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# Hidden inequalities: the gendered labour of women on micro-tasking platforms

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**Abstract:** Around the world, myriad workers perform micro-tasks on online platforms to train and calibrate artificial intelligence solutions. Despite its apparent openness to anyone with basic skills, this form of crowd-work fails to fill gender gaps, and may even exacerbate them. We demonstrate this result in three steps. First, inequalities in both the professional and domestic spheres turn micro-tasking into a 'third shift' that adds to already heavy schedules. Second, the human and social capital of male and female workers differ—leaving women with fewer career prospects within a tech-driven workforce. Third, female micro-work reproduces relegation of women to lower-level computing work observed in the history of science and technology.

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## Introduction: The gendered dimension of work on micro-tasking platforms

Micro-tasking platforms are digital infrastructures that fragment large data projects into small bits, and allocate them to masses of anonymous providers, each of them executing remotely a tiny part of the whole and receiving a small compensation for it. Examples of micro-tasks include labelling images, categorising messages, recording short sentences, and transcribing audio snippets. Generally simple and short, they nonetheless serve to meet the data needs of today's fast-growing artificial intelligence industry (Casilli, 2019; Tubaro & Casilli, 2019; Tubaro et al., 2020a).

At first glance, these platforms appear 'gender neutral' and largely inclusive. Clients companies target unidentified and uncredited masses, and are typically given very limited access to individual workers' profiles (if at all). Under these conditions, employment discrimination is unlikely to occur – and indeed the nascent literature on digital platforms has mostly taken it as non-existent. Recently, Adams-Prassl and Berg (2017), Adams-Prassl (2020), and Litman et al. (2020) have planted the seed of doubt, highlighting a wage gap between male and female micro-workers at the same level of experience and seniority. Adams-Prassl and Berg (2017) and Adams-Prassl (2020) explain women's disadvantage through their domestic responsibilities, which affect how they carry out their online work and thus what they can earn. Nevertheless, the precise social mechanisms that produce this outcome, and their embeddedness in inherited inequalities, are still poorly understood. The present paper contributes to filling this gap by exploring the social mechanisms through which legacy gender disparities affect participation to micro-tasking platforms and produce hidden inequalities.

To do so, we frame our research questions in three intersecting literatures: feminist-autonomist thought, theories of human and social capital, and the history of technology. Feminist literature exposes the unequal division of domestic chores and parental care, falling disproportionately on women, and increasing with the number of children (Delphy, 2003). For employed mothers, this becomes a 'second shift'—the unpaid household and childcare duties that await them when they return home from their main job (Hochshild & Machung, 1989). Our first research question (RQ1) then is: what is the place of micro-tasking in a population of working mothers who already do two shifts a day? Does it eat into their working time, domestic chores time, or leisure time? What is the typical day of these women, and how do they make sense of it?

Micro-tasking platforms are performed on computers, smartphones or tablets, and in this sense, it is not surprising to see them in the home. Huws (2019) notices how digitalisation has transformed domestic work, without fundamentally altering the gendered division of labour within households. Likewise, Fortunati (2018, p. 2677) notices that 'the domestic sphere has become the place where new technologies are used more [...] In many cases, competence on the use of new technologies is built at home, and from here, it is exported into the factories.' She and other feminist autonomist authors account for the role of technologies in developing personalised strategies to improve women's skills to be spent on the labour market. Therefore, our second research question (RQ2) is whether micro-tasks can constitute a bridge toward better career prospects in the digital economy. Can they be means of professional empowerment? How do women compare to men in this respect? To operationalise these questions, we rely on theories of human and social capital that associate access to these potential opportunities to the resources that men and women, respectively, can leverage to move up the ladder. If 'human' capital includes people's own resources, reflected in their educational attainment and skills (Goldin, 2016), 'social' capital encompasses the advice, information, and support that they can access through their personal network of family, friends and acquaintances (Bourdieu, 1986; Lin, 2001). Social capital is known to play a role in professional insertion, channelling information (Granovetter, 1973) and concretely helping job-seekers (Godechot, 2016).

By asking these questions, we posit that there is some degree of continuity between taskified platform labour and technology professions. This is because micro-tasks are allocated by platforms, and serve the needs of companies' digitalization as well as the production of artificial intelligence. But there are few women in tech work: for instance in Europe, the proportion of female scientists and engineers in the total labour force is lower than the male proportion (European Commission, 2019). Among online freelancers, few women perform activities related to technology and data analytics, and they constitute less than 2% of programmers (ILO, 2021). Efforts to fill the gap that focus exclusively on enabling women's access to highly coveted jobs such as software developers, data scientists, and engineers, may not be enough if more mundane, lower-skilled activities, more often performed by women, are disregarded. The history of technology showcases manifold past instances of women performing unfancy duties such as computation and data entry, under job classifications that undervalued their contribution, both symbolically and monetarily, by essentializing it as non-creative, less qualified 'woman's work' (Hicks, 2017). This literature grounds our third research question (RQ3): to what extent do micro-tasking platforms recreate this old cleavage between overvalued male and invisibilized female technology workers? But there are few women in tech work: for instance in Europe, the proportion of female scientists and engineers in the total labour force is lower than the male proportion (European Commission, 2019). Among online freelancers, few women perform activities related to technology and data analytics, and they constitute less than 2% of programmers (ILO, 2021). Efforts to fill the gap that focus exclusively on enabling women's access to highly coveted jobs such as software developers, data scientists, and engineers, may not be enough if more mundane, lower-skilled activities, more often performed by women, are disregarded. The history of technology showcases manifold past instances of women performing unfancy duties such as computation and data entry, under job classifications that undervalued their contribution, both symbolically and monetarily, by essentialising it as non-creative, less qualified 'woman's work' (Hicks, 2017). This literature grounds our third research question (RQ3): to what extent do micro-tasking platforms recreate this old cleavage between overvalued male and invisibilised female technology workers?

