Which workers bear the burden of social distancing policies?*

Simon Mongey† Laura Pilossoph‡ Alex Weinberg§

April 26, 2020

Abstract

What are the characteristics of workers in jobs likely to be initially affected by broad social distancing and later by narrower policy tailored to jobs with low risk of disease transmission? We use O*NET to construct a measure of the likelihood that jobs can be conducted from home (a variant of Dingel and Neiman, 2020) and a measure of low physical proximity to others at work. We validate the measures by showing how they relate to similar measures constructed using time use data from ATUS. Our main finding is that workers in low-work-from-home or high-physical-proximity jobs are more economically vulnerable across various measures constructed from the CPS and PSID: they are less educated, of lower income, have fewer liquid assets relative to income, and are more likely renters. We further substantiate the measures with behavior during the epidemic. First, we show that MSAs with less pre-virus employment in work-from-home jobs experienced smaller declines in the incidence of 'staying-at-home', as measured using *SafeGraph* cell phone data. Second, we show that both occupations and types of workers predicted to be employed in low work-from-home jobs experienced greater declines in employment according to the March 2020 CPS. For example, non-college educated workers experienced a 4ppt larger decline in employment relative to those with a college degree.

Keywords: Coronavirus, employment, social policy, occupations, demographics

*Thanks to SafeGraph for making their data available to us, as well as other researchers studying the consequences of the Coronavirus epidemic. Thanks to Gianluca Violante and Greg Kaplan for making available their codes. Our measures at the three digit occupation level are available on our websites. The views expressed in this study are those of the author and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System.

†Kenneth C. Griffin Department of Economics, University of Chicago and NBER: mongey@uchicago.edu.

‡Federal Reserve Bank of New York: pilossoph@gmail.com.

§Kenneth C. Griffin Department of Economics, University of Chicago: weinberga@uchicago.edu.

1 Introduction

The key public policy implemented during the Coronavirus pandemic is 'social distancing'. This has the economic consequence that many workers will be forced to work from home if feasible. Moreover, returning to work will likely occur more slowly for jobs that require a large degree of physical proximity to others.[1] To the extent that workers vary systematically across these jobs, social distancing policies will have systematically different effects across individuals. Understanding how individuals vary across these occupations is therefore important for policy makers interested in formulating targeted worker assistance programs.

In this paper, we combine multiple data sources to study how individuals vary across occupations which differ in their exposure to social distancing policies. We merge *individual-level* data from the Bureau of Labor Statistics' *Current Population Survey* (CPS) and the *Panel Study of Income Dynamics* (PSID) with a version of the Dingel and Neiman (2020) classification of an occupations' capacity to work from home as well as a measure of physical proximity in the workplace.[2] We construct these two measures using *occupation-level* data from the Department of Labor's *Occupational Information Network* (O*NET) data.[3] We show that despite being negatively correlated, some outlier occupations such as those related to education are both high work-from-home and high physical-proximity, hence relatively more affected when social distancing policies become targeted.

We validate the measures of work-from-home and physical-proximity using data from the *American Time Use Survey* (ATUS) that are meant to capture similar types of job characteristics. The O*NET work-from-home measure does not explicitly account for working at home, since it is designed to capture whether a job *could feasibly* be done from home, and instead is based on the types of activities conducted at work (e.g. heavy lifting, working outdoors etc). Nonetheless, the measure is highly correlated with the share of time working that *is* spent at home in ATUS. Moreover, the O*NET physical-proximity measure is correlated with the reported fraction of time spent working alone. We hope that this validation is useful for other researchers.

With validated occupation-level measures in hand, we proceed in two steps. First, we study how individual characteristics of workers vary across these types of occupations. Our main result is that workers in occupations that are more likely to be affected by social distancing policies are workers we would consider more economically vulnerable. Workers in these occupations are less likely to have a college degree and are less likely to have health insurance provided by their employer. They are less likely to be white, less likely to work at a large firm, and less likely to be born in the USA. Workers in low work-from-home occupations also have disproportionately low levels of liquid assets,

[1] For example, Governor Andrew Cuomo's policy for NY State consists of a Phase I reopening with *Construction* and *Manufacturing* jobs, which the state views as *low risk* and highly essential.

[2] See https://bfi.uchicago.edu/wp-content/uploads/BFI_White-Paper_Dingel_Neiman_3.2020.pdf

[3] In these occupation-level data, occupational classifications are finer than those available in the individual-level data. To make the data conformable we develop a cross-walk that allows us to use the Bureau of Labor Statistics' *Occupation Employment Statistics* (OES) to employment weight O*NET measures within the coarser occupations defined in the CPS. Code is available on request.

which is especially important for policies that provide liquidity to households. Finally, we show that these effects are monotonic in that occupations that score *relatively lower* (higher) in terms of the work-from-home (personal-proximity) measure, are *even more* economically vulnerable.[4]

These relationships are in general stronger when we split occupations by the work-from-home measure rather than the physical-proximity measure. Relative to occupations that score low in terms of the work-from-home measure, there is greater economic diversity among occupations associated with high levels of physical proximity. For example, salon workers, sales assistants and dentists all work in high personal-proximity environments. This suggests that the economic costs of social distancing policies may be more tightly related to pre-epidemic economic status, while the economic costs of a slow return to work that starts with low physical-proximity occupations may be more broadly distributed.

Second, using the limited data available since the start of the epidemic, we show how different occupations and workers have been effected. To begin, we construct a pre-epidemic MSA-level work-from-home measure and show that it is (i) uncorrelated with pre-epidemic mobility as measured using cellphone data from *SafeGraph*, but (ii) strongly correlated with the change in mobility during the epidemic. We then turn to employment changes across the February and March 2020 CPS surveys. Occupations that rank low in the work-from-home measure and high in the physical-proximity measure experienced larger employment declines relative to pre-epidemic February-March changes. Finally, workers that our main results suggested would be more vulnerable did indeed experience larger declines in employment. For example, non-college educated workers experienced a 4ppt larger decline in employment relative to those with a college degree.

