Specificity of Human Capital: An Occupation Space Based on Job-to-Job Transitions

Eduardo Levy Yeyati and Martín Montané

CID Faculty Working Paper No. 379
April 2020

Working Papers
Center for International Development
at Harvard University

Specificity of human capital:

An occupation space based on job-to-job transitions

Eduardo Levy Yeyati

Martín Montané

Introduction[1]

The question of whether human capital is general or specific has been extensively studied in recent decades. Two factors have contributed strongly to this phenomenon: 1) a growing penetration of technology that could replace labor in various production processes, and the concerns associated with technological displacement, and 2) the emergence of new high-quality datasets relevant to these investigations.

Advances on this topic have appeared mainly in countries where administrative data is most accessible or long-standing panel type surveys are available. Because of that, the literature that analyzes labor mobility in a more granular form are available only for developed economies such as the United States, Germany or the UK, with conclusions that cannot be extended to developing ones without accounting for differences in human capital, labor regulations and the prevalence of informality.

For example, there is evidence that the distance between the skills requirement in the job before the transition and after the transition is highly correlated with the size of wage losses of displaced workers in the US (Poletaev and Robinson, 2008). There is also evidence of occupation-specific human capital in the US using long-term panel data (Kambourov and Manovskii, 2009) and in the UK (Zangelidis, 2008), task-specific human capital in Germany (Gathmann & Schonberg, 2010), occupation and industry specific human capital also for the US (Sulivan, 2010), to name some of the most relevant articles written about this topic.

In the case of Argentina, there is not yet a publicly available database that is suited to answer the question of whether human capital is specific. In this paper, we follow the methodology used by Neffke, F., & Henning, M. (2013), to answer our question: is human capital specific?

We address this question in two steps. First, we build an occupation space based on the turnover data –specifically, on the propensity to move from one occupation to the rest– from which extract a measure of the relative similarity between pairs of occupations. Second, we estimate the incidence of this similarity on the variation in wages when workers change occupations and show that similarity correlates positively with the wage increase associated with the change.

We interpret this result as indicating that the relative similarity in the Occupation Space captures, at least partially, the worker´s specific human capital: closer occupations share similar skill demands and task composition, in other words, demand similar workers, under the assumption that the wage

[1] We believe that replication of scientific studies is a necessary condition for the improvement of science. Codes and data are publicly available at https://github.com/martinmontane/OcupacionesEPH_WP. Any error or suggestions in the code or data will be most welcome at martinmontane@gmail.com

measures the worker´s marginal productivity and that this productivity is a function of the degree to which the worker matches the demands of the job.

To the extent that this relative similarity provides information about the characteristics (for example, the required skills, tasks and experience) of actual jobs, the findings of this paper could be a useful variable to orient employment and reskilling services to occupations that are not that far away from where the worker comes from. While, as noted, the results are country-specific, the methodology could be easily extended to other countries, and to more granular task data whenever available.

Similarity between occupations: Methodology

The methodology used in this work is based on the theoretical contributions of the literature of economic complexity (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009; Neffke and Henning, 2013; and Neffke et al. 2017). The objective of this literature was to identify similarities (for example, between national productive capacities, or skill demands) base on observed flows (international trade, workers´ transitions) between nodes (countries, occupations).

This approach requires a "base case" flow between the nodes, defined as the expected flow in the absence of a specific attraction between a pair of nodes. Once the expected flow is identified, this value is compared to the observed flow and conclusions are drawn based on the flow differences.

This way of detecting non-random patterns has analogies in other domains; for example, in spatial statistics, to compare crime rates in different regions relative to the average, which indicates a random distribution in spatial terms, or in the methodology used for contingency table tests (de Raco and Semeshenko, 2019).

However, the strategy used to determine the selection of this base scenario has varied throughout literature. In particular, Hidalgo et al. (2007) create this base scenario using Balassa's (1986) concept of Revealed Comparative Advantage (RCA). Analyzing international trade between countries they define the RCA of country *c* in product *p* as:

$$RCA_{cp} = (VE_{cp} / \sum_{p=1}^{P} VE_{cp}) \,/\, (\sum_{c=1}^{C} VE_{cp} \,/\, \sum_{c=1}^{C} \sum_{p=1}^{P} VE_{cp})$$

where VE_{cp} is the exported value of the product *p* by country *c*. Thus, a value less than one in this indicator implies that the country exports a lower proportion of that good relative to the global average, and a value greater than one implies the opposite. Therefore, the expected flow is the value that would have been observed if the export of that product were distributed evenly across countries.

This notion can be adapted to the movement of workers between occupations simply by observing the flows of workers (renamed *F*) coming out of occupation *i* to occupation *j*. Following Neffke et al. (2017), we establish the expected flow of workers between occupations combining the outflows from and inflows to the occupations between which the workers moved. If the relative output and input size could be used to explain the flow of workers, then the expected flow between occupation *i* and *j* would be given by $\widehat{F_{i,j}} = \frac{F_{i,*} * F_{*,j}}{F_{*,*}}$. In this way, we can measure the "likeness" between occupations by the ratio between expected and observed flows, which, after a small algebraic arrangement, takes the following form:

$$R_{i,j} = \frac{F_{ij} * F_{*}}{F_{i,*} * F_{*,j}}$$

where asterisks (*) refer to all sectors. In this way, the similarity R_{ij} between occupation *i* and occupation *j* is given by a variable that goes between zero and infinite. A value smaller than 1 implies a movement of workers below the expectations, while one greater than 1 implies the opposite. However, this similarity has an asymmetric distribution, with extreme values on the positive side. To count with a measure that is symmetrically distributed around a value (0) we make the following transformation:

$$\overline{R_{i,j}} = \frac{(R_{ij} - 1)}{(R_{ij} + 1)}$$

This measure of similarity is symmetrical and bounded between -1 and 1.