## Background on micro-tasking platforms

The digital platforms under study offer activities that are usually described as micro-work (Irani, 2015) or crowd-work (Ross et al., 2010). Either denomination emphasises specific and relevant features, namely the small size of tasks (whence the prefix 'micro') and their allocation to potentially large groups of workers ('crowds'). It is not an uncommon occurrence to be recruited for less than a minute to perform tasks rewarded as little as one or two cents on arguably the most famous of those platforms, Amazon Mechanical Turk, whose median hourly remuneration has been estimated at just two dollars (Hara et al., 2018).

Micro-tasking stands out as a distinct type of platform labour, although existing literature often conflates it with gig-economy activities such as urban transportation and personal services on the one hand, and with qualified freelancing on the other (Berg et al., 2018). Unlike the former which is geographically sticky (Wood et al., 2019), micro-tasking is performed remotely, often allowing recruitment of workers across national boundaries, and exposing them to fierce international competition that drives down remunerations. Conversely, micro-taskers seldom enjoy the recognition of highly qualified freelance professionals such as IT experts or graphic designers, though both groups typically involve self-employment. Their autonomy is nominal, and their activities repetitive and unrewarding. Micro-tasking mirrors trends in contemporary labour economy, such as a drive towards taskification and atomisation of human contributions to productive processes (Gray & Suri, 2019), the corporate tendency to rely on humans-as-a-service disposable pools of workers (Prassl, 2018), and the role of human data-intensive labour in producing artificial intelligence solutions (Ekbia & Nardi, 2017).

In this perspective, micro-tasking represents a new and acute manifestation of the increase of non-standard forms of employment (ILO, 2021) that both constitute a risk of precarisation and exclusion for workers and an opportunity of easy access to the labour market, removing barriers, formalities, and non-flexible working hours. How these promises of emancipation play out is largely influenced by socio-economic variables—and we focus here on gender.

## Data and methods

We rely on a mixed-method study of French micro-workers, conducted in 2018-19 and consisting in over 900 completed questionnaires and follow-up interviews with about 70 questionnaire respondents (Casilli et al., 2019a). Both questionnaire and interviews were fielded as paid micro-tasks on the platform FouleFactory (subsequently re-branded Wirk) which is based in Paris and recruits exclusively French residents. FouleFactory tailors its services to the needs of client companies, helping them to design their micro-tasks and publishing them on its proprietary listing. Workers are familiarly called '*fouleurs*' ('crowders') and can register freely on the platform subject to availability (there is now a waiting list). The platform sports 50,000 workers, but we estimate the number of active monthly users to revolve around 7,000 (Tubaro et al., 2020b).

The questionnaire included 127 questions covering basic socio-demographic information, family situation, professional status, income, internet usage, and practices of micro-tasking on platforms. A detailed description of the population studied, and an appreciation of its specificities, can be found in Casilli et al. (2019a) and in abridged versions, in Casilli et al. (2019b), and in Tubaro and Casilli (2020). In sum, the majority are between 25 and 44 years of age, and more than a third are inactive (aside from their micro-tasking). Almost one fourth of these micro-taskers live below the poverty threshold, and only a few manage to generate sufficient additional income on micro-working platforms (Casilli et al., 2019a). Importantly for the purposes of this paper, women are slightly more numerous (56%) in our sample[1].

Here, we present in more detail the variables that have not been used, or have been used to a very limited extent in previous publications, notably those that measure the human and social capital of micro-workers. We assessed human capital through highest degree obtained, subject of specialisation, student status at the time of completing the survey, fluency in foreign languages, and basic digital skills. To measure the latter, we asked respondents to rate on a 1-4 Likert scale their proficiency in the use of search engines, information mining from online sources (like Wikipedia), spreadsheets, and word-processors. We find that these skills are strongly correlated to each other and can thus be taken as a single indicator (Table 2a, bottom section).

For social capital, our questionnaire included a 'position generator' instrument—a series of questions aimed at establishing respondents' relational access to a range of occupations such as lawyer, engineer, teacher, or driver (Lin & Dumin, 1986; Lin, 2001). The respondent's social capital is the aggregation of all contacts with these professionals, as a proxy of potential access to the knowledge, information, and other resources linked to their occupations (Li & Verhaege, 2015; van der Gaag et al., 2008). Because occupations are unequally prestigious in the social stratification, this instrument has also been used to infer the class structure of society (Savage et al., 2013).