Our results have clear implications for public economic policy. First, they provide guidance as to how income replacement and liquidity injection policies may be targeted. Second, since low work-from-home and high physical-proximity workers tend to have lower incomes and lower liquidity, the marginal social cost of income support is low, while the marginal private benefits are high. Third, the correlation between low work-from-home and high physical-proximity jobs creates a double-edged sword. It induces a correlation between *economic risks* under tight social distancing and *health risks* under relaxed social distancing. Already more economically vulnerable workers are disproportionately exposed to unemployment now, and infection in the future, suggesting the need for on-going policy interventions.

Literature. Our two contributions are to look at the *characteristics of workers* in occupations that differ by the aforementioned measures, and study the experience of these workers in the epidemic, using carefully validated occupation-level measures. Dingel and Neiman (2020) use the OES to ask the important question of what fraction of employment and income is accounted for by jobs

[4]When we compare the top quartile of occupations by the work-from-home measure, to the bottom quartile of occupations by the work-from-home measure, we find that the estimated treatment effects are larger. When we compare the third quartile of occupations by this measure, to the second quartile of occupations by this measure, we find that the estimated treatment effects are smaller but still statistically significant in all cases.

that can be done from home. Leibovici et al. (2020) conduct a similar analysis, instead considering low physical-proximity occupations rather than high work-from-home occupations.[5] Both use the O*NET to classify occupations, and then employment and income data from the OES to study the geographic distribution of employment and income accounted for by types of jobs. Our focus here is on understanding the characteristics of the underlying workers that comprise employment in these jobs, validating the measures by showing they are consistent with measures from other datasets, and verifying that they are indeed correlated with post-outbreak outcomes. This requires a careful merging of the O*NET data by occupational code with other datasets containing worker characteristics, such as the CPS, the PSID, and the ATUS.

Overview. Section 2 describes how we construct our measures of work-from-home and physical-proximity using the O*NET and OES data. We compare the two measures across occupations, and validate each against comparable measures constructed from the ATUS. Section 3 integrates the CPS and PSID data and gives our main results, which are summarized in Figure 3. Section 4 shows how occupations characterized by their work-from-home and physical-proximity measures behaved over the implementation of social-distancing. Section 5 concludes.

2 Low work-from-home and high physical-proximity jobs

Here we describe how we construct our measures of work-from-home and personal-proximity, how the two measures compare across occupations, and then validate the two measures against ATUS data.

2.1 Characteristics of jobs

To construct occupation-level measures that can be merged into worker-level data from ATUS, CPS and PSID, we combine two data sets:

> **O*NET** - Occupation-level data on work activities by occupation, where occupations are defined at the fine SOC level. SOC codes are finer than the Census OCC codes used to define occupations in ATUS, CPS, and PSID.
>
> **OES** - Occupation-level data on employment and income at the SOC level. This data is used to employment-weight when aggregating skills across SOC level occupations, within OCC level occupations.

Rather than pooling data over time we take the most recent snapshot of the US economy available to us concurrently from these data, which is 2018. We use O*NET Database 24, OES data from

[5] St. Louis Federal Reserve, *On the Economy* blog: https://www.stlouisfed.org/on-the-economy/2020/march/social-distancing-contact-intensive-occupations

2018, and the 2019 March CPS which asks questions regarding occupation and income in the prior year. In Section 4 we add the 2020 March CPS.

Using the O*NET and OES data we construct two measures for each occupation. We sign these in terms of expected negative economic impacts of the crisis: (i) *low work-from-home* ($LWFH$), and (ii) *high physical-proximity* (HPP). For our main results, we split occupations into groups based on these measures, and then use the CPS and PSID to compare the attributes of workers in occupations in each group.

We first detail how we construct $LWFH$ and then describe the construction of HPP which follows many of the same steps. Let $j \in \{1, \ldots, J\}$ denote a 3-digit OCC-code occupation, which is the measure available in worker-level data. Let $l \in \{1, \ldots, L\}$ denote the fine SOC-code categorization of occupations in O*NET and OES. We differ from Dingel and Neiman (2020) in how we aggregate skills, but use their set of O*NET job characteristics.

1. We take the following 17 measures of SOC-level occupation attributes in the O*NET data from Dingel and Neiman (2020). We index them by $k = 1, \ldots, K$. In the publicly available data, each takes on a value $m_{lk} \in [1, 5]$, representing the average response of workers to an underlying survey in which the options are $\{1, \ldots, 5\}$:

   - **Work Activities module**: Performing General Physical Activities; Handling and Moving Objects; Controlling Machines and Processes; Operating Vehicles, Mechanized Devices, or Equipment; Performing for or Working Directly with the Public; Inspecting Equipment, Structures, or Material; Repairing and Maintaining Electronic Equipment; Repairing and Maintaining Mechanical Equipment.

   - **Work Contexts module**: Electronic Mail Use;[6] Outdoors, Exposed to Weather; Outdoors, Under Cover; Deal With Physically Aggressive People; Wear Specialized Protective or Safety Equipment such as Breathing Apparatus, Safety Harness, Full Protection Suits, or Radiation Protection; Wear Common Protective or Safety Equipment such as Breathing Apparatus Safety Harness, Full Protection Suits, or Radiation Protection; Spend Time Walking and Running; Exposed to Minor Burns, Cuts, Bites, or Stings; Exposed to Disease or Infections.

