Working-From-Home and Contact-Intensive Jobs in Uruguay*

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Abstract

I apply the methodology of Dingel and Neiman (2020), and Mongey, Pilossoph, and Weinberg (2020) to identify which jobs can be performed at home (WFH) and are performed in close physical contact to others (CI) in Uruguay. My baseline estimates show that around 78% of the workers in the private can't WFH and 22% have CI. Using data on the characteristics of households I find large heterogeneity in WFH and CI across the income distribution, geographical locations, age groups, education levels, and production sectors. In addition, I study the relation of WFH and CI with the access to social insurance, hand-to-mouth propensity, intra-household insurance and job-automation risk. Finally, I show that my baseline estimates of WFH are consistent with ex-post survey estimations during the COVID-19 pandemic lockdown.

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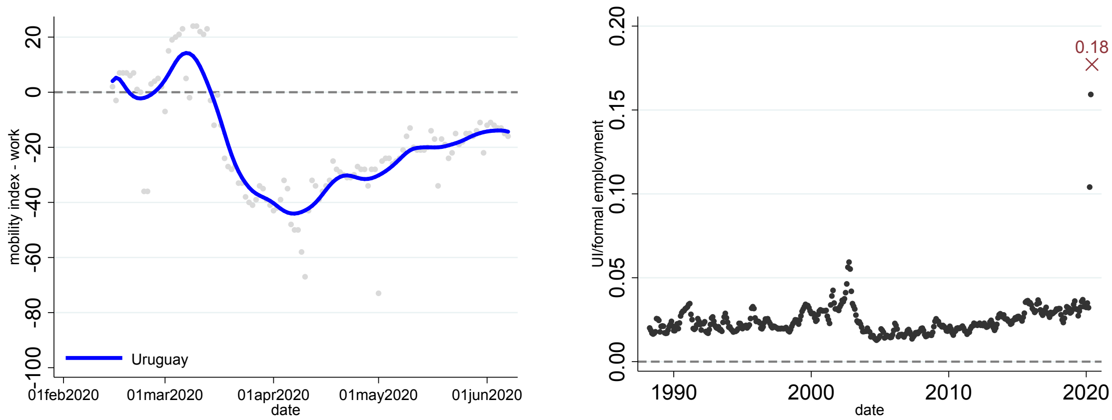
1 Introduction

As a response to the COVID-19 pandemic governments and individuals quickly adopted policies and changed their behavior in order the reduce the spread of the virus.[1] Uruguay was no exception. Figure 1 panel (a) shows that from mid-March to mid-April in Uruguay mobility to workplaces is reduced by 40%. Simultaneously, see Figure 1 panel (b), there is a historic spike in the unemployment insurance claims which increments by around 15 p.p., in terms of the formal labor force.

Table 1: Mobility in Workplace and Unemployment Claims in Uruguay

(a) Workplace Mobility Index **(b)** Unemployment Claims



Notes: Panel (a) shows the mobility in workplace index relative to pre-covid levels in January and February. The solid line is the locally weighted smoother. Panel (b) shows the unemployment claims, traditional type, as a fraction of formal active workers in Uruguay. Data source: Google mobility reports BPS. various media outles and unaimagen.uy.

One of the key drivers of the economic disruption created by the social distancing policies is the nature of the job of workers. Workers that can't work from home or have usually very close physical contact to others find their jobs at stake. Motivated by this, in this short paper I provide estimates and a thorough characterization of the households that can work-from-home (WFH) and have contact-intensive jobs (CI) in Uruguay.

In order to identify which workers can WFH and have CI in Uruguay, I follow a methodology close to the one used by Dingel and Neiman (2020) and Mongey, Pilossoph, and Weinberg (2020) for U.S.. The methodology classifies the different occupations by WFH and CI using data from several tasks per occupation. I combine the *O*NET* database that includes detailed information regarding each occupation's tasks with the *Encuesta Continua de Hogares* (ECH) of Uruguay that includes information about Uruguayan worker's characteristics, and with the Survey of Household Finances of Uruguay (EFHU) that provides household's balance sheet information.

[1] Throughout the text I will use the word policy interchangeably to describe individual behavior and government policies.

The baseline estimation indicates that 78% of the workers can't WFH and 22% have CI jobs. Most of the workers with CI jobs can't WFH, thus we can classify workers on three large subgroups: (i) workers that can WFH; (ii) workers that have CI jobs; and (iii) workers that can't WFH, but they don't have CI jobs. This provides an interesting characterization since workers in the third group are the ones whose job is very likely to be affected if they can't go physically to work, but it may not disrupted by mild workplace social distancing policies. For Uruguay I find that this group is large, about 55% of the private sector workers.

Next, I focus on the heterogeneity across various characteristics. I find that low income workers are less likely to WFH and are more likely to have CI jobs. This pattern is exacerbated when considering inequities on Internet access. Following this, I analyze across geographical locations. The pattern replicates across countries, Uruguayan regions and neighborhoods in Montevideo. Poor areas have much lower rates of WFH and higher CI shares. Next, I found that older and less educated workers exhibit low levels of WFH, but a flat pattern for CI shares. Finally, there is large heterogeneity across economic sectors, and I find that exposed sectors have a sizable economic participation in aggregate employment and output.

To study what are the predictors of WFH and CI in Uruguay I do some simple estimations using observable characteristics of the workers (income, education, age, etc). I find that education is the best predictor of WFH likelihood and the estimation can explain around 40% of the variability in WFH. On the contrary, the observable characteristics are significantly weaker predictors for the CI likelihood.

In the following section I study how vulnerable are workers that can't WFH and have CI jobs. First, in line with other studies, I find that a large fraction of the WFH are self-employed and informal workers which are not covered by the pre-COVID standard social insurance tools (e.g. unemployment insurance). Second, a large fraction of the WFH and CI workers live in households that have scarce liquid assets, thus even transitory shocks to income may result in large consumption adjustments. Third, I find that workers that can't WFH and CI have low levels of intra-household insurance, in terms of their direct exposition to the pandemic. Lastly, workers that WFH are particularly exposed to manual jobs automation risk, while CI jobs are particularly exposed to artificial intelligence automation risk.

In the last section, I show that the baseline estimates of WFH are very close to ex-post survey estimates during the Covid-19 pandemic. My estimates are also consistent across various characteristics.

This paper relies heavily on the approach and analysis of Dingel and Neiman (2020), and Mongey, Pilossoph, and Weinberg (2020) that do similar estimations for U.S.. Other papers that estimate WFH and CI for other countries are Kaplan, Moll, and Violante

(2020), and Leibovici, Santacreu, and Famiglietti (2020) for U.S., Stratton (2020) for Australia, Boeri, Caiumi, and Paccagnella (2020) for 6 European countries, Barbieri, Basso, and Scicchitano (2020) for Italy, Albrieu (2020) for Argentina, and Monroy-Gomez-Franco (2020) for Mexico, among many others. In addition, Dingel and Neiman (2020) and Gottlieb, Grobovsek, and Poschke (2020) estimate this for a large cross-section of countries.

Other studies that do similar estimations for Uruguay are Capotale, Pereira, and Zunino (2020), and Santos and Fynn (2020). These studies , both, focus on the WFH possibilities for informal and self-employed workers. In this paper I further expand on the characterization and include estimations of the CI jobs.

The goal of this paper is to contribute to the characterization of the WFH and CI in Uruguay. The characterization can be helpful as a guide to understand which households and workers across the country are likely to be the most hardly hit either by a strong lock-down policy (i.e. not WFH workers) or even a milder policies (i.e. CI workers).

The paper is divided in four sections. Section II describes the methodology and the data, Section III presents the main results, Section IV compares my estimations to ex-post Covid-19 estimations, and Section V concludes. The paper includes an Appendix with further details and results.

2 Data and Methodology

In the following section I describe the data and methodology used to identify the workers that can WFH and have CI jobs, and their characteristics.

2.1 Data

In this section I will explain the databases used for these estimations. I use five different data sources: (i) O*NET for occupation level data; (ii) ECH for worker's and household's characteristics; (iii) EFHU for worker's balance sheet data; (iv) cross-country data from ILO, and Dingel and Neiman (2020); (v) occupation level estimates of risk of automation by Webb (2020).