Our version of the position generator included a list of 48 occupations, based on a standard occupational classification (France's '*Professions et Catégories Socioprofessionnelles*', PCS, 2-digit, 2003), with some items being disaggregated into more concrete descriptions. Specifically, we included eight occupations related to computing and digital technologies: software developer, data scientist, community manager/influencer, web designer, digital business analyst, digital consultant, computer engineer, and computer technician. Participants had to indicate a maximum of one contact per occupation—choosing the one they knew best if they had many—and could qualify them as man or woman. We use these data to see whether the social capital of male and female micro-taskers differs—especially in terms of contacts with digital and computing professionals, best suited to provide knowledge and advice to navigate the platform world and, ideally, to transition to better work opportunities. To establish the extent to which respondents nominate men or women in the different occupations, we use a variant of the 'EI index' developed by Krackhardt and Stern (1988). For each gender group, we take the number of same-gender nominations ('Internal', *I*), subtract the number of nominations

1. The questionnaire offered the option to self-identify as woman (56%), man (44%) or other (0%). Lack of data on non-binary persons prevents us from extending our analysis to this group.

to the other gender ('External', *E*), and divide by the total number of nominations. The resulting index *EI = (I−E)/(I+E)* ranges from -1 (all nominations to the other gender) to +1 (all nominations to the same gender), with 0 indicating a balanced choice (Table 2c).

## How work on micro-tasking platforms mirrors gender disparities in standard labour markets

As mentioned above, women constitute slightly over half of our sample. Similarly, Difallah et al. (2018, p. 138) observe that 55% of US-based micro-workers on the renowned platform Amazon Mechanical Turk are women. However, these ratios do not hold everywhere, and the same study notices an opposite bias in India (the second most-represented country on Mechanical Turk) and elsewhere. A Europe-wide study over four micro-tasking platforms (Mechanical Turk, Clickworker, Microworkers and Crowdflower) found a higher proportion (60%) of men than women (Forde et al., 2017). Covering seventy-five countries and five international platforms, ILO counted one woman out of every three workers, and in developing countries, only one woman out of five workers (Berg et al., 2018).

How to make sense of these disparities? Ipeirotis (2010) suggested that in a country like the USA, micro-work is often a supplementary source of income, used by stay-at-home parents, unemployed and underemployed workers—all categories in which women are over-represented—while in a country like India, the platform is often a primary source of income, and attracts more men. Participation rates are not mere numbers, then, and reveal how, conditional on the state of the job market in a given country, a persistent gender divide shapes activity on platforms and the meanings that users attach to it. Like the USA, France is an industrial country where most women have a job and micro-work is mostly a supplementary activity. In our sample, 61% of women and 68% of men have some non-platform-based occupation (Table 1), just slightly below the general French population where 68.2% of 15-64 year-old women and 75.8% of men in the same age range participated to the labour force in 2018 (Insee, 2020). The main difference among them concerns their working time. Among the micro-workers who have a non-platform job, 32% of women work part-time, against 11% of men—like the general French population, where in 2018, 29.3% of employed women and 8.4% of employed men worked part-time (Bodier et al., 2020).

Another difference is that micro-working women are more likely to have dependents (Table 1). Narrowing the analysis to cohabiting underage children, 46% of our female respondents, and 30% of males are concerned. While these data do not allow cross-national comparisons, in a high-income country like France they corroborate the above-mentioned view that micro-working platforms attract second-earners, who are often disadvantaged in the labour market and are more likely to have care responsibilities.

## How micro-tasks represent a 'third shift', after main job and reproductive work

These preliminary results set the context to address our RQ1—the place of micro-tasking in the personal and professional lives of these women. To move forward, we shall now take into account the unequal division of reproductive work, a staple of feminist literature despite recent evidence that the gap between men and women has diminished (Milkie et al., 2009). Our finding that micro-tasking women devote an average of 70 minutes more than men to house chores every day, is very close to French general-population data, which attested 78 minutes more housework for women in 2010 (Champagne et al., 2015). The gap is negligible among childless men and women (12 minutes a day on average), but becomes sizeable when there are children (104 minutes a day). More precisely as already noted by Delphy (2003), the extra burden of women—but not of men—increases with the number of children. On average, micro-tasking fathers do about the same amount of domestic chores regardless of the number of their children, while mothers with three or more children do 68 more minutes a day than those with one or two children (Table 1).

Delphy (2003) insisted that this inequality is less an effect of capitalist exploitation than of the immediate profit sought by 'the class of men'. If the patriarchal expectation that mothers take primary responsibility for dependents and children now begins to be called into question, our data also stresses differences due to the presence of a main non-platform job. When both parents are employed, the gender gap shrinks although women still devote more time to reproductive work than men. This is what the literature refers to as the 'second shift' (Hochschild & Machung, 1989): even when both fathers and mothers in dual-earning households experience it, mothers bear most of the responsibility.

For these women who already shoulder the bulk of domestic and parental duties in addition to a paid job, micro-work constitutes a 'third shift' (Casilli et al., 2019a), another layer of burdensome activity that serves to keep the family going—and incidentally, benefits the platform economy. Admittedly, some men—especially fathers—can also be said to do their third shift when they do micro-tasks on platforms. What is, then, the two groups' experience of it? How do they differ?

To see this, let us look at frequency, time and duration of connections to micro-tasking platforms. In principle anyone can log in at any time, for as long as desired. We find that the total weekly time spent doing micro-tasks does not differ significantly between women and men, regardless of their parental status. Yet women are much more numerous to sign in at least once a day, while men more commonly connect one or few times a week, but not every day. Put differently, women connect more frequently, and for a shorter duration. The days of connection do not differ (all perform slightly more micro-tasks on Monday, slightly fewer on Sunday, and about the same on all other days) but the times of the day do. About half of the participants to our survey have a preference for a single, specific time in the day, most often the 6pm-10pm slot—just after returning home from work, which is also when children are usually back from school or daycare. It is probably for this reason that this is not the preferred slot for almost 60% of mothers, and about half of fathers, in our sample. Interestingly, a bit over 70% of women with children do micro-tasks at times that are commonly associated with office hours, notably 9am-12pm and 2pm-6pm (Table 1).