   Within each 3-digit OCC occupation j, we take the employment-weighted average of m_{lk} across SOC occupations $l \in j$. This gives a measure for each occupation-attribute pair: $\overline{m}_{jk} = \sum_{l \in j} \omega_l m_{lk}$, where $\omega_l = n_l / \sum_{l' \in j} n_{l'}$. To map SOC code occupations into OCC code occupations we start with a cross-walk obtained from US Census, which we then substantially edit and verify.[7]

2. We convert these into binary variables $m^*_{jk} \in \{0, 1\}$ based on whether $\overline{m}_{jk} \geq 3.5$. Since we employment-weighted when computing $\overline{m}_{jk}$ then $m^*_{jk} = 1$ if *"The average respondent to the*

[6] In the case of Electronic Mail Use, we reverse the values such that a *high value* implies that the occupation is less suited to working from home.

[7] The basic cross-walk from Census is available here: https://www2.census.gov/programs-surveys/demo/guidance/industry-occupation/2010-occ-codes-with-crosswalk-from-2002-2011.xls

*question in the underlying O*NET survey answered at least 4."*

3. We then construct a single measure for each occupation $\overline{LWFH}_j$ by taking the unweighted mean of m^*_{jk}: $\overline{LWFH}_j = K^{-1}\sum_{k=1}^{K} m^*_{jk}$. In words, this gives the fraction of the K low work-from-home measures $\overline{m}_{jk}$ for which occupation j has a high score. We rescale this to $[0,1]$ by subtracting the minimum value and dividing by the maximum minus the minimum values.

4. We then assign the binary variable $LWFH^*_j = 1$ (*low work-from-home*) if occupation j is *above* the employment-weighted median value of $\overline{LWFH}_j$.

This procedure delivers a continuous variable $\overline{LWFH}_j$ and a binary variable $LWFH^*_j$ that can be mapped into the occupational codes contained in the CPS, ATUS, and PSID.

The procedure to construct $\overline{HPP}_j$ and HPP^*_j is similar to the above. We start with a measure m_l from O*NET at the SOC level that reflects physical-proximity at work and takes on a value $m_l \in [1,5]$. We use the OES to compute an employment-weighted mean $\overline{m}_j$ for all SOC occupations $l \in j$. We then re-scale to the interval $[0,1]$ by subtracting $\overline{m}^{Min}_j$ and dividing by $\left(\overline{m}^{Max}_j - \overline{m}^{Min}_j\right)$, which gives our measure $\overline{HPP}_j$. We then assign the dummy $HPP^*_j = 1$ (*high physical-proximity*) if the occupation is *above* the employment-weighted median of this variable. For context, before this scaling, the median value of $\overline{m}_j$ is 3.6. Therefore, in the underlying survey, the average worker in jobs we have classified as high physical proximity reports working at or within arm's length of others.[8]

To recap, by construction HPP^*_j and $LWFH^*_j$ are binary variables that equal 1 for the occupations that are *most* likely to be effected by the epidemic and ensuing policies. Half of employment is in $HPP^*_j = 1$ jobs and half of employment is in $LWFH^*_j = 1$ jobs.

2.2 Which jobs are low work-from-home and high physical-proximity?

Figure 1 shows how occupations vary across these two metrics, and where our cut-offs lie for the binary measures.[9] Unsurprisingly, there is a strong positive correlation between low work-from-home and high physical-proximity occupations. Typical 'office jobs' in financial service provision or the legal profession deliver $\widetilde{m}_{jk} = 0$ for almost all of the K features of work used to construct the low work-from-home measure. There is also little work done within arm's length in these jobs. On

[8] Workers that respond to the survey administered by O*NET choose one of: 1 = 'I don't work near other people (beyond 100ft)', 2 = 'I work with others but not closely (e.g. private office)', 3 = 'Slightly close (e.g. shared office)', 4 = 'Moderately close (at arm's length)', 5 = 'Very close (near touching)'. Publicly available O*NET data consists of an average of these responses. Since the cut-off value of $\overline{m}_j$ is 3.6, then $HPP^*_j = 1$ for occupations in which the average response to the survey question is at least 4. Our high physical-proximity occupations therefore represent occupations for which the average respondent said they worked at arm's length or less away from others. For additional information regarding this question, see https://www.onetonline.org/find/descriptor/result/4.C.2.a.3.

[9] For readability of this figure, we employment-weight using the OES to aggregate $\overline{LWFH}_j$ and $\overline{HPP}_j$ to the 2 digit level. We then linearly transform each measure $\overline{X}_j$ using its minimum and maximum: $(\overline{X}_j - \overline{X}^{Min}_j)/(\overline{X}^{Max}_j - \overline{X}^{Min}_j)$.

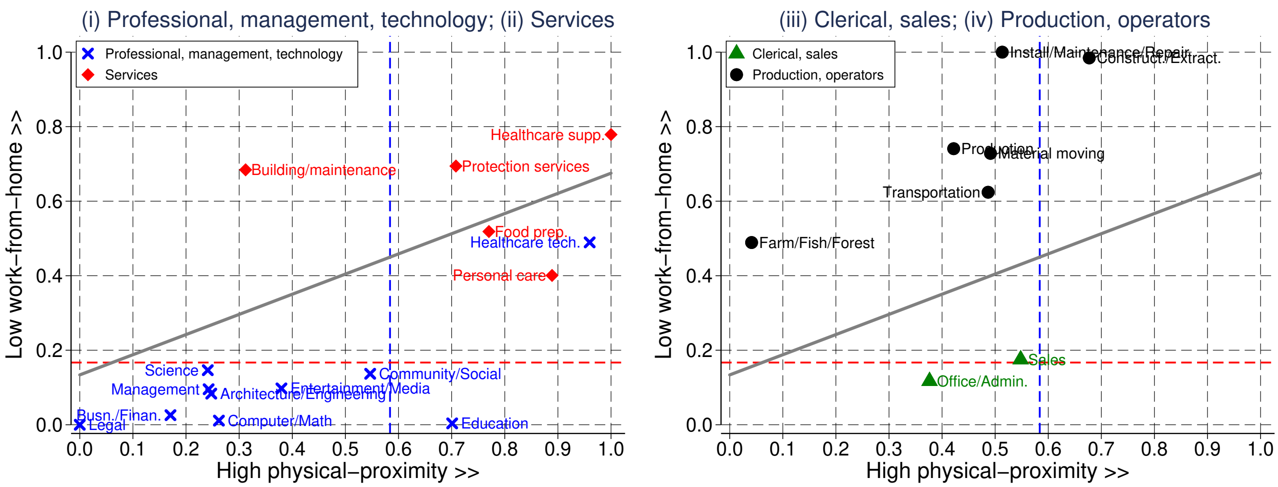

Figure 1: Occupations by Work-from-home and Physical-proximity (2 digit, Census OCC)