Data: Permanent Household Survey

We use data from Argentina´s Household Survey (EPH), which systematically collects information on the socio-economic situation of most of Argentina's urban areas, reaching approximately 64% of the country's population. The survey is carried out continuously and on a quarterly basis since the second quarter of 2003, with some missing quarters in 2007, 2015 and 2016. Like many household surveys in other countries, the sample design has a rotating nature: the same home is surveyed for four noncontiguous quarters. A household is surveyed twice in a row, stays out two quarters, and is surveyed again for two additional quarters. In this way, the job dynamics within an individual household is observed for a maximum of approximately 18 months. This work exploits these time windows to work with short panels and compute transitions across occupations and infer similarities between occupations based on those transition flows.

Occupations are included in the National Occupational Code (CNO/2001). It is a hierarchical occupation classifier, in which the first two digits correspond to occupations with a high level of aggregation, while the rest of the digits refer to the level of qualification, technology, and hierarchy.

We are interested in the switched between occupations, as opposed to qualification, technology or hierarchy, so only the first two digits of the CNO, those referring to the occupation group, are taken into account. In total, these are 52 large occupation groups (see Annex Table 1). In addition to this data, we have information on income from the main occupation, which will be used to analyze the relationship between change of occupation and change in wages.

Although these are short trajectories, they are comparable to those used by Nedelkoska et al (2018), who looked at monthly data from the U.S. Current Population Survey (CPS), with a 15-month time window virtually identical to the one of the EPH.

A factor relevant in the measurement of the similarity between occupations is the regional dimension of labor markets, namely, the presence of commuting zones. To the extent that flows can be in part explained by the simple fact that some occupations are more in demand in some commuting zones, aggregated flows at the national level would mask this effect and measure similarity inconsistently. For this reason, in this paper we work only with data from the Buenos Aires metropolitan area, which for practical purposes can be considered as a single commuting zone. This leaves us with 212,455 observations from people who at least once reported to be working while they were in the survey.

The next step is to determine when a person changed jobs. This is far from trivial, as the literature has already noted (Kambourov and Manovskii, 2009). To do that, we use two criteria: a *seniority rule* and an *interim occupation rule*. In the specific case of the EPH, there is a question that informs the respondent´s seniority in her principal occupation. Base on this question, we can identify when there is a job change –and, if so, whether there is an occupational change– whenever the time difference between the surveyed quarters is greater than seniority. We also considered that there is an employment transition whenever a person reports being unemployed or inactive between two observations in which he reports being occupied (regardless of the seniority rule). Based on these conditions, we identify 9,299 job changes between 2003 and 2019.

Descriptive transition analysis

Before displaying the analysis of the resulting graph and estimating the regression and machine learning models, in this section we focus on the detected transitions and the robustness of the switch detection. Of the 9,299 transitions, 3,717 correspond to the interim occupation rule, while the remaining 5,582 were detected through the seniority rule.

The importance of differentiating these labor transitions is that we expect a different wage impact: specifically, ceteris paribus, the wage change after an unemployment spell may be differ from that after a job-to-job transition. On the one hand, people may be inactive/unoccupied during the transition because they are more demanding, so that, when they finally get a job, it is on average better than those that move without waiting. On the other hand, it is also likely that those who go through unemployment or inactivity should be cash-strapped or may have more difficulty in getting a new job, including because of the negative signaling effect of unemployment, so that they may be willing to move to an occupation further away from its expertise and accept a lower pay.

Figure 1 shows that job insertions are indeed different between the two groups: switchers that go through a period of unemployment or inactivity make less money than the rest. This difference, however, relates to wage levels and does not extend to *changes* in wages, as we will see. The relevance of distinguishing the different transition types is highlight in more detail below.[2]