If women with children connect to micro-tasking platforms more often, but for shorter time periods and at pretty much any time in the day, it is because their leisure time is more fragmented. In the in-depth interviews that we conducted, men often described fairly long stretches of time devoted to micro-work (from the end of their workday until dinner, or after dinner until bedtime, for example). Instead, women often described themselves as multitasking, that is, alternating micro-tasks with either their main job or domestic chores. Even very short breaks can be used to perform small online tasks, as platforms fill the interstices of their daily lives. This ensures steady access to tasks, but limited time to look for better-remunerated ones, to share information with other micro-workers, or to seek advice. For example, A. (a 50-year-old female engineer who raises her three children alone and earns 80-100 euros per month on several micro-tasking platforms) is always 'watching out for tasks to do'. She chooses them on the basis of remuneration, expected duration, and interest. She often micro-works after dinner while watching television, sometimes during her lunch break, and occasionally during office-time.

That these women experience micro-tasks differently from men becomes apparent when asked to rank the three main reasons why they do micro-tasks. Even though 90% of women and 80% of men choose 'I need money' as their first, second or third reason, when invited to give other reasons men more commonly envision micro-tasks as a form of leisure, while women have a more instrumental view of them—as an activity that brings money in, and can be done from home (Table 1).

For example, L. (a 40-year-old trained accountant unemployed since 2008, and juggling between short-term and part-time jobs ranging from freelance accounting missions to selling underwear and sex toys on eBay) signed up on several micro-tasking platforms to complement her online businesses. She spends ‘the whole day in front of the screen’, searching for buyers for her lingerie and at the same time watching out for new available micro-tasks. Similarly M. (a 30-year-old who left an employment she liked in retail to follow her husband, and has settled for a short-term, less qualified job to complement a tight family budget) depends on micro-tasking sites to get ‘pocket money’. She does micro-tasks as soon as she gets home from work every day, then she does some domestic chores, and returns to micro-tasks later in the evening.

These women offer examples of how the third shift is experienced. Earning activities on online platforms are part of their daily lives, and are closely integrated into their offline routines. They appropriate technologies as strategies for enhancing the family income. Digital technologies expand their opportunities for paid labour, and enable them to adjust their relationship to paid work and unpaid domestic chores and childcare. Wilson and Chivers Yochim (2015) characterise women who maintain family autonomy through non-standard, technology-enabled home-based labour as ‘mamapreneurs’. Their extra labour often erodes leisure time—as in the case of A. who makes her TV time productive by simultaneously doing micro-tasks. It is a third shift that is performed in the intermissions of family and working life, ‘snuck in during naptimes or late at night, multitasked with the use of mobile technologies during brief moments at the playground or while waiting in the carpool line’ (Wilson & Chivers Yochim, 2015, p. 9).

If technology has its full place in the home (Fortunati, 2018) and integrates the economy of the family, it also accompanies women’s effort to develop personal and professional strategies, and heighten their capacities to optimise their own and their families’ prospects. These considerations lead us to address our RQ2. Can micro-tasks, beyond their role as a coping strategy in the interest of the family, represent a bridge toward the digital economy and its opportunities? There is some evidence in the existing literature that micro-tasks may be an empowerment tool for highly educated but underemployed women. Gray and Suri (2019, p. 21) report cases of Indian women who operate on these platforms to update or even improve their technical know-how, hoping to fill gaps in their resumes, to later re-enter the labour force. As long as no longitudinal data indicate how likely such a trajectory might be, we should rather look at the resources (human and social capital) that women can leverage to enhance their future employment prospects after micro-work, possibly in the very tech sectors in which digital platforms are embedded.

## How human and social capital put women at disadvantage to build a career in tech

To set RQ2 in context, it is useful to recall the received view of micro-tasks as extremely simple, requiring no special qualification – every human being, so goes a common example, can distinguish a cat from a dog and label them in a picture. However, a closer look at the types and requirements of tasks, as they are usually proposed through platforms today, reveals a more nuanced picture. Linguistic skills are often required, for example for transcription, translation or writing of sentences or words. Image labelling to train computer vision systems increasingly requires use of state-of-the-art tools for pixel-level annotation (Schmidt, 2019). Margaryan (2019) shows that users of micro-tasking platforms gain experience on the job. The relative simplicity of most tasks must thus be interpreted in a context that requires at least some digital equipment (computer, internet connection) and some computer literacy to, for example, discard scams, activate online payment systems, scout for best-paying tasks on multiple platforms, and browse discussion fora.