To determine which occupations are the ones that can be performed at home (WFH) and are contact-intensive I used data from *O*NET* which provides detailed information on 8-digit O*NET-SOC occupations' tasks. O*NET is sponsored by the U.S. Department of Labor and collects data from surveys to a large pool of firms and workers in U.S..

For detailed information on household's and worker's characteristics I use the last publicly available wave, 2019, of the *Encuesta Continua de Hogares* (ECH) elaborated by the Instituto Nacional de Estadistica (INE) from Uruguay. The survey samples around 40,000 households that is representative of the Uruguayan population. To include household level balance sheet data I use the 2017 Encuesta Financiera de los Hogares Uruguayos (EFHU) elaborated by various government agencies and was gently provided by the Faculty of Social Sciences of UdelaR. This survey is contained within the ECH survey for a representative sub-sample. For both surveys, the baseline estimations are for private sector workers and the sample selection impact on the sample is detailed in Table A.1. The ECH includes 412 different occupation categories.

For the cross-country comparison I use the data from Dingel and Neiman (2020) that combine O*NET and ILO data to compute WFH share across countries. I extend on this by doing the same for CI.

The last data source I use is from Webb (2020) that provides for the occupations in O*NET scores related to the exposure to automation for various technologies (AI, software and robots). This data is available online if requested.

2.2 Methodology

I follow closely Dingel and Neiman (2020) and Mongey, Pilossoph, and Weinberg (2020) approach to identify the workers that can WFH and have CI jobs. The variables I use are the same as those papers (see Table A.2), but the cross-walk and aggregation from 8-digit O*NET-SOC to 4-digit ISCO occupation level codes is slightly different.[2]

The procedure to compute the WFH and CI indicators for the Uruguayan workers is as follows:

1. For each SOC occupation I calculate the mean for the normalized O*NET task-level score using the selected tasks. Scores for each task-occupation have values from 1 to 5. The larger the score the easier to work-from-home or the more proximity to others in the workplace.

2. If an occupation has a score larger than 4 we consider the occupation can be done at home or has a close proximity to others.

3. Since the ECH and EFHU classify occupations using the ISCO code, I use the SOC-O*NET to ISCO crosswalk to aggregate for each occupation in the ECH. I use the same method as the one described by Dingel and Neiman (2020) in their methodological appendix for their cross-country estimates. For robustness, I aggregate also using the maximum and minimum.

[2] I use the cross-walk provided online by Hardy (2016) that is based on Acemoglu and Autor (2011).

3 Main Results

In the following section I show the main results of the paper. First I present estimations and examples of WFH and CI for Uruguay. Second, I describe the heterogeneity in WFH and CI across various characteristics (e.g. income, education, etc). Lastly, I include further results that relate WFH and CI to social insurance, self-insurance, intra-family insurance and automation risk.

3.1 Work-From-Home and Contact-Intensive Jobs

Applying the methodology described in Section 2 I can identify which occupations can be performed at home and which ones require close physical contact to be performed properly.

Table 2: Selected Occupations in Uruguay

Occupation (2-digit ISCO-08)	WFH	CI	Examples
Information and comm. technology	1.00	0.00	software developers
General and keyboard clerks	1.00	0.00	office clerks
Administrative and commercial	0.90	0.00	commercial managers
Sales workers	0.20	0.03	retail store workers
Skilled forestry, fishery and hunting	0.00	0.00	agricultural producers
Stationary plant and machine operators	0.00	0.00	manufacturing workers
Personal service workers	0.01	0.73	waiters, hairdressers
Health professionals	0.09	0.93	medical doctors
Education professionals	0.89	0.53	teachers, professors

*Notes: data is for Uruguay in 2019. Data source: O*NET and ECH-INE Uruguay 2019.*

Table 2 shows the share of workers that can WFH and have CI jobs in Uruguay for selected occupations. Occupations related to the information and communication technology sector and office jobs tend to have characteristics that make them easy to be performed at home and also they don't require a close contact with others. Other set of occupations, such as the ones related to retail, industrial or agriculture sectors usually require physical presence, but not necessarily require close contact with customers or co-workers. On the other hand, other occupations that are in the service and health sector require both presence and close contact for their usual performance. Lastly, occupations in the educational sector are the most salient example of jobs that can be done at home and at the same time when not done at home require close contact.

Table 3: Work-From-Home and Contact-Intensive Jobs in Uruguay

	Work-from-home	Can't work-from-home
Not contact-intensive	0.20 [0.19 - 0.25]	0.58 [0.47 - 0.67]
Contact-intensive	0.02 [0.01 - 0.05]	0.20 [0.11 - 0.30]

*Notes: the table shows the proportion of private workers by characteristics. In brackets value corresponds to the upper and lower bound estimates for each category. Data source: O*NET and ECH-INE Uruguay 2019.*

Table 3 shows the main aggregate results. I find that only 22% of the workers can WFH in Uruguay. Most of the WFH doesn't require close contact (20%), thus the fraction of workers that WFH and CI, which are mostly in the educational sector, compose a small fraction of the total (2%). Moreover, I find that around 22% of the worker have CI jobs, with most of them not being able to WFH (20%). Finally, a large fraction of the workers are not able to WFH, but their job doesn't require close contact (58%).[3] This group is particularly interesting since these are workers that can potentially find their working possibilities strongly limited if being lock-down in their homes, but not necessarily if they can go to work even under mild workplace social distancing policies. This suggest that considering both measure can hint on the direct implications for some jobs for different set of social distancing policies.

3.2 Heterogeneity in WFH and CI Jobs

In this section I show how common are WFH and CI jobs across a relevant set of characteristics. First, I look across the income distribution and extend the analysis to consider the heterogeneity in Internet access. Second, I describe the propensity of WFH and CI across countries, Uruguayan regions and neighborhoods in Montevideo. Third, I study the share of WFH and CI across different age group and education levels. Lastly, characterize different economic sectors and calculate the economic relevance of high WFH and CI sectors.

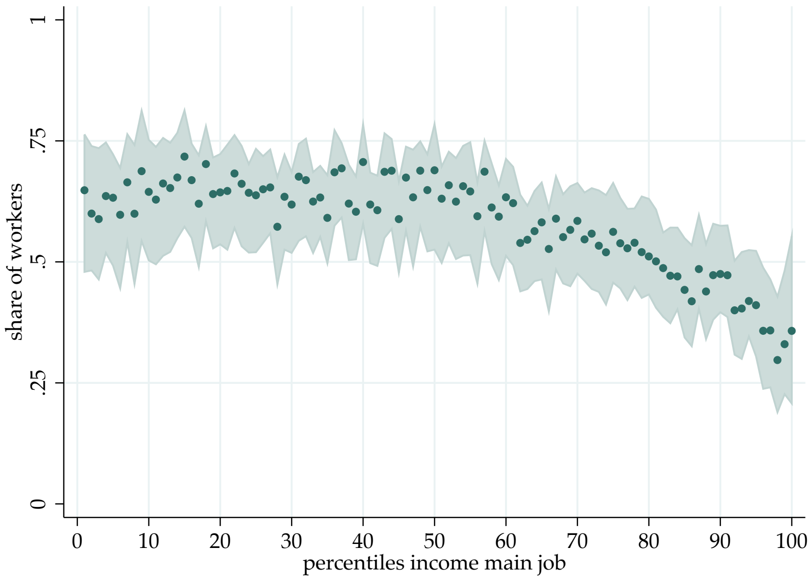
[3] In Figure A.1 I show at an occupation level the matrix using the WFH and CI scores from computed from O*NET importance scores.