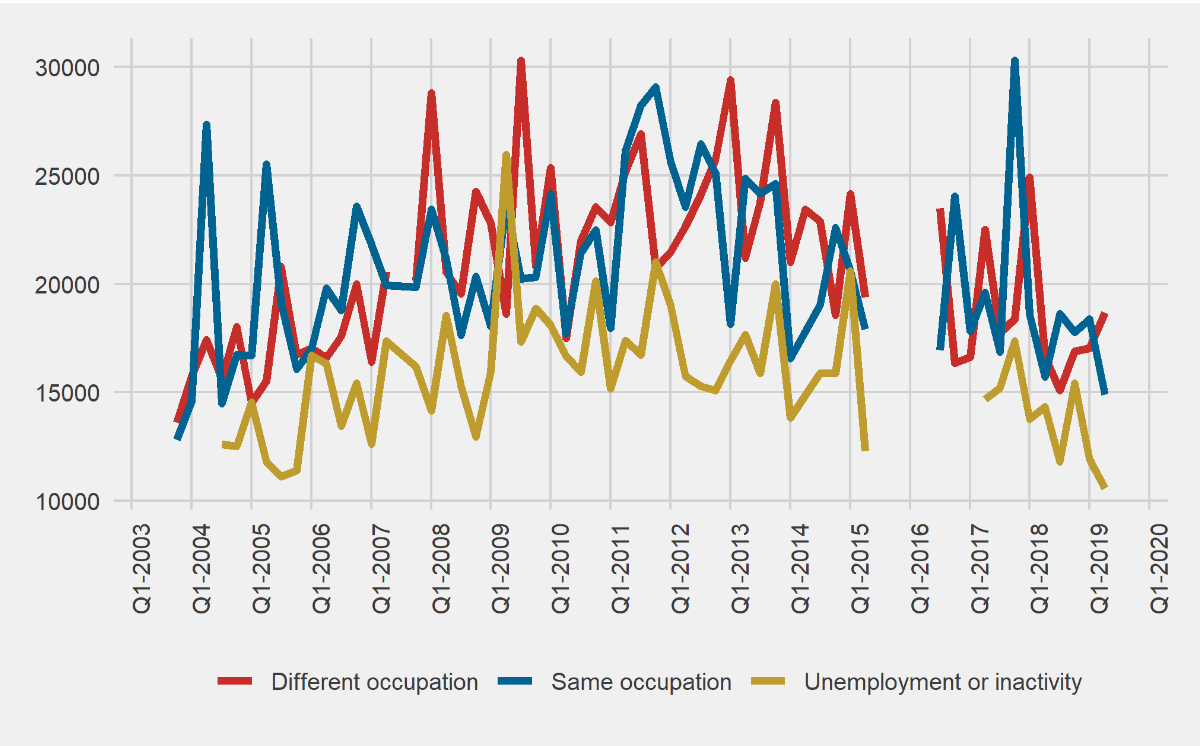

Figure 1. Evolution of the real wage of the main occupation according to the type of transition. Different occupation: they changed jobs from one occupation to a different occupation; same occupation: they shifted employment towards the same occupation; inactivity: they changed jobs and went through a period of unemployment or inactivity. Own elaboration based on the Permanent

[2] This period coincided with a sample change in the EPH, which could partially explain this change.

Household Survey (EPH) and Consumer Price Indexes (CPIs) of provincial statistics and census addresses and INDEC.

The National Occupational Code (CNO) is another important restriction for the analysis. The Annex describes the occupations that we are working with, a classification with a considerable degree of aggregation. Thus, a handful of occupations explain more than 50% of the transitions between occupancy groups (Figure 2) –indeed, only two occupations (construction and commerce) account for almost 33% of departure and arrival occupation groups (we come back to this below).

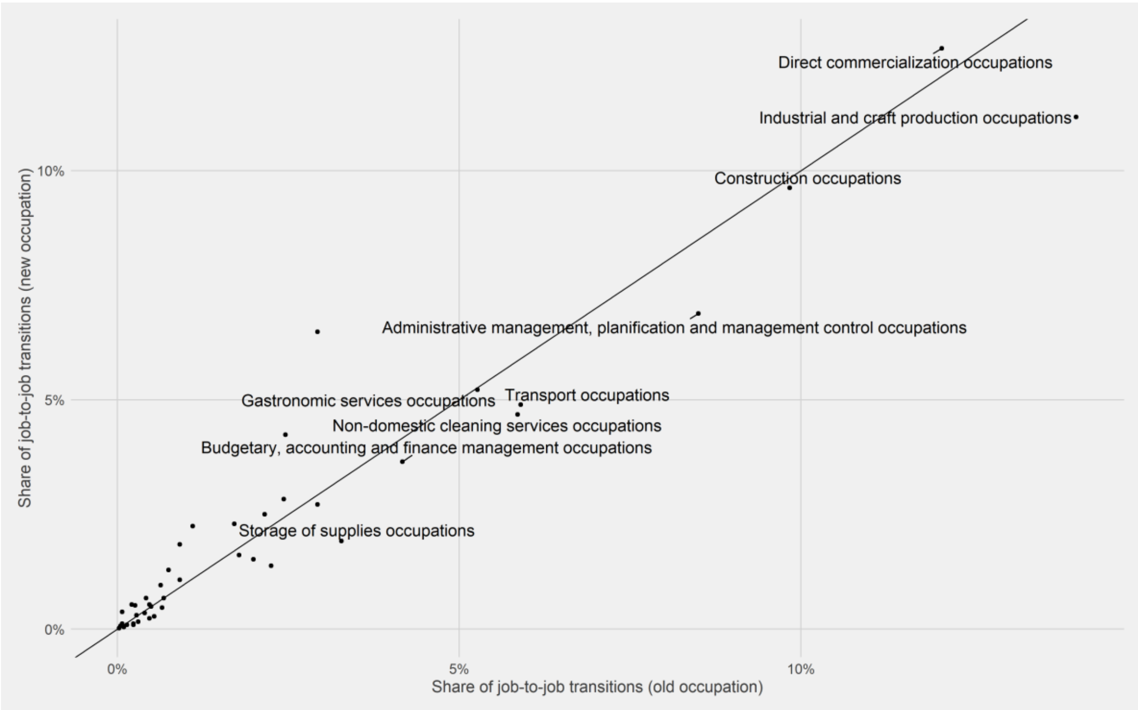

Figure 2. Distribution of occupations according to their participation in the total of transitions such as departure (old) and arrival (new) occupations. Elaborated by the authors based on the Permanent Household Survey (EPH).

Figure 3 shows the distribution of the similarity between each pair of occupations for the complete sample. In that plot we remove all pairs reporting a similarity index of -1, because a high number of pairs can be observed at the lowest part of the distribution showing almost no connection between them due to the fact that some small sectors are not fully captured by the EPH-based analysis.

