutability by co-workers’ by the number of highly synergistic co-workers and close substitutes in a worker’s establishment (see section SB.5), we can account for half of the LPP in the overall sample and for the entire LPP for workers with upper-secondary school degrees. This is remarkable, given that, on average, only 11.8% of co-workers are classified as highly synergistic and 8.6% as highly substitutable. This suggests that the LPP does not reward the overall size of an establishment’s workforce, but rather the size of a small subset of co-workers, namely, of the team of complementary co-workers.

**Urban wage premium**

Average wages rise not only with establishment size but also with city size. This phenomenon is known as the UWP in economics (30) or urban scaling in physics (31). The UWP is formally defined as the elasticity of local wages with respect to city size or as the scaling
Urban scaling and UWPs are often attributed to the fact that as cities grow larger, they allow for denser social interactions (31, 32) and provide better learning opportunities (33). Alternatively, they have been ascribed to efficient job matching in large labor markets (20). Here, a related explanation is put forward: Large cities facilitate the assembly of complementary teams.

Figure 5F shows that a substantial part of the UWP—up to 74% for the highest-educated workers—can be accounted for by co-worker synergy and co-worker substitutability. However, Fig. 5 (D and E) suggests that co-workers also matter in another way: Having complementary co-workers boosts the UWP, allowing workers to benefit more from their city’s size.

The variation in UWP across complementarity quintiles is remarkable: The UWP is almost completely contingent on workers’ having complementary co-workers, rising over fivefold from the bottom to the top complementarity quintile (Fig. 5D). Figure 5E shows that this gradient again is not simply due to sorting, i.e., due to large cities attracting better workers. This figure controls for worker fixed effects and therefore compares workers to themselves at different points in time. Together, these findings show that working in a large city benefits workers, but only those who manage to find complementary teams. Accordingly, both the LPP and the UWP are in part expressions of the social nature of human capital: These premiums reward workers for working with complementary co-workers.

**DISCUSSION**

When a society’s know-how exceeds individuals’ capacity to comprehend it in its entirety, knowledge must be distributed across different experts. As a result, human capital takes the shape of distributed expertise, and to be productive, workers require co-workers with different, yet complementary, skills. The notion that the division of labor allows a society to reap the benefits of specialization is as old as the discipline of economics. But specialization also creates interdependencies. To capture this, where most work on human capital focuses on the skills of individual workers, this paper investigated the interconnectedness of human capital. It did so by exploring the web of skill interdependencies in teams of co-workers, using networks that express synergy and substitutability among detailed educational tracks. These networks matter. To earn high wages, it is insufficient to be highly skilled oneself: Workers must also find co-workers with skills that complement but do not substitute their own.

The returns to having complementary co-workers are qualitatively important: For highly educated workers, they are comparable to the returns to having a college degree. Superficially, the importance of co-worker complementarity resembles the notion of peer effects in labor economics. However, peer effects, as well as the econometric challenges they pose, emerge when outcomes depend on the average characteristics of members of the same group [e.g., (34)]. In contrast, co-worker synergy and substitutability describe relations among co-workers. That is, whereas peer effects are due to the characteristics of neighboring nodes in a co-worker network, the role of complementarity and substitutability derives from the network’s edges. A closer connection exists to the literature on labor market matching. From this perspective, the paper defines a specific type of labor market match. However, this match is not unidimensional, as in assortative matching, but exists in a two-dimensional plane spanned by complementarity and substitutability. Moreover, this match exists among co-workers, not between a worker and a firm or between a worker and a job.

The study has some important limitations. First, a salient question is how well the findings in this paper translate to other settings. For instance, the modest returns to a worker’s own skills in Sweden suggest that the returns to skills of co-workers may also be higher in other countries. Second, the data only allowed defining skills in