3.2.1 Income Distribution

Figure 1: WFH and CI Across the Income Distribution

(a) WFH jobs and CI jobs

(b) Non-WFH and Non-CI jobs



*Notes: in the figure dots indicate the observed proportion of the workers that WFH (blue) and CI (orange). The shadowed area show the max and min when we aggregate from SOC to ISCO from O*NET to ECH. Income percentiles are constructed using the main job labor income at February 2020 Uruguayan pesos. Estimates use the official ECH survey weights. Data source: O*NET and ECH-INE Uruguay 2019.*

In Figure 1 I show the share of WFH (blue dots) and CI (yellow dots) across the income distribution. In the panel (a) a striking pattern emerges, income-poor workers are much less likely to have WFH jobs and much more CI jobs than income-rich workers. Suggesting that the inability to go to work would imply a larger direct impact for income-poor workers. The same follows for CI and mild workplace social distancing policies, but in a less stark fashion. Panel (b) shows the share of households across the income distribution that can't WFH and don't have CI jobs. These types of occupations are particularly frequent for income-poor workers, which suggests that mild social distancing policies are likely to be much less regressive in their direct impact than lock-down type of social distancing policies. [4]

Unequal Internet Access

One necessary condition for jobs to be performed at home is that workers have access to Internet connection. Although 74% of the workers are in households with access to Internet connection when we condition to WFH workers 90% of them have Internet access. Thus overall access to Internet is not a large impediment for WFH, differently from other emerging countries. In Figure A.2, I show that in spite of this, access to Internet is very unequal, therefore WFH is even more limited for income-poor workers than what the baseline estimates suggested.

3.2.2 Geographical Locations

The work by Dingel and Neiman (2020) and Gottlieb, Grobovsek, and Poschke (2020) shows that there is substantial heterogeneity in WFH across countries. In the same spirit, I extend this to CI jobs across countries, and explore heterogeneity in WFH and CI across regions within Uruguay.

In Figure 2 panel (a) and (b) I show the relation between WFH and CI across countries. Panel (a) is a replication of Figure 2 panel (a) in Dingel and Neiman (2020) and shows that richer countries have a larger fraction of workers that can WFH.[5] I extend also to CI, panel (b) shows an ambiguous relation between income and CI possibilities. Notices that CI occupations are located in various part of the income distribution, e.g. doctors and manual workers have CI jobs.

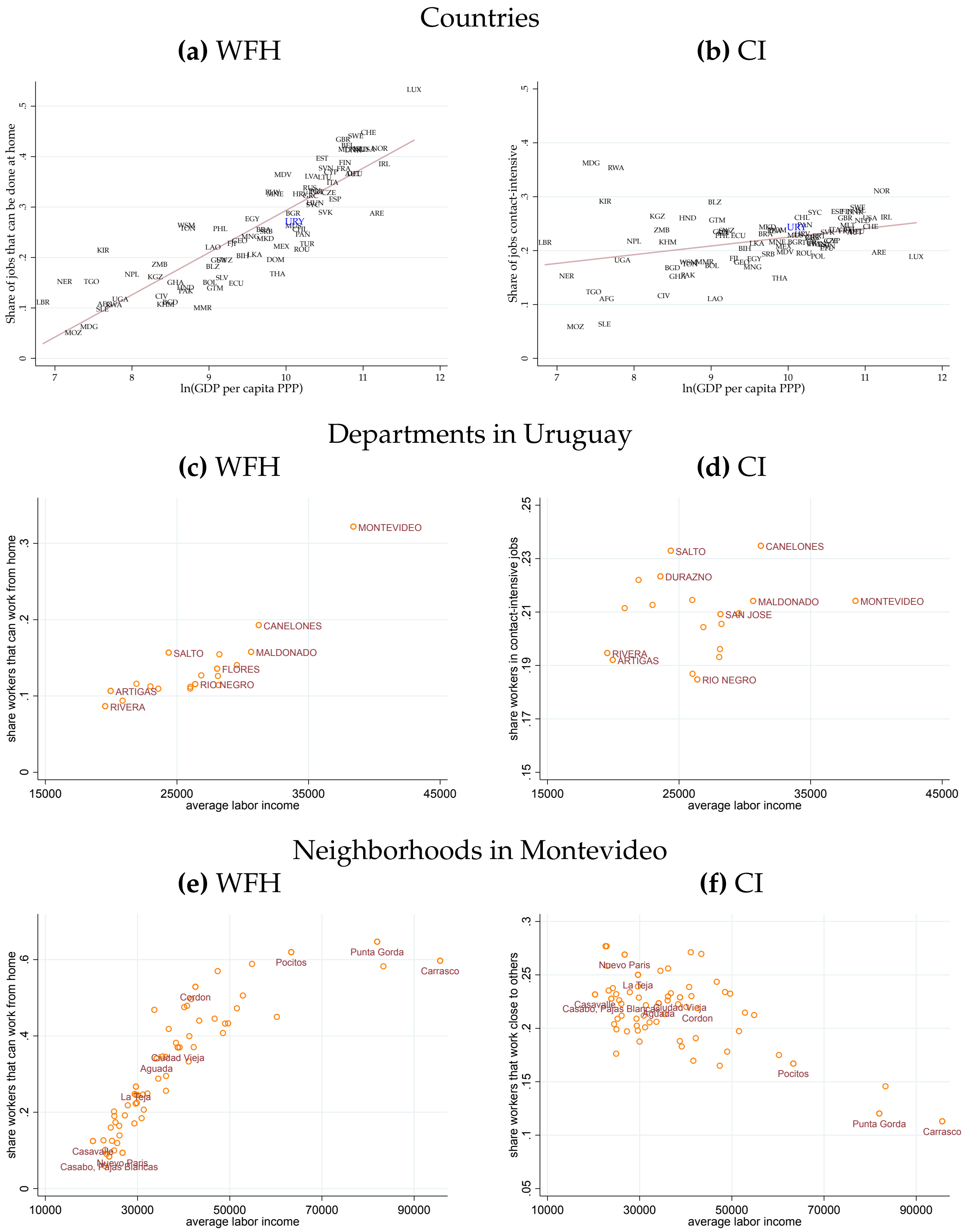
Then I perform the same analyze within Uruguay. Panel (c) shows WFH shares across Departments. The same pattern emerges as across countries. In particular, we can observe that Montevideo, which is the richest region, has a proportion of more than 30% of their workers doing WFH jobs. On the other hand, the rest of the Departments exhibit a share of WFH lower than 20% and the poorest regions close to only 10%. On the contrary, in panel (d) we don't observe a clear relation between CI job share and income levels across Departments. Both patterns remain unchanged even when

[4] In Appendix B.1 I compare these results with the ones for U.S..

[5] Gottlieb, Grobovsek, and Poschke (2020) argue that in part this relation is driven because poor country workers in the agricultural sector as considered as non-WFH. When relaxing this they find a U-shape between income and WFH.

excluding rural workers, see Figure A.3.

Figure 2: WFH and CI Across Regions in Uruguay



*Notes: Panel (a-b) shows the share of WFH and CI workers (includes private and public workers) across country. Panel (c-d) shows the share of WFH and CI workers by Uruguayan department. Panel(e-f) shows the share of WFH and CI workers across Montevideo's neighborhoods. Data source: O*NET and ECH-INE Uruguay 2019.*

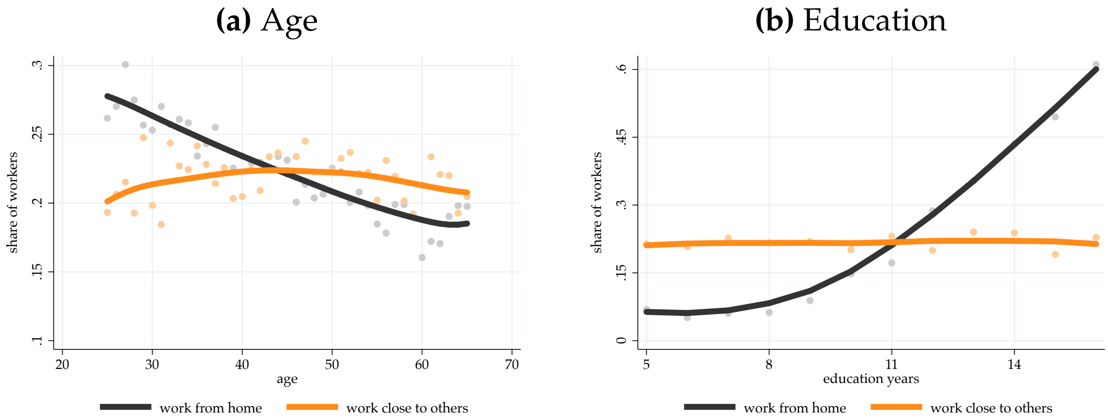
Finally, I focus on neighborhoods within Montevideo. Figure 2 panel (e-f) shows again an increasing pattern between WFH and income across neighborhoods. More than half of the workers that reside in the richest neighborhoods have the possibility to

WFH, while this share is less than 10% for poor neighborhoods. Differently from panel (b) and (d) now CI have a clearly decreasing pattern with income level across neighborhoods. At least one fourth of the workers have CI jobs in poor areas and less than one tenth for richer neighborhoods. This suggest that across the board within Montevideo we may expect a direct regressive impact of social distancing policies across areas.