In this respect, our data (Table 2a) confirm the findings of Berg et al. (2018), that micro-workers are overall very well educated. Our participants are twice as likely to have a bachelor's degree (44%) than the general French population of comparable age, with no noticeable difference between men and women (Casilli et al., 2019a). However, women tend to specialise in subjects such as health and management (46%, against 30% of men), and very few have a background in engineering (7%, against 34% of men). These differences in training, and especially women's choice of study subjects other than technology and engineering, are not specific to micro-workers (McDaniels, 2016) and are thought to be a major factor underpinning the uneven distribution of men and women across occupational sectors (Raabe et al., 2019), often referred to as 'horizontal' segregation (Levanon & Grusky, 2016). In contrast to much past research, though, our data display similar proportions of men and women trained in fundamental science (11% and 8%, respectively). Moreover, male and female micro-workers are equally endowed with our above-mentioned indicator of basic digital skills. In high-income, high-literacy countries such as France, platforms can tap into a reserve of human capital as reflected in their workers' educational achievements and abilities. In a world in which women are anyway less likely to specialise in technology, platforms even manage to attract a large proportion of relatively numerate female workers.

To see what resources can support these women's effort to leverage their knowledge and micro-working experience to build a career, we must shift our focus from the notion of ‘human’ to that of ‘social’ capital. The latter refers to the network of contacts and acquaintances that enhance the education and competencies that constitute human capital (Coleman, 1988), and convert them into a more stable and/or better remunerated position in the labour market (Granovetter, 1973).

Analysis of our position generator questions reveals no statistically significantly difference between men and women. The number of their contacts with professionals in our 48-item list of occupations suggests that they have personal networks of about the same size. Where differences appear is in the number of nominations in our eight digital and computing occupations: female respondents have only 1.72 tech contacts on average, against 2.65 for their male counterparts (Table 2b).

Let us look at the gender of these contacts, using the EI index introduced above. Within the full set of 48 professions, men’s choices are assortative, that is, they tend to choose more same-gender than other-gender contacts: their EI index is 0.33, on a scale that ranges from -1 (all nominations to the other gender) to +1 (all nominations to the same gender). Instead, women’s choices are about balanced, with an EI index of -0.083 (Table 2c). Both groups tend to nominate more men in traditionally masculine occupations such as truck driver and construction worker, and more women in stereotypically feminine occupations such as hairdresser and health technician (Figure 1).

Narrowing down our analysis to the subset of tech occupations (Table 2c), most men’s nominations are to the same gender (EI index 0.67), while women’s nominations are mostly to the other gender (EI index -0.47). Put differently, both groups nominate a minority of women (21% of all nominations). Interestingly, this ratio closely reflects women’s participation in the French digital workforce, which was 23% in 2017 (Desjonquères et al., 2019). Thus, this result is partly an effect of the occupational structure of France: if digital professionals are mostly men, then people’s contacts within this group will also be mostly men. If we look at *who nominates whom*, however, it appears that men and women do not respond equally to this same context: in our data, 26% of women’s nominations and only 16% of men’s nominations are women. Beyond the given occupational structure of society, there is a tendency for micro-working female respondents to slightly over-nominate women, while men clearly under-nominate them. Of note, in each of these eight professions, over half of female nominations are made by women.