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Fig. 5. Wage premiums. (A) Effect of co-worker complementarity, $m_{swpt}$, on wages in establishments of different sizes while controlling for workers’ age and educational level. As establishments become larger, the estimated benefits of having complementary co-workers increase. (B) Idem, adding worker fixed effects. (C) Estimated LPP for workers with different levels of education using no control variables (blue bars), controlling for the weighted average co-worker synergy and substitutability of Eqs. 4 and 5 (light red) and controlling for the logarithms of the number of co-workers that are highly synergic or close substitutes (dark red). The figure shows that, although the benefits of working in large establishments cannot be explained by workers’ average co-worker synergy and substitutability, for workers with over upper secondary schooling, they can be fully explained by the greater number of highly complementary co-workers in large plants. (D) UWPs by complementarity quintile, estimated by regressing the logarithm of wages on the logarithm of total employment in a labor market area. The UWP rises from below 1% to above 9% for each doubling of a region’s size when comparing workers in the bottom to workers in the top complementarity quintile. (E) Idem, adding worker fixed effects. (F) Idem (C), but now for the UWP. The worker-count controls can account for 21% of the UWP for workers with postsecondary degrees, 34% for college-educated workers, and 74% for workers with postgraduate degrees. This shows that, especially for higher educated workers, an important part of the high wages earned in large cities can be attributed to the co-worker environments these cities offer.
terms of formal degrees. This ignores skills that are acquired through work experience and through on-the-job training. Therefore, co-worker synergy and substitutability only approximate the actual skill interdependencies among co-workers. Future research could instead start from data on workers’ complete skill profiles. Third, we have interpreted a worker’s wage as a proxy for his or her productivity. However, wages do not just depend on a worker’s productivity but also on his or her bargaining power. This may, for instance, explain why returns to co-worker complementarity are asymmetric, favoring higher-educated workers. With information on a team’s collective output, complementarity effects can be assessed in a more direct way. Fourth, and related to this, the complementarity in this paper refers to a specific type of skill complementarity, namely, the complementarity that needs such close coordination that it must be organized within one and the same economic establishment. However, as in (13, 14), some skills need even closer coordination and therefore coincide within a single individual. At the other extreme, the complementarity between a cotton farmer and a tailor is coordinated through a long value chain. Bargaining takes different forms across these different modes of coordination, from the tight collaboration in co-worker teams studied in this paper to arms-length sourcing between customer and supplier firms. How the surpluses from collaboration will be divided in each case depends on how bargaining is structured. Fifth, the paper focused on co-worker complementarity in the labor market as a whole. If co-worker complementarity indeed reflects a society’s need to divide labor to accommodate an increasing body of collective knowledge, complementarity effects should be strongest at the knowledge frontier. In line with this, returns to complementarities proved highest at the highest levels of education. However, co-worker complementarities may play an even more important role in collaborative efforts that aim to move the frontier of our collective knowledge. In these efforts, they may manifest themselves not as higher wages but as new ideas and technologies, as reflected in academic papers and patents.

In practical terms, the findings in this paper suggest new ways of matching workers to jobs based on an assessment of how well their qualifications complement the workforce of potential employers. However, they also have consequences beyond individual careers, shedding light on the inner workings of economic establishments and challenging us to rethink cities as places where economic complexity is organized. Moreover, the existence of educational complementarities means that investing in skills only pays off if others invest in complementary skills. Complementarity may therefore create coordination challenges in economic development. If educational tracks are complements, it is insufficient that the education system produces skilled individuals. Instead, when a country invests in schooling to upgrade its labor force, it will have to produce the entire skill ecosystems these individuals need to thrive.

SUPPLEMENTARY MATERIALS
Supplementary material for this article is available at http://advances.sciencemag.org/cgi/content/full/5/12/eaax3370/DC1

Fig. S1. Part-time work in Sweden.
Fig. S2. Scatter plot of educational synergy against educational substitutability.
Fig. S3. Educational synergies network.
Fig. S4. Educational substitutability network.

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Data and materials availability: The data were derived from Swedish administrative and tax records. They can therefore not be shared. However, all results can be replicated with the original data, access to which can be requested from Statistics Sweden (online instructions are provided here: www.scb.se/en_/Services/Guidance-for-researchers-and-universities/MONA/). Further data visualizations and the code to reproduce the paper’s findings can be found here: https://growthlab.cid.harvard.edu/academic-research/complementarity. Furthermore, the Harvard Institutional Review Board has determined that the data used in this research are not human subject, security level 1. Additional data related to this paper may be requested directly from the author.

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