Notes This figure compares groups of 2 digit OCC code occupations. To construct this figure, we employment-weight using the OES to aggregate $\overline{LWFH}_j$ and $\overline{HPP}_j$ to the 2 digit level. The gray line gives fitted values are from an employment-weighted linear regression across 2 digit occupations. Occupations *above* the red-dashed line have $LWFH_j^* = 1$, and account for half of employment. Occupations *to the right* of the blue-dashed line have $HPP_j^* = 1$, and account for half of employment.

the other hand, construction, material moving, and healthcare jobs are low work-from-home and high physical proximity.

A number of occupations stand out as deviations from this pattern. Education jobs require close physical-proximity, but little of the features that would prevent the job being conducted at home. Under broad public policies of social-distancing, workers in these jobs can successfully stay employed while operating from home, which has occurred through virtual teaching. More targeted social-distancing policies in the recovery phase could be expected to feature education jobs late to reintegrate. Agricultural jobs (Farm/Fish/Forest), meanwhile, may pose lower contagion risk due to low physical-proximity, but are difficult to be done from home. Such jobs may be punished somewhat unduly by indiscriminate social-distancing policies.

2.3 Comparison to measures constructed from ATUS

We construct ATUS-based measures of a job's ability to be done from home as well as the degree of physical-proximity to others involved. From the 2018 microdata files we use information on the share of work time spent in certain places and with certain people. As a work-from-home measure, we compute the aggregate share of work hours that are spent at home. As a physical-proximity measure, we compute the aggregate share of work hours spent alone.[10]

[10] We use the question in the ATUS "who" file which asks - for each activity the respondent recorded - "Who was in the room with you/Who accompanied you?" for the measure of hours working spent alone. We use the question from the interview file which asks "where were you during this activity?" for the measure of hours spend working at home.

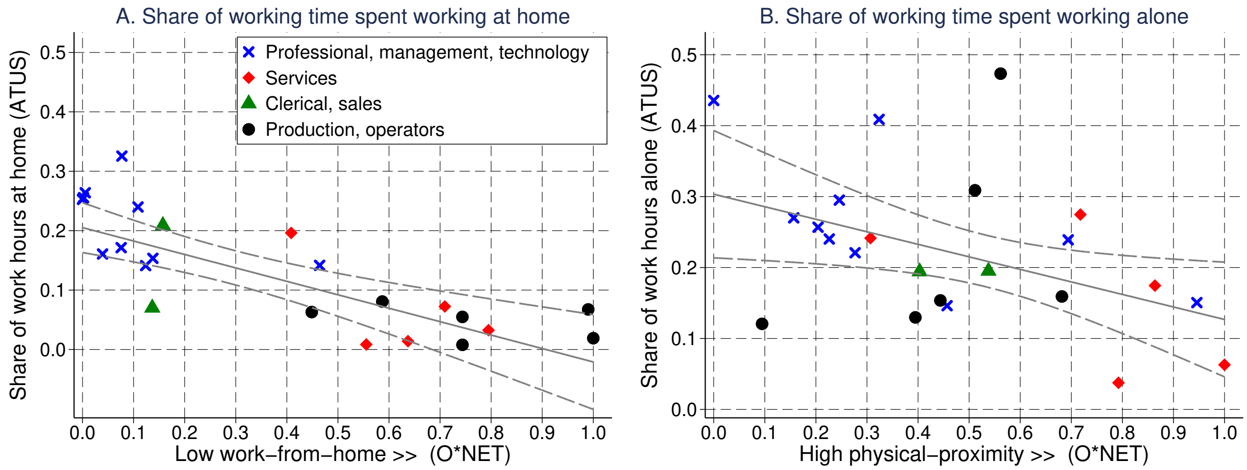

Figure 2: Comparing work-from-home and physical-proximity measures to ATUS

Notes This figure compares the fraction of individuals reporting that they can work from home in the ATUS against the O*NET WFH measure (Panel A). Panel B compares the physical proximity measures constructed from the two datasets. The share of adjusted work hours accounts for the fact that respondents can answer that they are with multiple individuals while performing a particular activity. Fitted values are from employment-weighted linear regressions, and display 95 percent confidence intervals for the conditional expectation of the dependent variable.

Figure 2A plots the ATUS measure of share of hours worked from home against the O*NET $LWFH_j^*$ measure for 2 digit occupations (Panel A). Figure 2B compares physical proximity measures. Both sets of measures are negatively correlated, which we view as validation of the O*NET measures. In particular, the work-from-home measures have a correlation of -0.83 . The physical proximity measure is less tightly linked, with a correlation of -0.44 , but this is to be expected given that the ATUS measure uses information on whether people are around you when you work, while the O*NET measure uses information on how close by those individuals are.

Figure 2 provides preliminary evidence on the distributional effects of social distancing public policies. Workers in professional services jobs (blue markers) already spend a significant fraction of time working from home and more time working alone. These types of workers—usually higher income and college educated—will be less likely impacted by social distancing policies. We now study this in detail using individual-level data.