Across all the regional levels studied in this section I find that WFH shares are increasing the higher is the income, this suggest a regressive spatial income of the pandemic. On the other hand, CI seems to have only a this kind of heterogeneity across neighborhoods within Montevideo.

3.2.3 Age Groups

Figure 3: WFH and CI Across Age and Education



*Notes: Panel (a) shows the share of WFH and CI workers (includes private and public workers) across age groups. Panel (b) shows the share of WFH and CI workers across years of education completed by the workers. Data source: O*NET and ECH-INE Uruguay 2019.*

Recent research suggest that the pandemic has distinctive medical impact across different age groups and therefore lock-down policies may be optimally targeted using different age groups. For example, Acemoglu et al (2020) argue that for people over 65 years of age have a mortality from the Covid-19 infection that is about 60 times that of those aged between 20-49. They find using a quantitative multi-group SIR model that this heterogeneity in mortality rates leads to an optimal policy with stronger lock-down policies over the old aged.

Motivated by these, I find particularly interesting to explore how many WFH and CI are in Uruguay across age groups. Figure 3 panel (a) shows that there is a stark decreasing pattern in WFH share across age of the workers. At least one out of four young workers can WFH, and less than one out of five close to retirement aged workers. This suggest that also old aged workers may be more affected by strong lock-down policies. On the other hand, CI have a slightly inverted U-shaped pattern across age, but mostly the differences seem not to be economically relevant.

3.2.4 Education Levels

Intuitively we expect that more educated workers do proportionally more WFH jobs, but as we observed in Table 2 some well paid jobs such as doctors have are CI and not WFH. Figure 3 panel (b) quantifies this relation. We find that highly educated workers are more likely to have WFH and workers with few years of education mostly have jobs that have to be performed in person. This pattern was expected as education is usually a good predictor of future income. Moreover, I explore using a simple regression setup which are the best predictors of WFH. I find that education explains most of the predictable variability of WFH. Results are summarized in Figure A.3.

Lastly, the relation of CI and education is flat. The lack of heterogeneity of CI is consistent with various of the previous results.

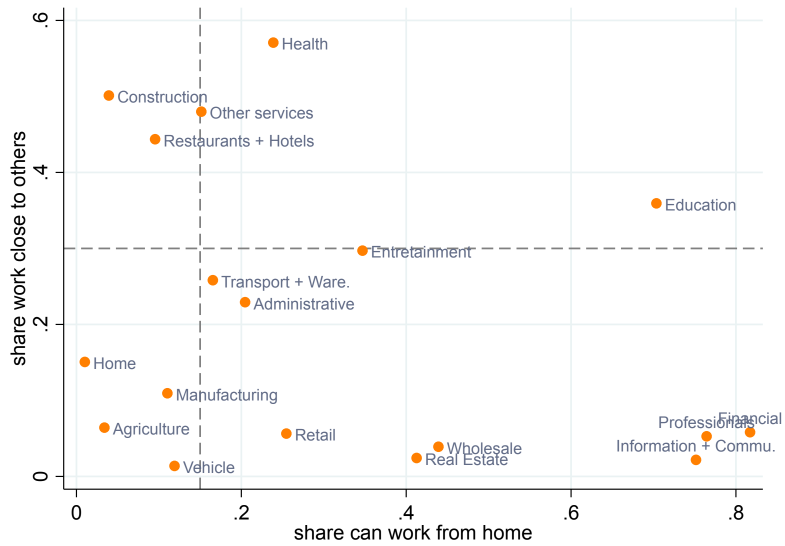
3.2.5 Production Sectors

Other relevant aspect is the sector level impact of the crisis. For example, in principle a lawyer that can WFH is likely not be directly impacted by physical impediments to go to work, but a lawyer that works in the manufacturing sector, which is a sector where most of the worker's are required to be physically present, may be indirectly impacted by lock-down policies.

Figure 4 shows the share of WFH and CI across sectors. There is a large heterogeneity. Sectors such as the manufacturing, agriculture, restaurants and hotels, and construction among others have very low WFH shares, but not necessarily a large share of CI. On the opposite side, other sectors have very low levels of CI and high WFH shares. These sectors are mostly related to professional and technological services. With two notable exceptions, the health sector, which is considered essential during the pandemic, and educational sector, which can also performed at home.

Lastly, sectors with high levels of CI (more than 30%) have a share of 29% of GDP and 31% of aggregate employment. Moreover, sectors with low levels of WFH (less than 15%) have a share of 45% of GDP and 38% of aggregate employment. Therefore, sectors highly exposed, through these channels, are relevant in the aggregate economy.

Figure 4: WFH and CI Across Production Sectors



*Notes: the figure shows on a 4-digit level sector categories the share of WFH and CI. Data source: O*NET and ECH-INE Uruguay 2019.*

3.3 Further Results

In the following section I try to quantify the share of workers that lack public insurance, self-insurance, intra-familiar insurance and are exposed to new technologies that can't WFH and have CI jobs.

3.3.1 Vulnerable Workers

As shown in Figure 1 panel (b) there was an abnormal spike in UI claims. Workers that can claim the UI are able to access to a transfer that compensates temporarily for the labor income losses. Not every worker is able to access this benefit neither for very low income workers the insurance benefits are large enough to provide a subsistence level of income. Specifically, in the following exercise I will try to quantify how many workers that are vulnerable can't work-from-home and have contact-intensive jobs. Where vulnerable workers are those that before the pandemic were informal, self-employed, low income, and unemployed.

Table 4 shows the results. Between 40%-50% of the workers are particularly vulnerable to this crisis. This number is close to a similar exercise done by Capotale, Pereira, and Zunino (2020). The quantitative relevance of these numbers suggest that the welfare effects of the pandemic in the short term could be sizable if these households are not insured through new public insurance mechanisms or other channels I'm going to study in the following subsections.

Table 4: Vulnerable Workers that can't WFH and have CI jobs

	Not WFH	CI	All
Workers (private)	1,055,002	290,961	1,350,471
Informal	343,944	106,485	391,421
Self-employed	301,763	102,233	383,009
Low Income	241,180	61,932	267,464
Unemployed	117,724	27,866	137,452
Vulnerable (w/o unemployed)	523,432	147,203	622,061
Vulnerable (w/ unemployed)	641,156	175,069	759,513

*Notes: low income workers are those with an income lower than 1.5 times the poverty line. Informal workers are those that don't contribute to social insurance. Self-employed workers exclude business owners with workers. Unemployed workers include, both, those who are not employed and seeking for a job or not. Data source: O*NET and ECH-INE Uruguay 2019.*

3.3.2 Hand-to-Mouth

Other source of insurance is self-insurance through the accumulation of liquid assets. In Uruguay access to credit is very limited for the households, private credit account for only around 20% of GDP. Tight credit conditions precludes households, that hold few liquid assets, from smoothing consumption when having a negative transitory shock to income. This implies that if a large fraction of the households have low levels of liquid assets during the Covid-19 crisis we would expect a large contraction of aggregate consumption, even if the crisis is temporary. A sharp reduction in aggregate demand through this mechanism may spillover to a prior unaffected sectors as argue by Guerrieri et al. (2020).

To characterize the workers that have low levels of liquid assets, i.e. hand-to-mouth, we use data regarding the balance sheet of the households collected in the EFHU. Using this survey I identify the hand-to-mouth workers as those who hold less liquid asset than two weeks of their income.[6]

I find that 77% of the households are hand-to-mouth under this definition in Uruguay. Moreover, I find that around 64% of the households are hand-to-mouth and can't WFH, and 17% have CI jobs and are hand-to-mouth. This combined with the fact that credit markets in Uruguay are very underdeveloped suggest a sharp contraction of aggregate consumption through this channel.