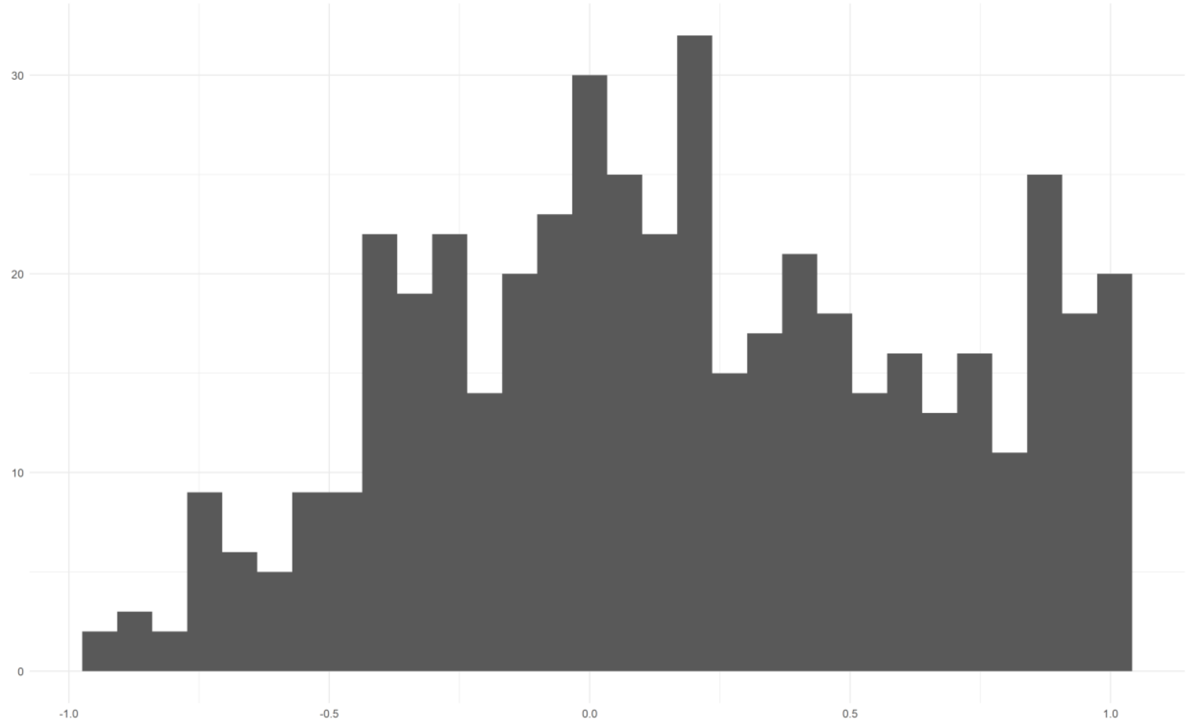

Figure 3. Similarity distribution between pairs of occupations. Elaboration by the authors based on data from the Permanent Household Survey (EPH). Values of -1 are excluded from the plot.

In turn, Figure 4 shows the density map of similarity between the occupations analyzed with the formula based on Neffke et al (2017), centered on 0 and with limits between -1 and 1. As can be seen, the main diagonal shows the highest values in the measure of similarity derived simply from observing the flows between occupations and comparing them against a theoretical expected flow.

Even more interesting is the fact that the similarity measure appears to have high values in areas close to the main diagonal, while values represented by dark colors (low) are in the regions farther away from this diagonal, on average.

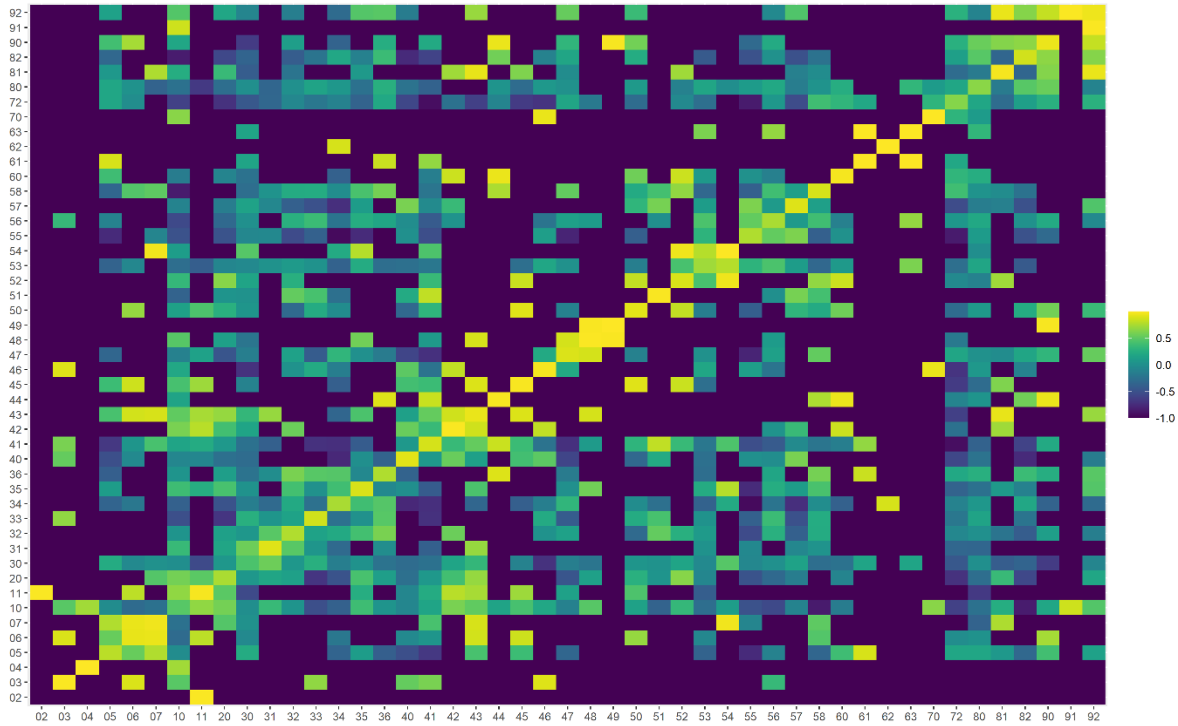

Figure 4. Density map among occupations of the National Occupation Code (CNO) based on data from the Permanent Household Survey (EPH)

This pattern suggests that the most common occupational transitions occur between occupational groups that generally have some similarity according to the CNO. This can be inferred form the high values along the main diagonal, which shows the similarity between the same CNO code and neighboring codes. The density also shows how many occupations are disconnected based on job-to-job transitions (similarity value of -1), but only a few are heavily connected occupational codes.