3 Characteristics of workers by jobs

With $LWFH_j$ and HPP_j measured for occupations that are consistent with the CPS and PSID, we can compare the characteristics of workers in occupations for which these measures are high and for which these measures are low. Throughout we use the sample selection criteria of Heathcote et al. (2010) as well as their construction of wages.[11]

[11] We follow their sample selection criteria for their Sample C which is as follows. We construct wages by taking total wage and salary income plus two-third of self-employment income, and dividing this by total hours worked which we compute as the product of weeks worked last year and usual weekly hours. We keep individuals that have: age

Our approach is simple. Let y_{ij} be a characteristic of a worker i that reports that they mostly worked in occupation j last year.[12] For simplicity, we only consider binary variables in the CPS; for example we construct a variable $y_{ij} = 1$ if the continuous variable 'wage' is above the median. We then estimate the following regression for each of our observables, using $LWFH_j^*$ as an example:

$$y_{ij} = \alpha_y + \beta_y LWFH_j^* + \varepsilon_{ij}. \tag{1}$$

We then plot the values for $\widehat{\beta}_y$. This sample moment gives

$$\widehat{\beta}_y = \mathbb{E}\left[y_{ij} \middle| LWFH_j^* = 1\right] - \mathbb{E}\left[y_{ij} \middle| LWFH_j^* = 0\right] \quad ,$$

where $\mathbb{E}$ is the sample mean. Given that y_{ij} is binary, $\widehat{\beta}_y$ simply gives the fraction of workers for which $y_{ij} = 1$ in *low* work-from-home occupations, relative to the fraction of workers for which $y_{ij} = 1$ in *high* work-from-home occupations. Clearly $\widehat{\beta}_y \in [-1, 1]$ and takes the maximum value of 1 when $y_{ij} = 1$ for all individuals for which $LWFH_j^* = 1$, and $y_{ij} = 0$ for all individuals for which $LWFH_j^* = 0$. Comparing estimates across measures y and y', a higher value of $\widehat{\beta}_y > \widehat{\beta}_{y'}$ can be interpreted as

> *"Workers in occupations for which $LWFH_j^* = 1$ are relatively more different from workers in occupations for which $LWFH_j^* = 0$ along dimension y than along dimension y'".*

We estimate (1) for a number of individual characteristics. In each case we assign $y_{ij} = 1$ to the individuals with the characteristic most related to being in a low work-from-home occupation. This gives $\widehat{\beta}_y \in [0, 1]$. With this approach, we have the following characteristics of workers, all of which take on a value $y_{ij} = 1$:

- **Demographics.** (i) Non-white, (ii) No college degree, (iii) Age below 50, (iv) Male, (v) Single, (vi) Born outside USA, (vii) Non-US citizen, (viii) Rent their home
- **Work.** (i) No healthcare provided by employer,[13] (ii) Employed at a small firm ($<$ 500 employees), (iii) Part-time employed
- **Income.** (i) Below median wage,[14] (ii) Experienced a spell of unemployment in the last year.

Work and income characteristics are associated with the job at which the worker was employed for the longest period of time in 2018.

In Figure 3A, in blue, we plot the estimates for each of these characteristics for the low work-from-home regression, ordering these attributes from the highest to the lowest point estimate. Figure 3B repeats the exercise for the high personal-proximity regression. We discuss low work-from-home first, and defer our discussion to the PSID measures in red.

25-65, wages that are greater than half of the Federal minimum wage, and total hours worked more than one working month of 8 hour days (176hrs).

[12] We use the IPUMS coding of the March CPS in which this is *OCCLY*.

[13] We set the indicator for employer provided healthcare to 1 if the employer pays for any part of the individual's health insurance premiums.

[14] See footnote 10 for computation of wage.

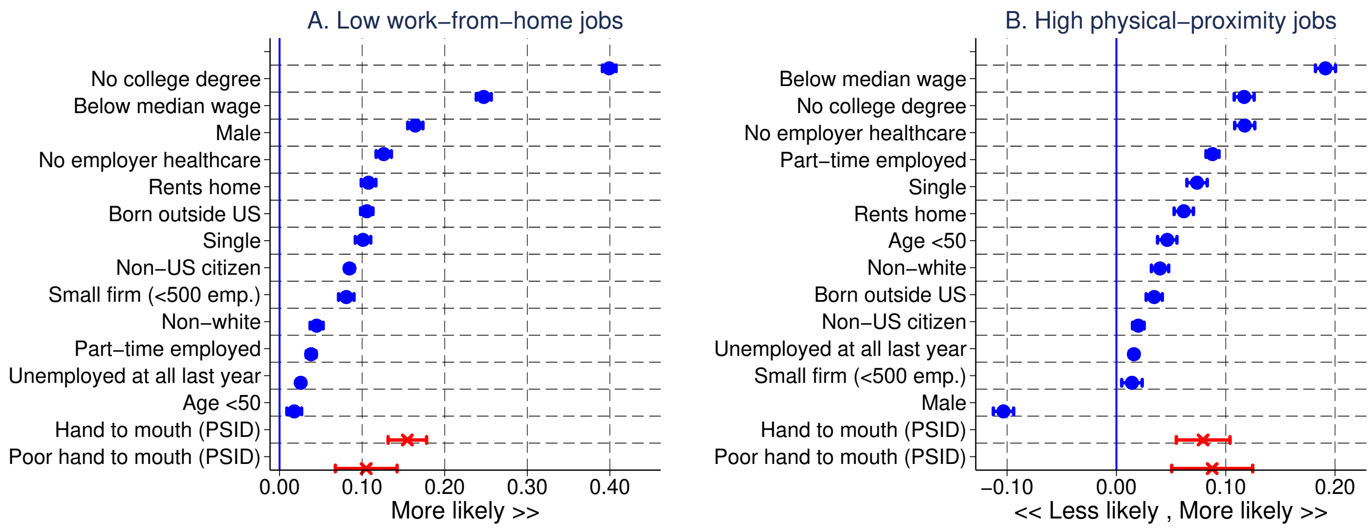

Figure 3: Characteristics of workers in *Low Work-from-home* and *High physical-proximity* jobs

Notes This figure plots estimates of $\widehat{\beta}_y$ for 10 characteristics y from regressions in which $LWFH_j^* \in \{0,1\}$ is the independent variable (Panel A), and in which $HPP_j \in \{0,1\}$ is the independent variable (Panel B). If $x\%$ of workers in *high work-from-home* occupations have, for example, *no college degree*, then Panel A shows that $(x+38)\%$ of workers in *low work-from-home* occupations have *no college degree*. A high value of $\widehat{\beta}_y$ therefore means that workers in *low work-from-home occupations* are more likely than workers in *high work-from-home occupations* to be in the category listed on the vertical axis. Point estimates are given by the circle markers, and 95 percent confidence intervals are given by the lines through each marker. All blue results are derived from the CPS, red results are derived from the PSID.