Lastly, if we explore across the income distribution, see Figure A.4, we can find that hand-to-mouth households are dis-proportionally income- and wealth-poor house-

[6] Results are qualitatively aligned with Kaplan, Moll, and Violante (2020) that find that exposed households are much more likely to be hand-to-mouth.

holds. A large fraction of poor hand-to-mouth households suggest that also low income households lack self-insurance, and welfare consequences could be potentially large in the case of a strict lock-down policy.

3.3.3 Intra-Familiar Diversification

Insurance may also come from other household members. For example, it may be the case that even if a worker can't WFH other member of the household can. In the same fashion as Albanesi et al. (2020), I analyze the share of households that are exposed and diversified, and those which are exposed and not diversified.

Table 5: Intra-Familiar Diversification in Uruguay

		# WFH				*# CI*				*All*
		0	1	2	3+	0	1	2	3+	
# HH members	1	0.33	0.15	-	-	0.40	0.09	-	-	0.49
	2	0.20	0.14	0.08	-	0.29	0.11	0.02	-	0.42
	3+	0.04	0.03	0.02	0.01	0.05	0.03	0.01	0.00	0.09
	total	0.57	0.32	0.10	0.01	0.74	0.23	0.03	0.00	1.00

Notes: Numbers indicate the share of households over the total population of households with workers. Number of members refers to the number of members that work, # WFH corresponds to the numbers of HH members that work and can WFH, and # CI refers to the number of household members that work and have CI jobs. Data source: own estimates, INE Uruguay and Equipos Consultores.

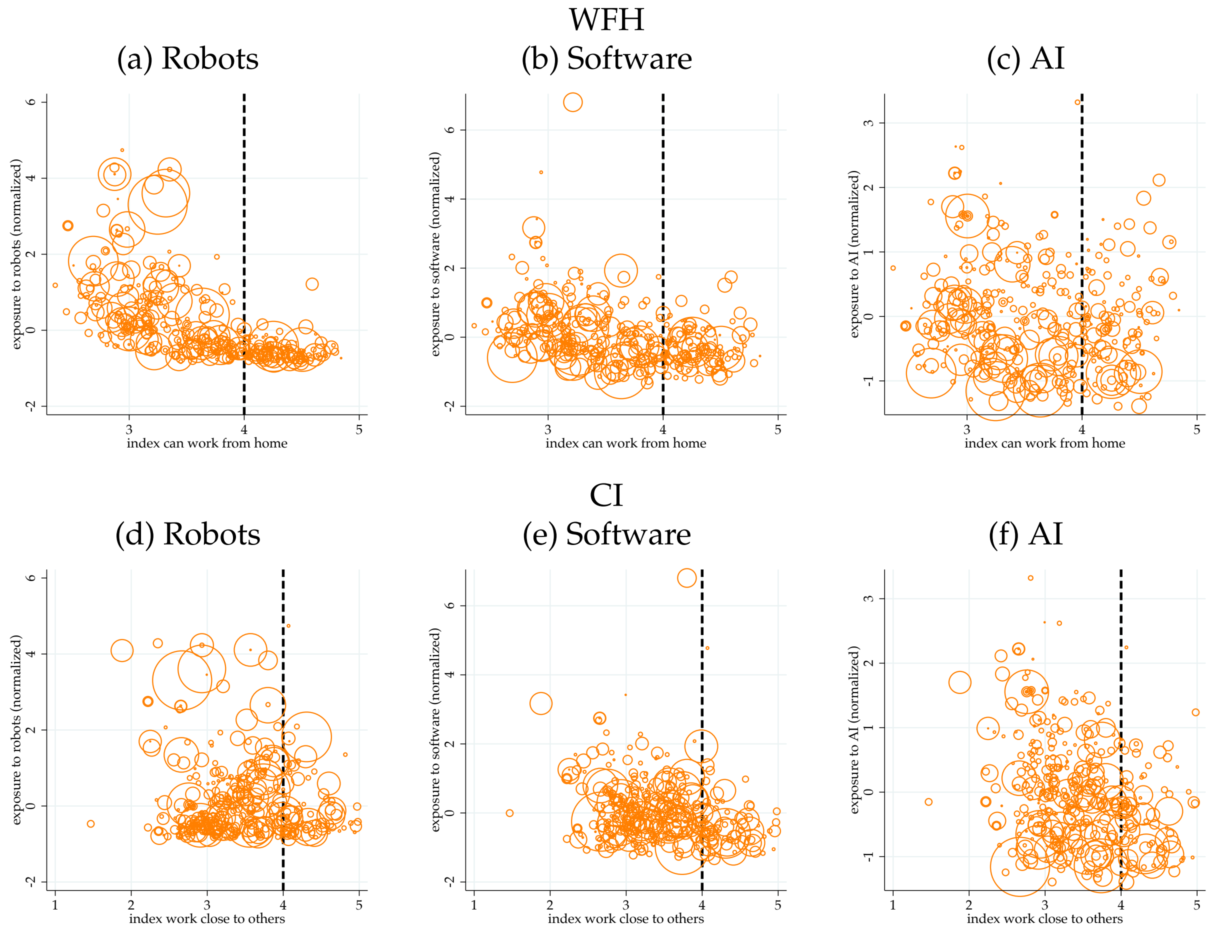
In Table 5 shows the results. I find that 57% of the households non of it's members can't WFH, and in 11% of them all their members have CI jobs. Also in figure A.5 I explore the intra-household insurance by their share in income instead of number of workers, i.e. is how much of the labor income within households is exposed. I find that the share of households with a worker that can't WFH with at least 20% of their income exposed is close to 90%, this number is around 60% for households with at least one worker that has a CI occupation.

Overall we have that a large fraction of the households are non-diversified in case of a strict lock-down, naturally the fraction is lower if CI jobs are the only ones directly affected.

3.3.4 Automation Exposure

Even though the impact of the pandemic which is related to the nature of the jobs may disappear once social distancing policies are over and the vaccine is widely available, there is some speculation that those jobs affected by the pandemic may be replaced sooner than before because of an acceleration of the automation process.[7] Motivated by this I use some measure of automation risk elaborate by Webb (2020). The risk measures are on an occupation level and for different kinds of technologies, i.e. robots, software and AI.

Figure 5: WFH and CI, and Automation Risk



*Notes: the figures shows the relation between the WFH and CI index, and the index of automation risk exposition for each occupation. The size of the circles indicate the share of workers in Uruguay. Data source: O*NET and ECH-INE Uruguay 2019.*

Figure 5 shows the relation between automation, and the possibilities of WFH and CI. Two patterns emerge, panel (a) shows that jobs that are less likely to be performed at home have a higher risk of being substituted by robot type of technologies. These technologies substitute usually jobs that have a high manual component which naturally are very likely to be necessarily performed in-person. On the other hand, panel (b) shows that less CI jobs are more likely to be substituted by AI technologies. This last result is consistent with the fact that high CI jobs such as the ones related to medical and educational services which tend to be non-routine are the ones exposed to AI as shown by Webb (2020). The last suggests non-trivial effects of an apparent acceleration

[7]See for example this article.

of the automation process over the most disrupted jobs during the pandemic.

4 Comparison with Ex-Post Survey Estimates

In this final section I will compare some publicly available ex-post survey measures of WFH during the Covid-19 pandemic in Uruguay and the estimates in this paper. Table 6 shows the comparison between the baseline estimates for WFH with effective WFH during the pandemic estimated in two waves by the polling firm Equipos Consultores and the ECH 2020 preliminar aggregate estimates.[8] We can see that the estimates for WFH though they are slightly larger they are very close to ex-post survey estimates. Moreover, when comparing our measure by characteristics with those done by Equipos, see Figure A.6, we find the share of WFH across characteristics distributes in a very similar way. This suggests that this approach provides a sensible estimate for WFH.