This pattern is similar to that observed by Montané and Sartorio (2019) and De Raco and Semeshenko (2019) for transitions between activity sectors, both based on the Permanent Household Survey (EPH) and administrative data from the Argentine Integrated System of Pensions (SIPA) –as well as that found, for country exports, by Hidalgo et al (2007).

The occupational space

We can express this measure of similarity between occupations through a weighted graph, as shown in Figure 5, based on all occupational codes, with the exception of managers and high-ranking officials in the government, and their ties to other codes. The width of the lines between a pair of nodes is proportional to the size of the relationship between the nodes, while the size of the node represents the strength of each node –where the strength is the weighted graph's adaptation of the node degree, which shows the sum of all the links to other occupations, taking into account the intensity of the attraction.

In the figure, we can see that that some occupations are closely linked to many other occupations. This is the case, for example, of consulting, recreative services, administrative management, planification and management control, and education, among others. By contrast, two occupations that explained 14% of the total employment in 2019 (construction and domestic services) show little connectivity to other nodes.

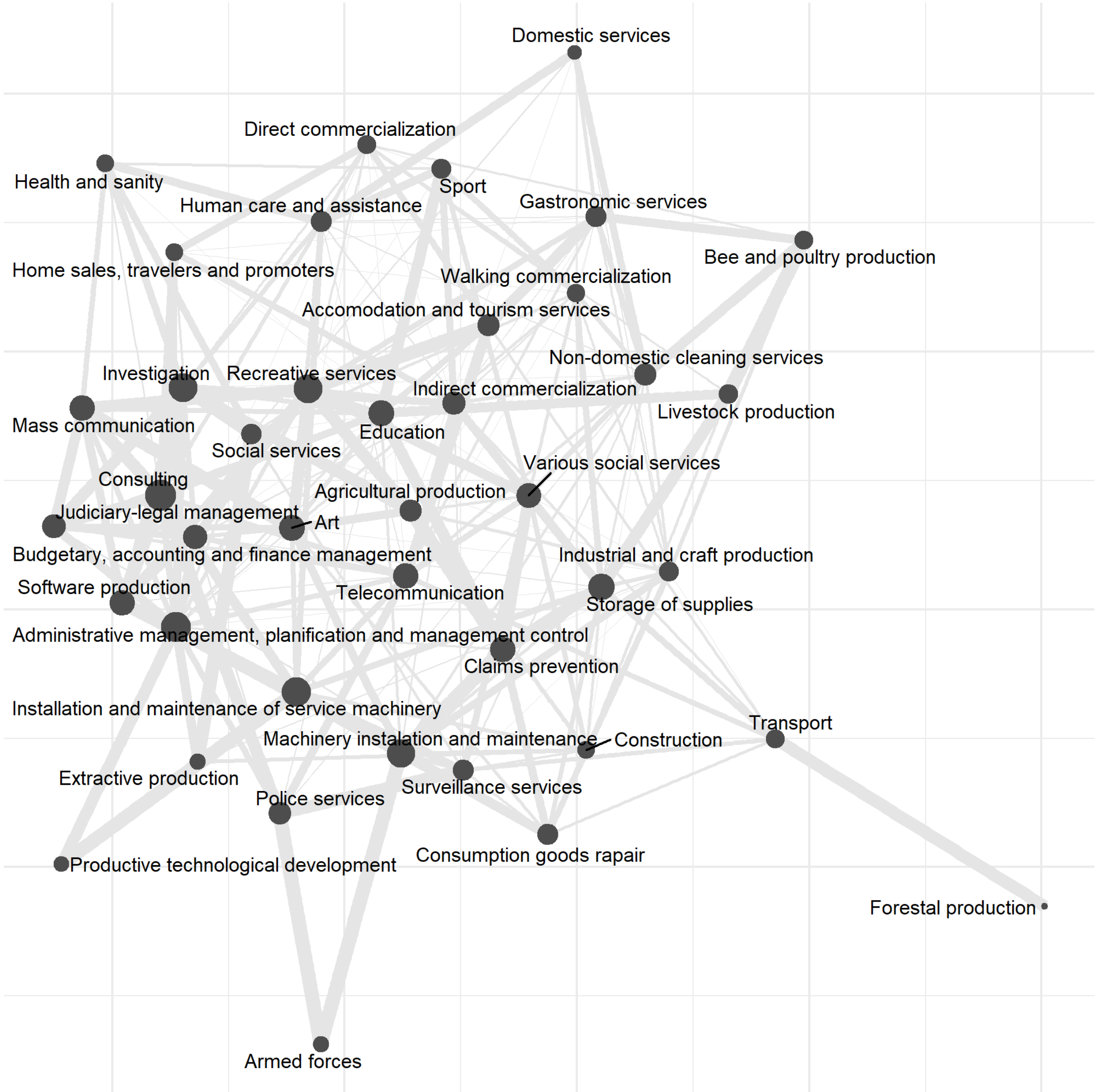

Figure 5. Weighted graph of occupation codes the transitions from the Permanent Household Survey (EPH). Negative similarity values are excluded.