Economic and demographic. Our main result is that occupations that score low in terms of the work-from-home measure feature workers that by all measures are economically more vulnerable. Workers in these occupations are less likely to be white or to have a college degree, which relate to the fact that they are 25 ppt more likely to be below median income. They are more likely to work in smaller firms, which are on average less financially robust and so less likely to suffer from the financial effects of the crisis (Chodorow-Reich, 2014). They are more likely to rent rather than own their homes and so will not be in positions to take advantage of interest rate cuts, and have fewer collateralizable assets to borrow against to compensate for earnings losses.

Workers in these jobs are also less likely to have access to *informal insurance channels* that may help them weather the crisis. They are less likely to be married, which diversifies household income against individual income risk. They are less likely to be US citizens or born in the US, which may lead to less family support, as well as restricted access to emergency government programs. Finally, workers in low work-from-home occupations are more likely to have unstable employment. They are less likely to be employed full-time and more likely to have recently experienced unemployment.

Healthcare. Availability of healthcare is obviously a key insurance mechanism in a health crisis. Workers in low work from home occupations are less likely to have any employer-provided healthcare.

Meanwhile those in jobs that are more readily able to be performed from home are more likely to have employer provided healthcare.

Age. The mortality rate for those with COVID-19 is significantly higher for older individuals.[15] However, we find that the age of workers across these high- and low- work-from-home occupations does not systematically differ. Workers in low work-from-home jobs have the same fundamental health risks, but to the extent that these are also high physical-proximity jobs, higher occupation related health risks.

High physical-proximity. For most of the individual characteristics the results for high work-from-home occupations and low physical-proximity occupations are the same in terms of their sign. For example, workers in both high physical-proximity occupations and low work-from-home occupations are less likely to have a college degree than workers in low physical-proximity and high work-from-home occupations, respectively. The results, however, are less stark, as evidenced by the magnitudes of the coefficients. Differences in workers across high and low personal-proximity occupations are less pronounced than the differences between workers in low and high work-from-home occupations. If we consider high personal proximity occupations to be slower to be brought back as social distancing policies unwind, this suggests that the slow recovery may be more broadly experienced than the concentrated effects of unconditional social distancing.

Nonetheless, the correlation between low work-from-home and high physical-proximity jobs creates a double-edged sword. It induces a correlation in *economic risks* due to policy and *health risks* due to transmission of Coronavirus. More vulnerable workers are therefore relatively more exposed to both.

Sex. The results differ across these two measures most sharply for sex. Individuals in occupations that score highly in terms of work-from-home are more likely to be women, but this is also true for occupations that have high physical-proximity. This relates to the earlier example of Education jobs from Figure 1, which are female-dominated. Taking these results at face value, female workers may be relatively less affected by the universal social distancing measures currently in place, but could be relatively more affected in the future as these restrictions are targeted toward occupations with higher personal-proximity.

Liquidity. We expect that low access to liquid savings will compound the economic consequences of job loss or reduction in hours. To understand whether workers in low work-from-home jobs have disproportionately lower levels of liquid savings we add data from the PSID and construct measures of *hand-to-mouth*-ness of households following Kaplan and Violante (2014).[16] Hand-to-

[15] See `https://www.cdc.gov/nchs/nvss/vsrr/covid19/index.htm`.

[16] We use the code made publicly available from Kaplan et al. (2014).

mouth households are households with liquid assets that are less than half of one month's income.

Results are shown in red in Figure 3. We find that households in which the highest earner is employed in a low work-from-home or high physical-proximity job are disproportionately hand-to-mouth. Conditional on being hand-to-mouth, households may be poor-hand-to-mouth or wealthy-hand-to-mouth depending on whether they have positive or negative net-assets, respectively. Conditional on being hand-to-mouth, workers in jobs most likely affected by social distancing policy are disproportionately poor-hand-to-mouth.

The magnitudes of the point estimates are economically significant. Hand-to-mouth low work-from-home households are 10 percent more likely to be *poor hand-to-mouth* than hand-to-mouth high work-from-home households. To put this in perspective we could compare this to how, as households age, the composition of hand-to-mouth households shifts from poor- to wealthy-. Starting at age 30, one would need to move all the way up to age 50—a period of high income growth—in order to obtain a 10 percent decline in the fraction of hand-to-mouth households that are poor hand-to-mouth (Kaplan et al., 2014, Figure 6). Despite not being significantly younger, low work-from-home households have finances *as if* they are twenty years further back in their lifecycle.

Comparing extremes. A policy maker might not be interested in policies targeted below and above the median of the indexes we create since they rule in too many individuals. We therefore verify that if we make more extreme comparisons using the tails of our measures, then we get more extreme results in terms of the economic situation of households. Figure A1 in Appendix A compares the lower quartile to the upper quartile (dropping the middle quartile, in red), and the second quartile to the third quartile (dropping the upper and lower quartile, in green). When we compare workers in *very low* work-from-home occupations to workers in *very high* work-from-home occupations (in red), the coefficients are uniformly larger in magnitude. For example, workers in the lowest quantile of work-from-home occupations are nearly 50 ppt more likely to not have a college degree. Targeting policies into the lower tail of the distribution is both cheaper (lower incomes to replace) and more effective (lower resources initially available).