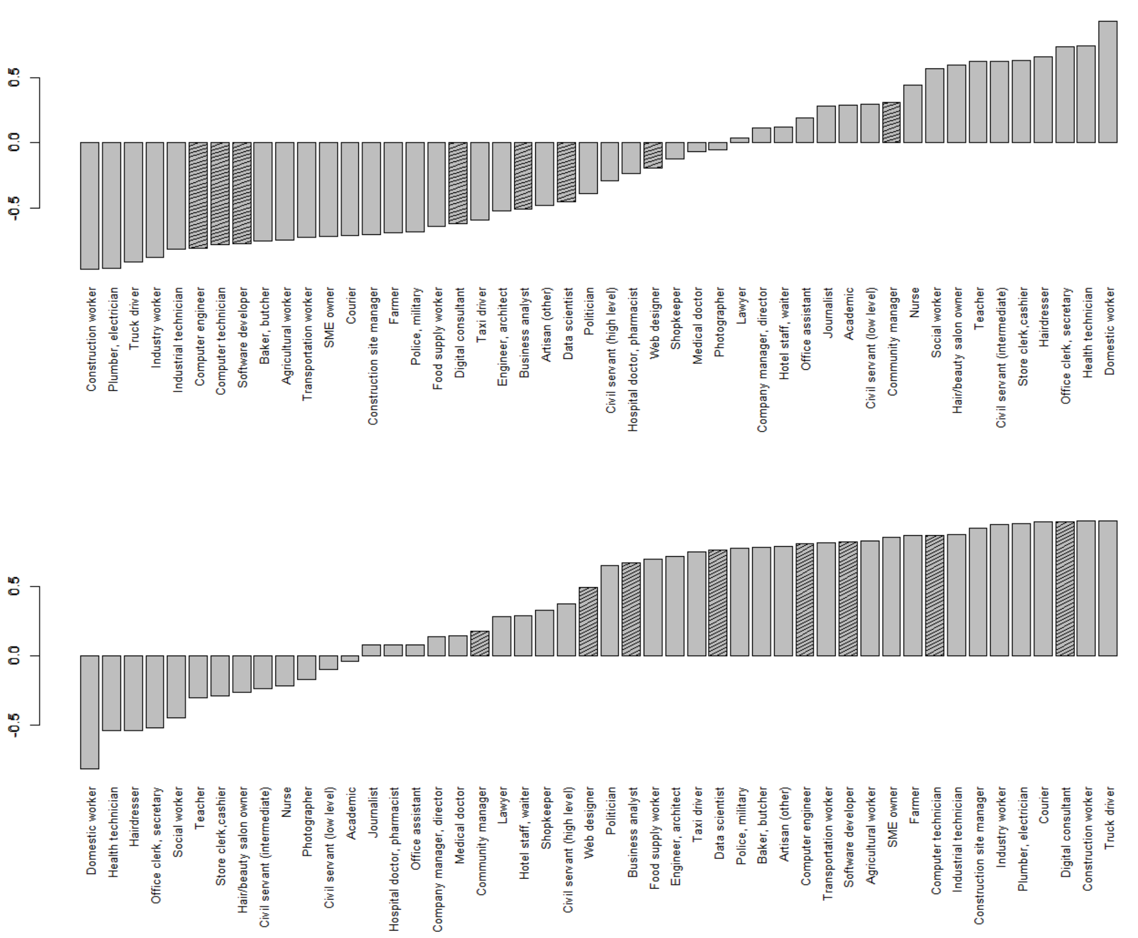


**FIGURE 1**: Gender homophily index for each occupation in the 48-item position generator list. Each panel represents respondents' choices, ordered from lowest (negative) to highest (positive) degree of similarity. Top panel: female respondents, bottom panel: male respondents. The bars corresponding to digital and computing occupations are hatched. Source: authors' elaboration.

This finding is not surprising in light of the large literature that shows how the relationships of advice, support and mentoring that help access the labour market are more likely to occur between people who share salient attributes—notably gender. This social regularity, often referred to as 'homophily' (McPherson et al., 2001), explains people's tendency to choose a same-gender person when asked to think about a technology professional. Doing so is much easier for our male survey participants, both because they have more contacts within these occupational groups, and because these groups happen to be predominantly masculine. Among women, the tendency to form same-gender contacts is curbed by their less numerous connections to tech professionals, and by the more limited presence of women among them.

This overall trend is weaker in the cases of communication and marketing activities such as community manager, the only technology occupation in which women nominate more women than men (Figure 1). This result points toward the attribution of an essentialistic ‘feminine character’ to skills in this set of activities. Common representations of these jobs as ‘social and emotional labour’ are closer to clichéd views of women as caring and nurturing, and involve monetary devaluation and isolation (deWinter et al., 2016).

In sum, women have fewer contacts in technology occupations, and although they pay attention to other women in these occupations, they know few of them. In this respect, women are at a disadvantage on micro-tasking platforms. They are less able to leverage their social capital to convert their experience into the first step toward a career in digital technology industries.

## Stacked inequalities and women’s work on digital platforms

Our starting point was extant evidence (Adams-Prassl & Berg, 2017) of women’s disadvantage in the digital working environments where they seek a primary or secondary income, or build skills for a future career. We have endeavoured to look deeper at the causes and determinants of this disadvantage, building on the vast literature that shows how women’s reproductive activity contributes to the income and opportunity gap that separates them from men.

We have answered our RQ1 in two steps. First, we have highlighted the importance of the structure and composition of the formal labour market. The proportion of women in the micro-working population reflects its composition and existing asymmetries, with a rather even gender split in a rich country like France, but more part-time work (see above). Instead of offering alternative means to enter the job market, platforms conform to its structure and gender segmentation, so that women’s prospects to take up tasks online go hand-in-hand with their opportunities to access the traditional workforce.

Second, we have taken into account persisting asymmetries in the division of household chores that stem from an overvaluation of productive over reproductive labour, and are not decoupled from inclusion in the formal labour market. We have shown that most French female micro-workers participate in the labour market, performing a full- or part-time job in addition to domestic chores. When micro-tasking adds to the mix, it sits at the centre of a dramatic time squeeze. Women who perform three-shift days are particularly penalised by the need to perform productive *and* reproductive labour in addition to micro-tasks. We may speculate that if these time constraints prevent them from taking the time to search for better-paid tasks, curate their profiles, and seek advice from peers in specialised online groups, they can be one cause of the lower remunerations observed in the literature (Adams-Prassl & Berg, 2017).

To answer RQ2, we have looked at the human and social capital of women who work on micro-tasking platforms. Despite levels of education and technical competency comparable to those of their male counterparts, women lack network ties with digital and computing professionals. This brings us back to the widely documented unequal representation of women in technology professions. If the obstacles stressed in the literature reside primarily in structural biases and study choices, our analysis highlights the additional potential effects of the informal relational dynamics that produce assortative social mixing among men, and sparser, disassortative connections for women. Less able to rely on their social contacts for information, support, and training, they have fewer means to transform their platform experience into an asset to boost their prospects in the tech world.

These results outline a situation of 'stacked inequalities' to which female platform workers are subject. On the internet, legacy inequalities pertaining to class, gender, sexuality, race, disability and geography persist alongside new inequalities connected to digital literacy, access to computing equipment, and online/offline networks (Robinson et al., 2020a, 2020b). There is evidence that the internet remains more beneficial for those with higher social status, in terms of what they achieve as a result of its use for several important domains (van Deursen & Helsper, 2015). Micro-tasking platforms are a case in point insofar as they reproduce and maintain inequalities inherited from both the professional and reproductive spheres.