Table 6: WFH in Uruguay: Ex-Post Surveys Comparisons

	Guntin (2020)	Equipos	Equipos	INE
Previously	-	0.04	0.05	0.05
New	-	0.20	0.17	0.14
All	0.26	0.24	0.22	0.19
Date survey	-	03/2020	05/2020	04/2020

Notes: Workers are from the private and public sector. Previously are the share of workers that WFH before March 2020, New are the ones that started WFH after March 2020. Data source: own estimates, INE Uruguay and Equipos Consultores.

5 Final Remarks

Governments and individuals response to the Covid-19 pandemic has led us to lockdown and the disruption of certain economic activities. This abrupt change in behavior have direct consequences on jobs that can't be done at home and require close physical contact.

In this brief descriptive analysis for Uruguay, I showed that stricter policies that precludes workers from going to work physically could let to significant aggregate and redistributive consequences through the nature of the worker's jobs. Moreover, milder social distancing policies that disrupt only contact-intensive jobs might have significantly weaker aggregate and redistributive consequences.

This analysis is purely descriptive which may be suggestive about certain aspects of

[8] For the 2020 survey the INE included questions related to WFH.

the social distancing polices, but is not indicative of the desirability of different policies. For a normative analysis it is necessary to consider the proper trade-offs. In this spirit, a large body of research has approached the normative aspects of the pandemic by considering health and economic aspects jointly.

The main caveats of the estimations in this paper are: (i) the occupation classification is done using U.S. data, instead of Uruguayan. This may led to certain errors if for the same occupation the nature of job is significantly different in Uruguay relative to U.S.; (ii) other characteristics apart from Internet access of the households may prevent workers from WFH; (iii) for some jobs rapid technological advances, e.g. in the medical sector, and labor mobility across occupations may have diminish the role of the nature of the jobs in affecting the possibilities of WFH and CI.

Finally, one of the main purposes of this analysis is to serve as an input to other studies. For example, Brum and De Rosa (2020) use as part of their input the measures of WFH and CI elaborated in this paper to estimate the short-term impact of the Covid-19 pandemic on poverty in Uruguay.

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A Additional Figures and Tables

Table A.1: Sample Selection ECH 2019

Category	Observations
All	107,871
Worker	49,036
Private sector	40,714

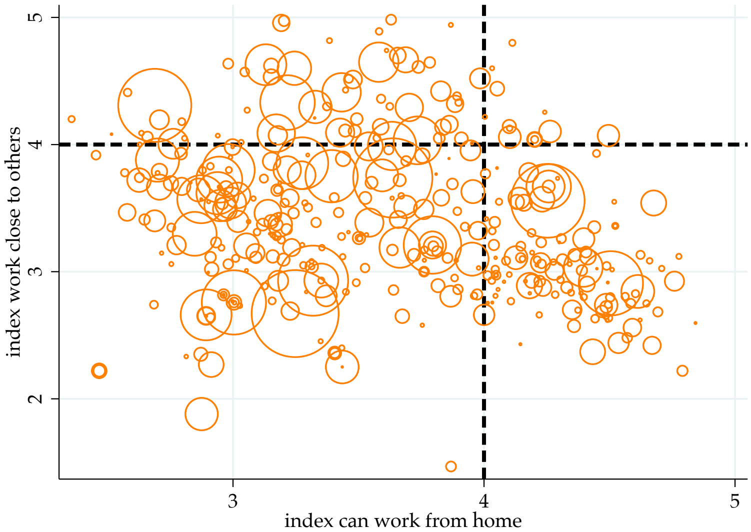
*Notes: Private sector excludes unpaid workers. Data source: O*NET and ECH-INE Uruguay 2019.*

Table A.2: Tasks used to identify WFH and CI

Category	Variable	Type
Distance	Inspecting Equipment, Structures, or Material	Activities
	Performing General Physical Activities	
	Handling and Moving Objects	
	Controlling Machines and Processes	
	Operating Vehicles, Mechanized Devices, or Equipment	
	Repairing and Maintaining Mechanical Equipment	
	Repairing and Maintaining Electronic Equipment	
	Performing for or Working Directly with the Public	
	Electronic Mail (-)	Context
	Deal With Physically Aggressive People	
	Outdoors, Exposed to Weather	
	Outdoors, Under Cover	
	Exposed to Disease or Infections	
	Exposed to Minor Burns, Cuts, Bites, or Stings	
	Spend Time Walking and Running	
	Wear Common Protective or Safety Equipment	
	Wear Specialized Protective or Safety Equipment	
Proximity	Physical Proximity	Context

Data source: based on Dingel and Neiman (2020) and Mongey, Pilossoph, and Weinberg (2020).

Figure A.1: Relation between WFH and CI

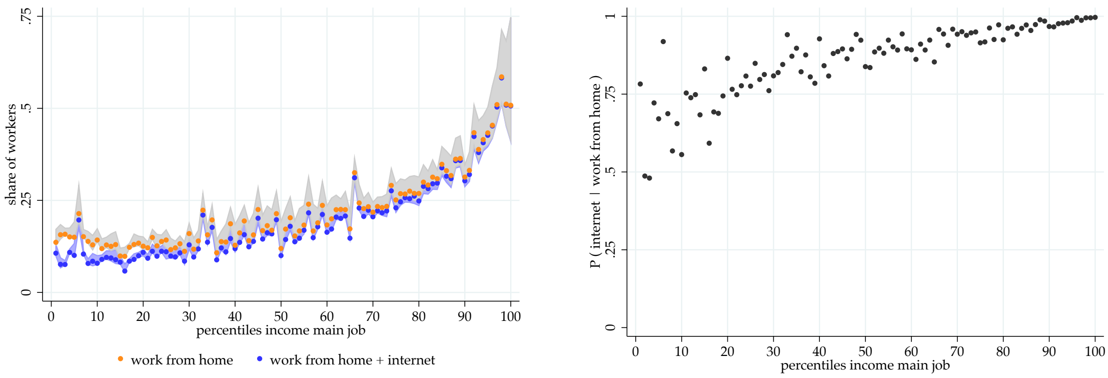


*Notes: the figure shows for each occupation the WFH and CI index constructed as an average of the task importance scores of O*NET. The size of the circles represent the amount of workers in Uruguay for each occupation The black dashed lines indicate the cut-off used to define an occupation as WFH or CI. Data source: O*NET and ECH-INE Uruguay 2019.*

Figure A.2: WFH and CI Across the Income Distribution

(a) WFH

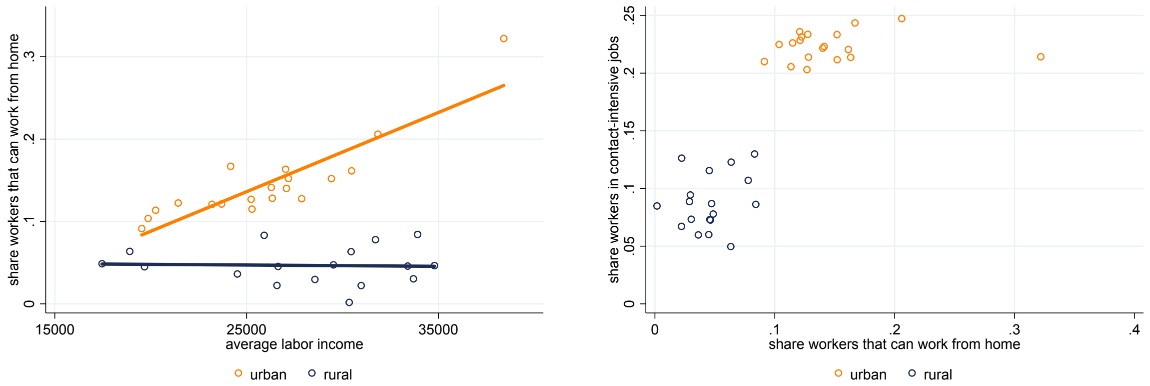
(b) Internet Access



*Notes: Panel (a) shows the observed proportion of the workers that WFH with access to Internet (blue dots) and WFH baselines estimates (orange dots). The shadowed area show the max and min when we aggregate from SOC to ISCO from O*NET to ECH. Panel (b) shows the proportion of workers that have internet access at home. Income percentiles are constructed using the main job labor income at February 2020 Uruguayan pesos. Estimates use the official ECH survey weights. Data source: O*NET and ECH-INE Uruguay 2019.*