Although self-loops (self-similarities) are excluded from the graph, it is interesting to observe that transitions between same occupations are the rule rather than the exception. As an example, 7 of the 10 edges with the highest similarity value and more than 43.5% of all job changes occur between the same occupations.

This pattern is not unusual. The economic literature has studied the specificity of human capital at the level of occupations and tasks, finding important economic returns associated with practicing the same occupations or tasks for years. Nedelkoska et al (2018) has found that the similarity between tasks, estimated the same way as we built ours for occupations, help predict wage changes –an exercise to which we come back below.

What can we say about central occupations in the constructed graph? The distribution of strength can give us information about what occupations are more directly related to other occupations (Figure 6): the first 5 occupations with greater *strength* are those linked to consulting, administrative management, planification and management control. In addition to the aforementioned domestic services and construction, transport and industrial and craft productions also have low "attraction" to other occupational codes.

Figure 6. Strength of each of the vertices (occupations) of the weighted and addressed graph of occupations based on the transitions detected in the Permanent Household Survey (EPH)

The specificity of human capital

Several studies have examined in depth how general our human capital is (Poleteav and Robinson, 2008; Kambourov and Manovskii, 2009; Gathmann & Schonberg, 2010; Sulivan, 2010; Yamaguchi, 2012; Nedelkoska et al; 2018). By human capital, we mean a set of intangible knowledge and experience that makes it possible for us to perform tasks and occupations in a successful way.

Knowing how specific our human capital is becoming especially relevant from the viewpoint of labor reconversion and reskilling. If human capital was not specific, it would be easy for a worker to find a new career path in the event demand for her occupation or tasks began to decline. But, if moving between occupations or tasks comes at a significant cost in terms of worker productivity, then the costs of reconversion are high and a set of informed policies that allow for a smoother transition between occupations through adequate reskilling provides an invaluable tool, particularly when a crisis hits sectors deeply and unevenly, and labor turnover peaks.

Ideally, testing the link about turnover and human capital loss requires some measure of worker productivity before and after a move, correcting for the seniority she has in each of the occupations. Unfortunately, productivity is not usually captured in household surveys or administrative data, and even if they do, the purely observational nature of these measures would fall short of what we need for a rigorous test.

Because of that, empirical research often resorts to an imperfect measure of labor productivity: the wages perceived by the worker. Along those lines, Kambourov and Manovskii (2009) find that, after time-monitoring the employer and the activity sector, seniority in the same occupation explains a significant part of the wage received. Gathmann and Schonberg (2010) go further and, based on administrative data from Germany with a disaggregation of tasks at the individual level, manage to identify a specific effect associated with the time that a worker has been performing the same task. Closer in time, Nedelkoska et al (2018) find that similarity between the occupations, measured in terms of the task-intensity, is a good predictor of wage changes.

The Permanent Household Survey allows us to perform a similar exercise for a developing economy: Argentina. The simplest way to relate similarity with wages is by adding similarity between occupations as a control to explain changes in wages. One of the challenges of building a regression based on the *leaps* between jobs is that economic theory is more informative about the *level* of wages than it is about their short-term variation. In fact, the Mincer equation, one of the most widely used wage models, only includes variables that in the short term can be considered constant (such as educational level or years of work experience).

Due to the lack of a theoretical benchmark, we estimate several econometric models that control for different variables that can affect the wage variation before and after a job change, starting from the most basic model, defined as follows:

$$(1)\ \Delta RealWage = c + R_{ij}$$

where $\Delta RealWage$ refers to the average quarterly change of the worker's real wage and R_{ij} the similarity between the exit and destination jobs, and c is a constant that represents the average wage variation.[3]

Although 8,249 job-to-job transitions were available, only 5,640 cases contain simultaneously data on wages and data on hours worked (different from zero). The expected sign of the coefficient associated with the variable of similarity between occupations is positive, since greater similarity between the new occupation and the previous one should be associated with a smaller human capital loss (a higher new salary relative to the initial one) and vice versa.

Table 1 shows the main results in the four alternative takes on the simple model (1) (see Annex 2 for a description). If the regression is estimated based on the total number of job-to-job transitions, we find a mild –not statistically significant– positive link between similarity and hourly real wage changes. However, this pooled sample conflates the two methods we used to detect job-to-job transitions: seniority and interim unemployment –where the latter may reflect similarity less accurately if, for example, transitions are driven by cyclical layoffs rather than voluntary job decision.

If we construct the similarity measure based on transitions detected by the seniority rule, the results are comparable (the coefficient is somewhat larger) and significant. The same is true when run the same regression limiting the sample on the transitions according to the seniority rule: now the coefficient is much larger, 6%, which means that a one unit increase in similarity lead is associated, on average, to a 6% rise in the quarterly hourly wage growth rate relative to the average job-to-job wage change.

Similarity based on	Sample based on	
	Full sample	**Seniority rule**
Full sample	0.02 (0.04)	0.04 (0.06)
Seniority rule	0.03* (0.018)	0.063* (0.037)

Table 1. Estimated coefficients corresponding to the similarity control. Each regression has as dependent variable the quarterly change in the hourly real wage during job transitions. Independent variables include similarity, industry dummies, two dummies that capture whether the worker was employed in a high paying industry before and after the transition, and two categorical variables that capture the employment relationship after and before the transition (independent worker, formal

[3] The quarterly average is calculated instead of the variation between the two points because the regression pools movements of 1, 3 and 4 quarters. In an inflationary context, such as the one that Argentina is experiencing, longer transitions may be penalized.

wage worker and informal wage worker) and time (year) dummies. * p value less than 10%. Standard errors in parentheses.