4 Employment during the epidemic

We now use the limited data available since the start of the epidemic for three purposes. First, we validate our measures by checking that MSAs with more employment in low work-from-home jobs—which we classified in Section 2 using pre-virus data—saw smaller increases in the rates at which individuals stayed at home. Second, we show that occupations with low work-from-home scores experienced larger employment losses. Third, we return to the characteristics of workers associated with low work-from-home jobs in Figure 3 and show that these workers experienced larger declines in employment.

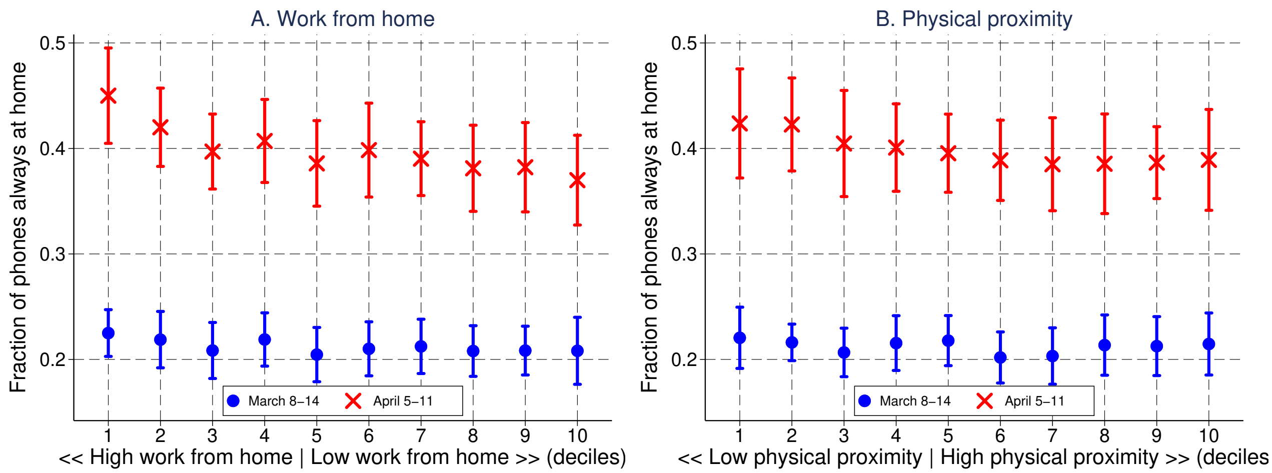

Figure 4: High work-from-home and Low physical-proximity MSAs had higher stay-at-home rates

Notes This figure compares the fraction of phones staying-at-home across MSAs. MSAs are grouped into population-weighted deciles of the work-from-home measure (Panel A), and physical-proximity measure (Panel B). Two weeks of data are plotted. The MSA level work-from-home measure is the employment-weighted average of occupation-level work-from-home measures. The MSA level phones-always-at-home measure time-aggregates over the week and geographically-aggregates over Census tracts, all phone-days in which a phone remains in a 153m×153m space, and divides by total phone-days. For example, in MSAs that are in the lowest (highest) decile of employment in work-from-home jobs, the fraction of phones at home increased by 24 ppt = 46%-22% (0.16 ppt = 37% - 21%).

4.1 Cell-phone behavior by work-from-home at the MSA level

Does the work-from-home measure formulated using pre-virus features of occupations actually relate to outcomes measured after the outbreak began? One way to assess this is to compute a work-from-home measure at the level of a geographic unit, and then study changes in stay-at-home behavior across these units. To do this we study MSAs and use SafeGraph cellphone data. SafeGraph provides daily data on the total number of cellphones that end the day in a Census block group. They also provide the number of these cellphones that stay-at-home, as measured by cellphones that do not leave a small area.[17] We do not have occupation employment data at the Census block group level, but the OES provides employment at the MSA level. We therefore aggregate phone-days and phone-days-at-home within each MSA to construct a weekly measure of the fraction of phones always at home. We construct a work-from-home measure at the MSA level by using OES data on MSA-occupation employment to take the employment-weighted average of $\overline{LWFH}_j$ at the MSA level.

Figure 4 is supportive of the measures being relevant for understanding changes in employment in the epidemic. We bin MSAs into deciles based on this measure, and then compute the average fraction of phones always-at-home. In the second week of March there is no correlation across MSAs between phone behavior and the work-from-home measure. Between the second week in March and

[17]The variable we use is *completely_home_device_count*, which gives the number of devices that do not leave an approximately 153m×153m block.

the second week in April, the average fraction of phones that are always at home jumps by around 15 ppt. However, low work-from-home and high physical-proximity MSAs see smaller increases in phones that stay-at-home, as workers are less easily able to relocate from their usual place of employment to their usual place of residence.

4.2 Employment losses by occupation

Excess employment losses from February to March of 2020 show a clear pattern: occupations with low WFH scores had relatively larger declines in employment than occupations with high WFH scores. Jobs that are more easily done at home are more likely to remain intact through the economic shutdown. We show that this is the case using CPS (2-digit) occupational employment data covering January 2010 to March 2020, the latest available CPS data. To account for seasonal factors in occupation employment changes, we construct excess employment losses by taking the log change in employment from February to March 2020 and subtracting the average February to March change in employment. Figure 5A compares the relationship between this excess decline in employment against $\overline{LWFH}_j$, showing that low work-from-home jobs experienced larger excess employment losses.