Table A.3: Departments: Urban and Rural Locations

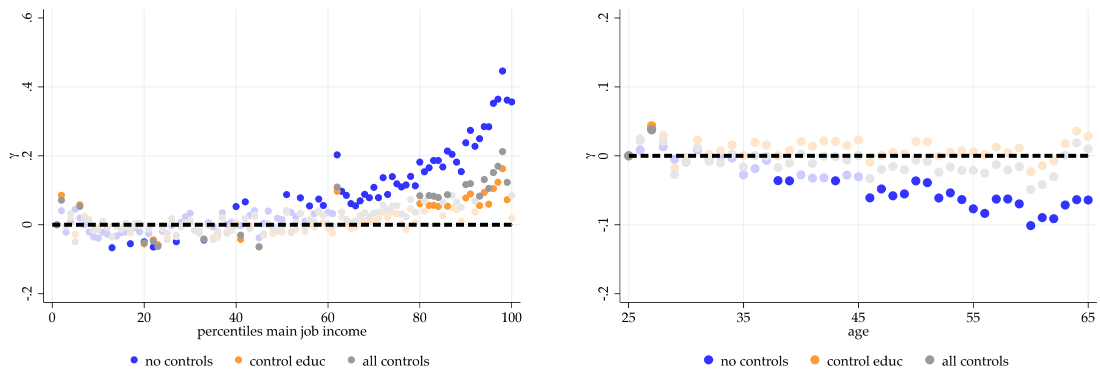
(a) WFH **(b)** CI



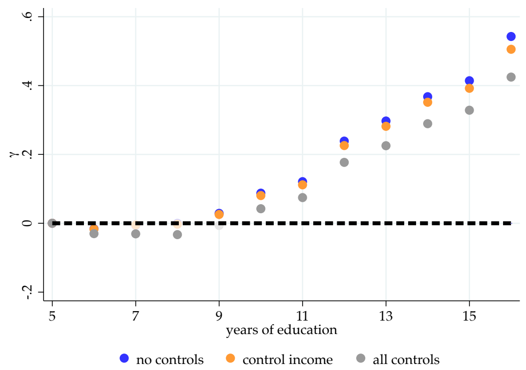
*Notes: Figure indicates proportion workers that WFH and CI by Department and conditional on rural (blue) and urban (orange) locations. Data source: O*NET and ECH-INE Uruguay 2019.*

Figure A.3: Predictors of WFH

(a) Age **(b)** Income



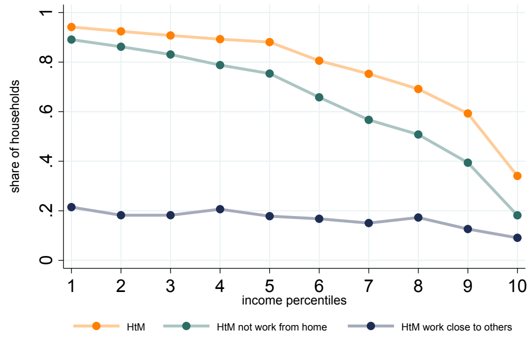
(c) Education



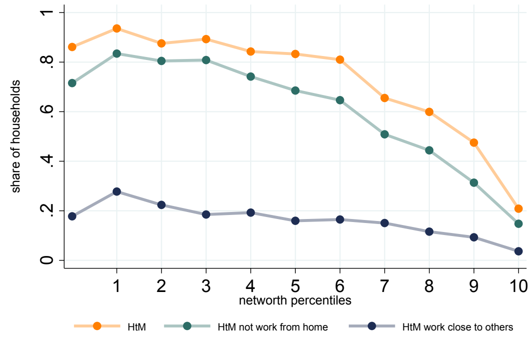
*Notes: For each predictor z_i we run the following regression $y_i = gammaz_i + \beta X_i + \varepsilon_i$ where y_i is an indicator if worker i WFH, X_i are the control variables and gamma the prediction over WFH. Panel (a) shows the γ with z_i being age and including different controls (specified in the legend of the figure). Panel (b) shows the γ with z_i being income level and including different controls (specified in the legend of the figure). Panel (c) shows the γ with z_i being education level and including different controls (specified in the legend of the figure). Estimates use the official ECH survey weights. Data source: O*NET and ECH-INE Uruguay 2019.*

Figure A.4: Hand-to-Mouth, and WFH and CI across the Income and Wealth Distribution

(a) Income

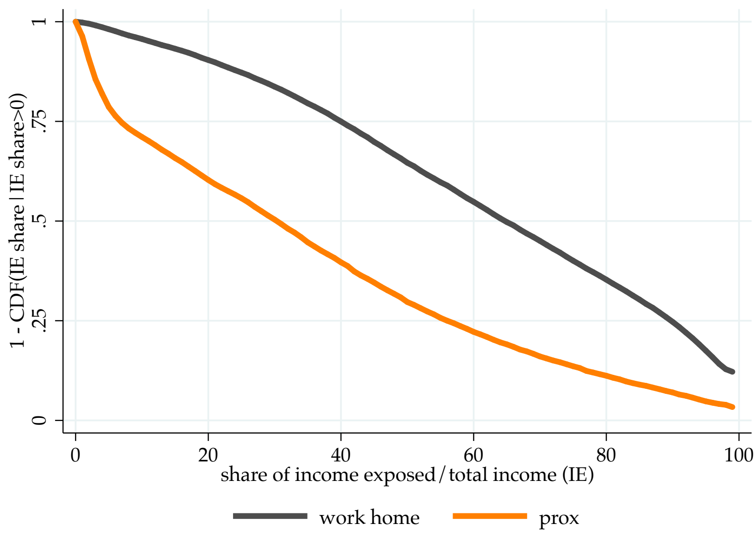


(b) Wealth



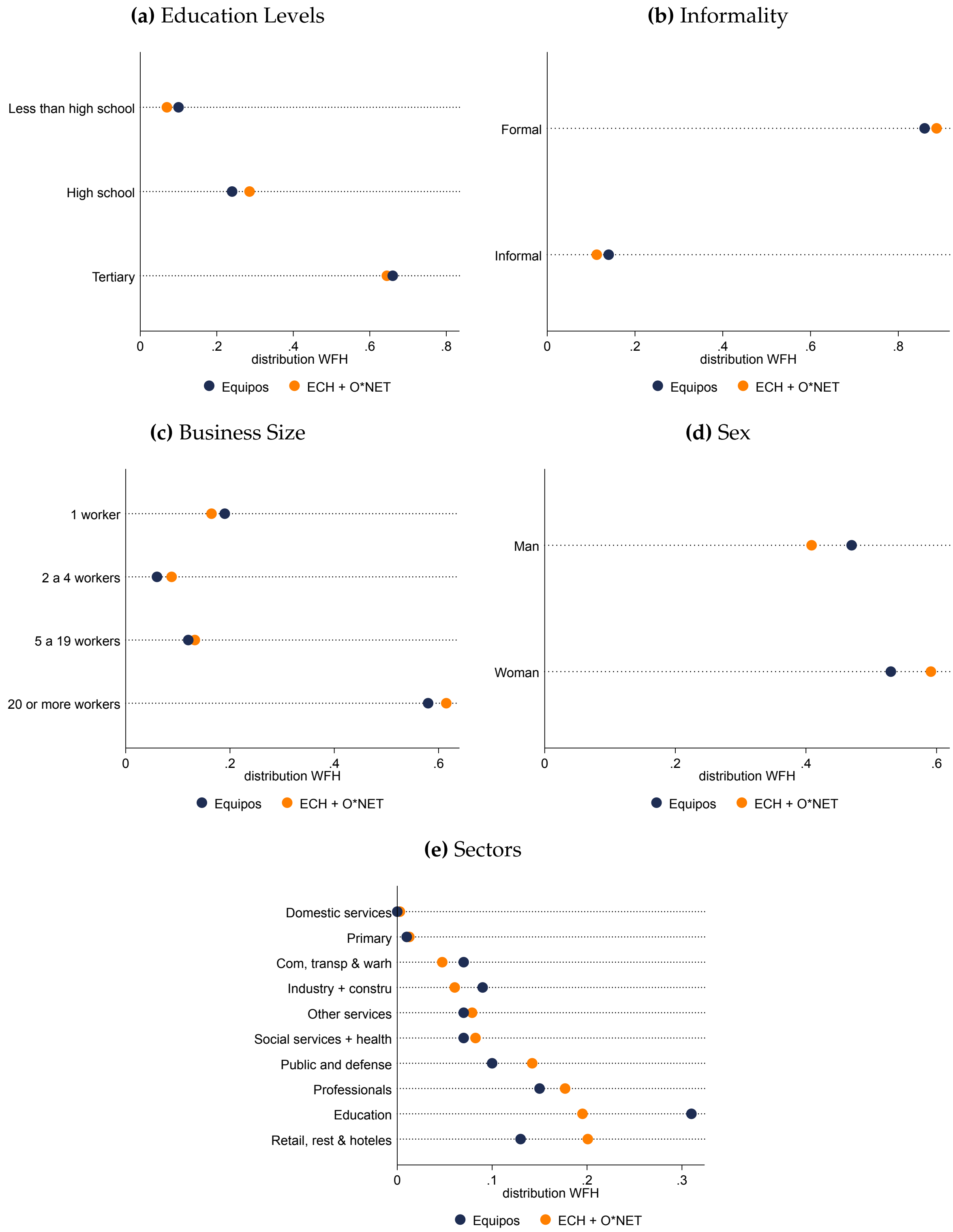
*Notes: Panels (a-b) shows the observed proportion of the workers that are hand-to-mouth(orange), hand-to-mouth that can't WFH (green) and hand-to-mouth that have CI jobs (blue) across the income and wealth distribution. Data source: O*NET and ECH-INE Uruguay 2019.*