That the link between similarity and wage changes is stronger when working under the seniority rule may indicate, as mentioned above, that workers that transition through a stage of unemployment are more prone to switching occupations without benefiting from the specificity of their human capital, as they prioritize the need to find a job above the job conditions, whereas job-to-job transitions are more likely to reflect the occupational specificity of human capital and it relationship with wage changes. At any rate, these are exploratory results in need of more testing.

Conclusion

The ability of workers to reconvert to new labor demands at the lowest possible cost has long been at the core of the political debate on the response to globalization, to technological change and, more recently, to the devastating effects of the COVID-19 crisis. A key question on this front in how general or "portable" our human capital is and, given the lack of total transferability, how we should inform our reskilling efforts based on the transitioning worker´s human capital.

In this paper, we used public data from Argentina to calibrate the pattern of occupational transitions to an occupation map that provides useful information about the human capital involved in each occupation and how similarities between them can help orient the reskilling of workers minimizing the human capital lost in transition.

This study has obvious limitations that need to be taken into account. First, these are short-term transitions: it would be useful to calibrate the occupation space based on a long data panel to follow longer job trajectories. Also, this is observational evidence that needs to be interpreted carefully. That said, we believe the methodology and results prove that this line of research is a valuable input in the design of active labor market policies.

Annex 1

Code	Description
0	Executive officials
1	Legislative officials
2	Judiciary officials
3	Agencies, firms and state managers
4	Social institution managers
5	Small firm managers
6	Medium firm managers
7	Big firm managers
10	Administrative management, planification and management control occupations
11	Judiciary-legal management occupations
20	Budgetary, accounting and finance management occupations
30	Direct commercialization occupations
31	Home sales, travelers and promoters occupations
32	Indirect commercialization occupations
33	Walking commercialization occupations
34	Transport occupations
35	Telecommunication occupations

36	Storage of supplies occupations
40	Health and sanity occupations
41	Education occupations
42	Investigation occupations
43	Consulting occupations
44	Claims prevention occupations
45	Mass communication occupations
46	Social services occupations
47	Surveillance services occupations
48	Police services occupations
49	Armed forces occupations
50	Art occupations
51	Sport occupations
52	Recreative services occupations
53	Gastronomic services occupations
54	Accomodation and tourism services occupations
55	Domestic services occupations
56	Non-domestic cleaning services occupations
57	Human care and assistance occupations
58	Various social services occupations

60	Agricultural production occupations
61	Livestock production occupations
62	Forestal production occupations
63	Bee and poultry production occupations
64	Fishing production occupations
65	Hunting occupations
70	Extractive production occupations
71	Energy, gas and water production occupations
72	Construction occupations
80	Industrial and craft production occupations
81	Software production occupations
82	Consumption goods rapair occupations
90	Machinery instalation and maintenance occupations
91	Productive technological development occupations
92	Installation and maintenance of service machinery occupations

Table A1. Occupations of the National Occupational Code (CNO) 2001.

Annex 2

Dep. Var. Quarterly Change Real Hourly Wage	estimate	std.error	p.value	Lb (CI 90%)	Ub (CI 90%)	coef
Intercept	0.48	0.14	0.00	0.26	0.70	0.48***
R_{ij} Occupation	0.03	0.04	0.47	-0.03	0.08	0.03
R_{ij} Industry	-0.04	0.03	0.30	-0.09	0.02	-0.04
IndustryAboveAvg_Lagged	-0.06	0.03	0.05	-0.11	-0.01	-0.06*
IndustryAboveAvg	0.04	0.03	0.18	-0.01	0.09	0.04
Labor Contract Lagged **(base case: informal wage worker)**						
Formal wage worker	-0.10	0.03	0.00	-0.15	-0.05	-0.1***
Independent worker	0.07	0.03	0.03	0.02	0.12	0.07**
Labor Contract **(base case: informal wage worker)**						
Formal wage worker	0.06	0.03	0.03	0.02	0.11	0.06**
Independent worker	-0.11	0.04	0.00	-0.16	-0.05	-0.11***
R2	0.011					
N	4918					

Table A2.1. Regression output. Dependent variable: average quarterly change in real hourly wage before and after a job transition. Independent variables include the similarity between occupations (RijOccupation), industries (RijIndustry), two dummies that captures whether the worker was employed in a high paying industry before (IndustryAboveAvg_Lagged) and after (IndustryAboveAvg) the transition, and two categorical variables that capture the employment relationship after (LaborContract) and before (LaborContractLagged) the transition (independent worker, formal waged worker and informal waged worker) and time (year) dummies. * p value less than 10%. ** p value less than 5%, *** p value less than 1%. Industry and occupation similarity have been build based on all transitions. The sample in this regression is the full sample.

Dep var QuarterlyChangeRealHourlyWage	estimate	std.error	p.value	Lb (CI 90%)	Ub (CI 90%)	coefPvalue
(Intercept)	0.47	0.13	0.00	0.25	0.69	0.47***
RijOccupation	0.03	0.02	0.07	0.00	0.06	0.03*
RijIndustry	-0.01	0.02	0.44	-0.04	0.02	-0.01
IndustryAboveAvg_Lagged	-0.06	0.03	0.07	-0.11	-0.01	-0.06*
IndustryAboveAvg	0.04	0.03	0.24	-0.01	0.09	0.04
LaborContractLagged (base case: informal wage worker)						
Formal wage worker	-0.10	0.03	0.00	-0.15	-0.05	-0.1***
Independent worker	0.06	0.03	0.05	0.01	0.11	0.06*
LaborContract (base case: informal wage worker)						
Formal wage worker	0.07	0.03	0.02	0.02	0.12	0.07**
Independent worker	-0.10	0.04	0.01	-0.16	-0.04	-0.1***
R2	0.01					
n	4770					

Table A2.2. Regression output. Dependent variable: average quarterly change in real hourly wage before and after a job transition. Independent variables include the similarity between occupations (RijOccupation), industries (RijIndustry), two dummies that captures whether the worker was employed in a high paying industry before (IndustryAboveAvg_Lagged) and after (IndustryAboveAvg) the transition, and two categorical variables that capture the employment relationship after (LaborContract) and before (LaborContractLagged) the transition (independent worker, formal waged worker and informal waged worker) and time (year) dummies. * p value less than 10%. ** p value less than 5%, *** p value less than 1%. Industry and occupation similarity have been build based on all job transitions that did not go through a period of unemployment. The sample in this regression is the full sample.