This brings us to RQ3, considering that these inequalities are also stacked because today's micro-tasking platforms sit in a continuum with the 'human computation' of the nineteenth and twentieth centuries (von Ahn, 2007; Ross et al., 2010), instrumental in performing the 'blue collar science labour' necessary to the progress of knowledge in domains as diverse as maritime transport, atmospheric science, statistics, electronic engineering, ballistics, and astronomy (Grier, 2004). Invariably erased from official reports, human computers usually belonged to minorities or groups excluded from standard labour markets. Among them, women formed a substantial proportion (Light, 1999). Because their activities required only basic mathematical knowledge, these women 'calculators' were seen as low-level workers and, even when they had formal degrees, they were forced into amateur roles in support of 'actual' scientists, usually males. In this sense, the observed relegation of female platform workers in more marginal roles with limited career prospects, despite their often high educational achievements, follows in century-long forms of employment segregation in science and technology.

A troubling similarity between this past and contemporary platform labour is the tendency to essentialise the characteristics of women computers in order to justify their disadvantage. Historically, women's wages were lower because the tasks they performed were considered too mundane or too boring for men, yet they were said to appeal to some supposedly feminine traits, in terms of behavioural patterns (being detail-oriented, dedicated, focused) or physical and psychological dispositions such as 'docility and nimble fingers' (Rana, 2000; Nakamura, 2014). The alleged suitability of the 'natural traits' of this category of workers and the activity they perform is not limited to their paid labour but percolates into the domestic sphere, rationalising the low pay of women platform workers by conflating micro-tasks with reproductive labour.

By its very nature, platform labour problematically overlaps the private and the public spheres, and as already noted, a woman's workday fails to neatly separate formal labour, micro-tasking, and domestic activities. The intense commodification and digitalisation of the domestic tasks in contemporary households (Huws, 2019) make this confusion all the more inextricable. Especially three-shift-day women are on the receiving end of these social and technological trends. The pithy designation 'digital housewife' epitomises the relationship between platform work and social reproduction (Jarret, 2015). Like domestic labour, female micro-work is subject to dynamics of suppression and invisibility, relegates women in received 'non-professional' roles and reactivates the springs of domestic servitude. This imposed state of amateurism, aligned with women's alleged disposition to take on reproductive tasks within the household, perpetuates an inherited narrative that condones the ideological mystifications historically imposed on their work, both online and offline (Dalla Costa, 2008).

## Conclusions

In sum, platform labour fails to mitigate gender-based exclusion from labour markets, reproduces existing gendered divisions of housework, and projects them over the workday of micro-tasking women. As a result, it relegates into invisibility many women who perform both underpaid productive and unpaid reproductive work. A set of stacked inequalities severely limit micro-working women's opportunities to leverage their experience to work their way toward better opportunities – whether on platforms or in more conventional jobs in technology industries. It is not a stretch to characterise these platform micro-tasks as 'the hidden housework' of the digital economy. As we have shown elsewhere, micro-tasking is the secret ingredient of technological innovations that invariably present themselves as fully automated or algorithmically managed, and that nevertheless rely on a steady supply of human workers to perform tasks of data generation and annotation, result verification, and sometimes even 'impersonation' when they replace failing automated tools (Tubaro et al., 2020a).

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# Tables and figures

**TABLE 1:** The place of micro-work in the three-shifts day of women

| Topic | Construct | | Women | Men | P-value |
|---|---|---|---|---|---|
| Socio-economic situation ‡ | Professional activity (Y/N) | | 61 % (310) | 68 % (270) | 0.04167* |
| | | of which, part-time job (Y/N) | 32 % (98, n = 310) | 11 % (31, n = 270) | 1.096e-08*** |
| | Any children (Y/N) | | 56 % (283) | 40 % (158) | 2.348e-06*** |
| | Any co-habiting underage children (Y/N) | | 46 % (232) | 30 % (121) | 4.002e-06*** |
| Domestic and parental chores § | All | | 149.69 | 79.05 | < 2.2e-16*** |
| | | Without children | 86.49 | 63.51 | < 2.2e-16*** |
| | | With 1-2 children | 211.8 | 114.69 | |
| | | With 3+ children | 279.34 | 114.77 | |
| Frequency of micro-work ‡ | Daily (Y/N) | | 56% (284) | 44 % (175) | 0.001367* |
| | Weekly (Y/N) | | 34 % (173) | 45 % (178) | |

| Topic | Construct | | Women | Men | P-value |
|---|---|---|---|---|---|
| | Rarely (Y/N) | | 10 % (52) | 12 % (46) | |
| Time slots for micro-work ‡ † | Office hours: 9am-12pm, 2pm-6pm (Y/N) | Without children | 62% (139) | 54% (131) | 0.0003921** |
| | | With children | 71% (202) | 57% (90) | |
| | Evening: 6pm-10pm (Y/N) | Without children | 57% (128) | 56% (134) | 0.001643* |
| | | With children | 42% (118) | 47% (75) | |
| Reasons for micro-working ‡ † | I need money | | 90 % (456) | 82 % (326) | 0.0009209** |
| | I do it for leisure | | 37 % (190) | 49 % (196) | 0.0004643** |
| | It just keeps me busy | | 47 % (241) | 60 % (238) | 0.0002968** |
| | I prefer to work from home | | 41 % (207) | 29 % (115) | 0.0002798** |
| | I can only work from home | | 12 % (60) | 11 % (42) | 0.623 |
| | I can choose my schedule | | 66 % (337) | 63 % (252) | 0.3758 |

Note: Measure: absolute number of nominations per gender of respondents and nominees.

N = 908 respondents (509 women, 399 men).