Figure A.5: Income Diversification, and WFH and CI



*Notes: the figure shows the accumulative proportion of households according to their income exposed to not WFH and CI. Data source: O*NET and ECH-INE Uruguay 2019.*

Figure A.6: WFH Distribution by Characteristics: Comparison with Ex-Post Surveys

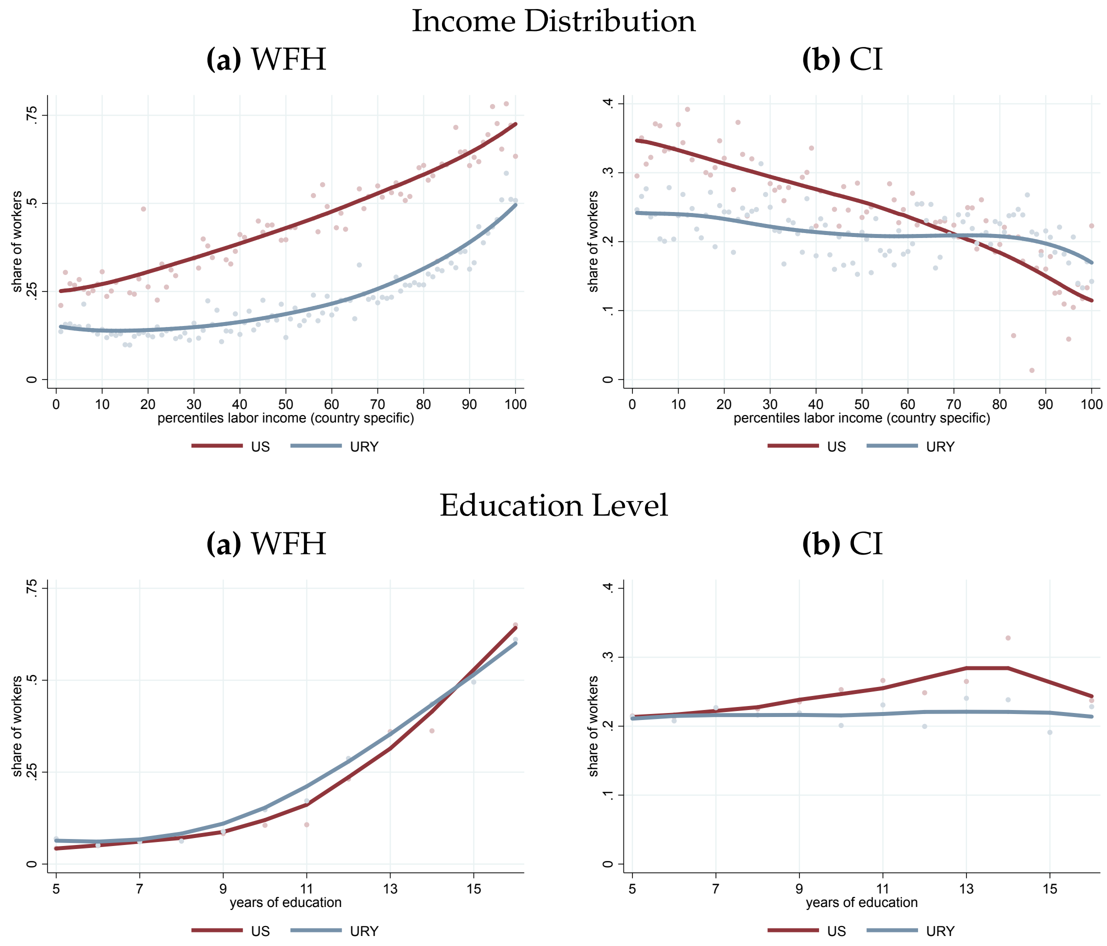


Notes: as aggregate rates are slightly different for exposition purposes I normalize $WFH_i / \sum_{i=1}^{n} WFH_i$ *so we can compare the distribution of WFH between my estimates and Equipos estimates. Data source: own estimates and Equipos Consultores May Labor Market Survey.*

B Additional Analysis

B.1 Case Study: U.S. and Uruguay

Figure B.1: Case Study: U.S. and Uruguay



*Notes: in the figure dots indicate the observed proportion of the workers that WFH and CI. Solid lines are the locally weighted smoother of the data points. For Uruguay income percentiles are constructed using the main job labor income at February 2020 Uruguayan pesos. For U.S. they are constructed using total wage and salary income. Estimates use the official survey weights for both countries. Data source: O*NET, CPS, Dingel and Neiman (2020), Mongey, Pilossoph, and Weinberg (2020) and ECH-INE Uruguay 2019.*

Dingel and Neiman (2020) and Gottlieb, Grobovsek, and Poschke (2020) find that across countries on average workers in advanced economies are much more likely to WFH than workers from emerging-market economies. In addition, in this paper I find that CI and average income level show no clear relation across countries. Following this, in this section I study the within country pattern of WFH and CI across the income distribution for U.S. and compare it to the one in Uruguay.

The WFH and CI indicators for U.S. are elaborated following Dingel and Neiman (2020) and household characteristics are from the 2019 March Current Population Survey cleaned data from Mongey, Pilossoph, and Weinberg (2020).[9] WFH and CI indicators, and households characteristics for Uruguay are the same as the ones used in Section 3.

Figure B.1 panel (a-b) show that qualitatively the same pattern emerges for U.S. and Uruguay. In both, WFH is increasing with income, and CI decreasing with income. Also there are differences. WFH shows a much higher level for the same position across the income distribution for U.S. relative to Uruguay. Workers in the 70th percentile of income in Uruguay have the same share of WFH than the bottom 10 of the income distribution in U.S.. Moreover, top incomes in U.S. are much more likely to have WFH than in Uruguay. On the contrary, CI decreasing pattern is starker in U.S. than in Uruguay. Low income workers in U.S. are much more likely to have CI jobs than low income workers, this relation reverses the higher the income.

Figure A.3 shows that one of the main predictors of WFH is education. In Figure B.1 panel (c-d) I sort workers by their years of education and find that for both countries the same pattern, qualitatively and quantitatively, emerges between U.S. and Uruguay. This suggests that workers with the same educational level in Uruguay and U.S. have jobs with similar possibilities to WFH. On the other hand, a similar pattern is observed for CI jobs, slightly increasing in U.S. and mostly flat in Uruguay. Overall, this suggest that the educational distribution may provide a simple explanation to the cross-country differences between U.S. and Uruguay in WFH, less so for CI.

[9] Also the cross-walks between O*NET, SOC and OCC occupation codes are from Mongey, Pilossoph, and Weinberg (2020).