Dep var QuarterlyChangeRealHourlyWage	estimate	std.error	p.value	Lb (CI 90%)	Ub (CI 90%)	coefPvalue
(Intercept)	0.47	0.18	0.01	0.18	0.77	0.47***
RijOccupation	0.06	0.04	0.09	0.00	0.12	0.06*
RijIndustry	-0.05	0.03	0.15	-0.10	0.01	-0.05
IndustryAboveAvg_Lagged	-0.07	0.05	0.17	-0.16	0.01	-0.07
IndustryAboveAvg	0.04	0.05	0.45	-0.05	0.13	0.04
LaborContractLagged (base case: informal wage worker)						
Formal wage worker	-0.14	0.05	0.01	-0.23	-0.05	-0.14***
Independent worker	0.05	0.06	0.39	-0.04	0.14	0.05
LaborContract (base case: informal wage worker)						
Formal wage worker	0.08	0.05	0.10	0.00	0.16	0.08
R2	0.01					
n	2588					

Table A2.3. Regression output. Dependent variable: average quarterly change in real hourly wage before and after a job transition. Independent variables include the similarity between occupations (RijOccupation), industries (RijIndustriy), two dummies that captures whether the worker was employed in a high paying industry before (IndustryAboveAvg_Lagged) and after (IndustryAboveAvg) the transition, and two categorical variables that capture the employment relationship after (LaborContract) and before (LaborContractLagged) the transition (independent worker, formal waged worker and informal waged worker) and time (year) dummies. * p value less than 10%. ** p value less than 5%, *** p value less than 1%. Industry and occupation similarity have been build based on all job transitions that did not go through a period of unemployment. The sample in this regression comprises all the job-to-job transitions that do not include a period of unemployment.

Dep var QuarterlyChangeRealHourlyWage	estimate	std.error	p.value	Lb (CI 90%)	Ub (CI 90%)	coefPvalue
(Intercept)	0.47	0.18	0.01	0.18	0.77	0.47***
RijOccupation	0.06	0.04	0.09	0.00	0.12	0.06*
RijIndustry	-0.05	0.03	0.15	-0.10	0.01	-0.05
IndustryAboveAvg_Lagged	-0.07	0.05	0.17	-0.16	0.01	-0.07
0.05	0.05	0.38	-0.04	0.13	0.05	0.05
LaborContractLagged (base case: informal wage worker)						
Formal wage worker	-0.14	0.05	0.01	-0.23	-0.06	-0.14***
Independent worker	0.06	0.06	0.31	-0.03	0.15	0.06
LaborContract (base case: informal wage worker)						
Formal wage worker	0.07	0.05	0.17	-0.01	0.15	0.07
R2	0.01					
n	2646					

Table A2.4. Regression output. Dependent variable: average quarterly change in real hourly wage before and after a job transition. Independent variables include the similarity between occupations (RijOccupation), industries (RijIndustriy), two dummies that captures whether the worker was employed in a high paying industry before (IndustryAboveAvg_Lagged) and after (IndustryAboveAvg) the transition, and two categorical variables that capture the employment relationship after (LaborContract) and before (LaborContractLagged) the transition (independent worker, formal waged worker and informal waged worker) and time (year) dummies. * p value less than 10%. ** p value less than 5%, *** p value less than 1%. Industry and occupation similarity have been build based on all job transitions. The sample in this regression comprises all the job-to-job transitions that do not include a period of unemployment.

References

Balassa, B. (1986). Intra-industry specialization: a cross-country analysis. *European Economic Review*, *30*(1), 27-42.

DE RACO, Sergio Andrés; SEMESHENKO, Viktoriya. Labor mobility and industrial space in Argentina. Journal of Dynamics & Games, 2019, vol. 6, no 2, p. 107-118.

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

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the national academy of sciences*, *106*(26), 10570-10575.

Hidalgo, C. A., Klinger, B., Barabási, A. L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, *317*(5837), 482-487.

Kambourov, G., & Manovskii, I. (2009). Occupational specificity of human capital. *International Economic Review*, *50*(1), 63-115.

MONTANÉ, Martín; SARTORIO, Luca. Tecnología y generación de empleo en el siglo XXI: desafíos y propuestas. Premio de la Academia Nacional de Ciencias Morales y Políticas, 2019.

Nedelkoska, L., Diodato, D., & Neffke, F. (2018). *Is Our Human Capital General Enough to Withstand the Current Wave of Technological Change?* (No. 93a). Center for International Development at Harvard University.

Neffke, F., & Henning, M. (2013). Skill relatedness and firm diversification. *Strategic Management Journal*, *34*(3), 297-316.

Sullivan, P. (2010). Empirical evidence on occupation and industry specific human capital. *Labour economics*, *17*(3), 567-580.

Yamaguchi, S. (2012). Tasks and heterogeneous human capital. *Journal of Labor Economics*, *30*(1), 1-53.