Interpretation: Female respondents nominated 2812 females throughout the 48 occupations.

All p-values are based on Pearson's chi-square tests. Interpretation: when the p-value is less than the desired significance level (typically 0.05 or lower), we can conclude that the observed distribution is not random, and a relationship exists between the categorical variables.

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

EI Index: (WW-WM)/(WW+WM) = (2812 - 3320)/ (2812+3320) = -0.083.

**TABLE 2A:** Human capital

| Topic | Construct | | Women | Men | P-value |
|---|---|---|---|---|---|
| Educational level ‡ | Primary school or lower | | 1 % (3) | 1 % (5) | 0.1878 |
| | Secondary school | | 16 % (83) | 15 % (58) | |
| | Short post-secondary | | 38% (194) | 30 % (121) | |
| | Vocational training | | 5 % (24) | 6 % (25) | |
| | Bachelor | | 19% (98) | 21 % (84) | |
| | Masters, PhD | | 20% (103) | 26 % (105) | |
| Educational subjects § | Agronomy | | 3 % (14) | 3 % (11) | < 2.2e-16 *** |
| | Arts, languages, literature | | 11 % (55) | 4 % (14) | |
| | Engineering | | 7 % (34) | 34 % (133) | |
| | Business, economics | | 40% (201) | 28 % (110) | |
| | Communication, journalism | | 3 % (16) | 4 % (14) | |
| | Law, politics | | 6 % (31) | 5 % (19) | |
| | Medicine, nursing | | 6 % (29) | 2 % (6) | |
| | Maths, physics, chemistry, biology | | 8 % (43) | 11 % (43) | |
| | Social sciences, education | | 13 % (64) | 6 % (25) | |
| | Other | | 4 % (19) | 5 % (19) | |
| Digital skills † | Search engines | 1 | 0 % (1) | 1 % (2) | 0.0357 . |
| | | 2 | 1 % (5) | 0 % (1) | |
| | | 3 | 23% (118) | 31 % (122) | |
| | | 4 | 77% (385) | 69 % (274) | |
| | Information-mining | 1 | 1 % (5) | 1 % (2) | 0.05215 |
| | | 2 | 3 % (17) | 3 % (12) | |
| | | 3 | 26 % (134) | 35 % (138) | |
| | | 4 | 69 % (353) | 62 % (247) | |

| Topic | Construct | | Women | Men | P-value |
|---|---|---|---|---|---|
| | Spreadsheets | 1 | 4 % (20) | 2 % (7) | 0.208 |
| | | 2 | 20 % (100) | 18 % (71) | |
| | | 3 | 40 % (205) | 41 % (165) | |
| | | 4 | 36 % (184) | 39 % (156) | |
| | Word processing | 1 | 0 % (2) | 1 % (2) | 0.05279 |
| | | 2 | 5 % (23) | 5 % (19) | |
| | | 3 | 35 % 179) | 44 % (175) | |
| | | 4 | 60 % (305) | 51 % (203) | |

Note: Measure: percentage and absolute values unless otherwise specified.

N = 908 (509 women, 399 men) unless otherwise specified.

All p-values are based on Pearson's chi-square tests. Interpretation: when the p-value is less than the desired significance level (typically 0.05 or lower), we can conclude that the observed distribution is not random, and a relationship exists between the categorical variables.

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

‡ Due to missing values, n = 503 (women), 398 (men).

§ Due to missing values, n = 506 (women), 394 (men).

† The four skills are self-assessed and measured on a 1-4 Likert scale (1=lowest, 4 = highest). Cronbach's alpha = 0.83..

Source: authors' elaboration.

**TABLE 2B:** Social capital

| | All (48) occupations | Tech (8) occupations |
|---|---|---|
| Women | 14.84 | 1.72 |
| Men | 16.08 | 2.65 |
| P-value | 0.3173 | 5.79e-09*** |

Note: Measure: average number of nominations by micro-working women and men, over different occupations.

N = 908 (509 women, 399 men).

p-values are based on Wilcoxon non-parametric tests of mean equality across two samples. Non-parametric tests have been chosen(

because of non-normality. Interpretation: when the p-value is less than the desired significance level (typically 0.05 or lower), we can conclude that there are significant differences between the groups.

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1.

Source: authors’ elaboration.

**TABLE 2C:** Social capital (detail)

| Reference set | Respondents (nominators) | Nominees | | P-value | EI-index |
|---|---|---|---|---|---|
| | | Women | Men | | |
| All (48) occupations | Women | 2812 | 3320 | < 2.2e-16*** | -0.083 |
| | Men | 1651 | 3284 | | 0.33 |
| | All | 4463 | 6604 | | |
| Tech (8) occupations | Women | 196 | 542 | 1.075e-06*** | -0.47 |
| | Men | 138 | 704 | | 0.67 |
| | All | 334 | 1246 | | |

Note: Measure: absolute number of nominations per gender of respondents and nominees.

N = 908 respondents (509 women, 399 men).

Interpretation: Female respondents nominated 2812 females throughout the 48 occupations.

All p-values are based on Pearson’s chi-square tests. Interpretation: when the p-value is less than the desired significance level (typically 0.05 or lower), we can conclude that the observed distribution is not random, and a relationship exists between the categorical variables.

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1.

EI Index: (WW-WM)/(WW+WM) = (2812 - 3320)/ (2812+3320) = -0.083.

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