An important exception to this relationship, as expected, are those jobs deemed essential by public policy.[18] These are unlikely to have employment losses that correlate with whether the job can be done from home or not. For example, front line medical workers have low WFH measures (healthcare supplemental workers have a WFH index of around 0.2), but because they have been declared essential they can continue to work. We do not have information on which occupations are deemed essential, so instead we use industry data created by Tomer and Kane (2020), who categorize certain 4-digit NAICS industries as "essential".[19] For each 2 digit occupation we use the 2018 OES to calculate the share of employment in essential industries, and categorize an occupation as essential if more than 75 percent of employment is in an essential industry. Occupations that meet this criterion are depicted in red in Figure 5. Among these occupations there is no significant relationship between the WFH measure and employment growth.[20]

4.3 Employment losses by worker characteristics

As a final exercise, we study how excess employment losses vary across the worker characteristics considered in Section 3. For each group of workers we compute the total employment change over

[18] See https://www.cisa.gov/publication/guidance-essential-critical-infrastructure-workforce

[19] Tomer and Kane (2020) use job descriptions from the government statement which announced guidelines for categorizing essential jobs. The text for this document can be found at https://www.cisa.gov/publication/guidance-essential-critical-infrastructure-workforce.

[20] The metric we use to categorize occupations as essential is able to pick up certain obvious 2-digit occupations such as healthcare technicians and healthcare support. However, some occupations seem to be left out despite having numerous mentions in the aforementioned government text. For example, the word *construction* is mentioned thirty three times; the word legal is mentioned only once. In other work we intend to incorporate a more direct mapping between the government text and the SOC occupation codes.

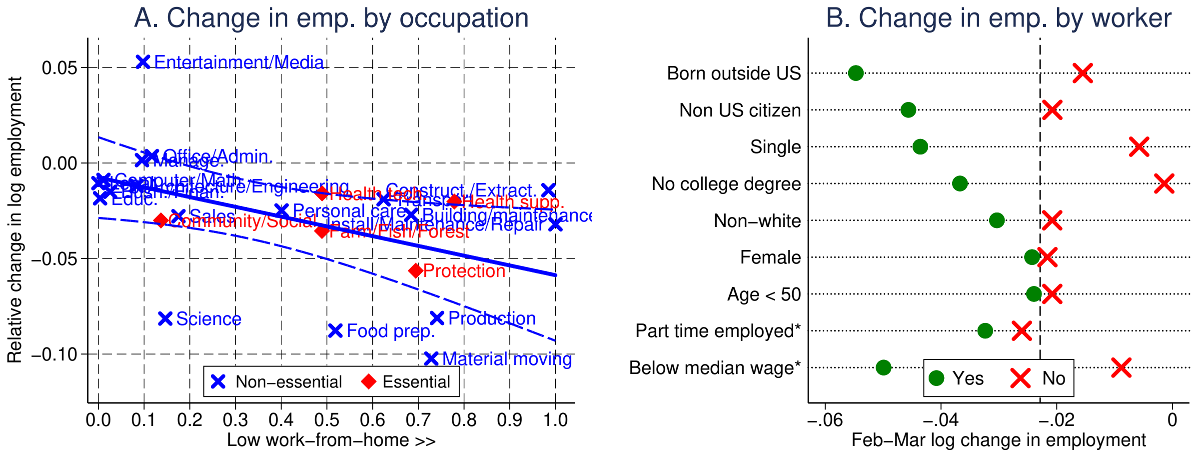

Figure 5: Employment declines by occupations and worker characteristics (February-March 2020)

Notes Both figures use employment data from the CPS. **Panel A.** This figure plots employment changes by 2-digit OCC occupation against $\overline{LWFH}_j$. Employment change is the Feb-Mar log change in employment in 2020 of each occupation, relative to the average Feb-Mar log change in employment over 2010-2019 for the occupation. Occupations marked with red diamonds are defined as "essential" using the grouping from Tomer and Kane (2020). Fitted values are from an employment-weighted linear regression estimated on non-essential occupations, and gives 95 percent confidence intervals for the conditional expectation of the dependent variable. **Panel B.** This figure plots employment changes by type of worker. The variables on the y-axes are used to split workers into two groups: those in the group given by the label ('Yes', marked with a green circle), and those outside that group ('No', marked with a red cross). We plot the log change in employment across February and March in 2020, adjusted by subtracting the average February-March change in employment for that group over 2010 to 2019. For the whole sample, we obtain a total decline in employment of -2.3 log points (black dashed line). ($*$) For the last two cases the sample is restricted to those reporting hours—in the case of *Part time employed*—and hours+earnings—in the case of *Below median wage*. In these subsamples, the average employment change is not -2.3 log points.

February-March 2020, and subtract off the mean total employment change for February-March for 2010-2019. We focus on employment rather than unemployment due to issues associated with the labeling of workers as unemployed versus out of the labor force. Figure 5 shows the results.[21]

Once again, a clear pattern emerges: those groups of individuals who have a higher employment share in low WFH occupations (as identified using the methodology of Section 2) experienced, on average, more severe employment outcomes in March 2020 relative to those in occupations with high work-from-home capability. The characteristics with the largest differential in employment outcomes between groups are citizenship, nativity, marital status, education, and age. Interestingly, while gender was an important margin which predicted the likelihood of being in low work-from-home jobs, the employment changes for February-March 2020 are not as extreme as other observable groups, which may be related to the issue of "essential" jobs discussed earlier.

[21] We check that the total employment losses that we construct using survey weights lines up with total employment losses reported by the BLS. We obtain a value of -1.82 percent. The official value from the BLS is -1.90 percent, which we compute as $\log(158,759/155,772)$ from Table 6 of the following: BLS 'Employment Situation' report - March, 2020.

5 Conclusion

We show that workers systematically differ across the types of occupations that were most likely to be hit by the public policies around social distancing required to stop the spread of the Coronavirus. Workers in occupations that are *most likely* to be affected—those with a low score in the work-from-home measure, or a high score in the O*NET measure of personal-proximity—are predominantly characterized by traits associated with the more economically vulnerable in the US economy. These workers are disproportionately less educated, have limited healthcare, are toward the bottom of the income distribution, and have low levels of liquid assets. We showed that this was a useful way of understanding job losses following the start of the outbreak in 2020.

Given the occupation-level indicators we have constructed and made available with this paper, our measures can be used to capture geographic or group level exposure to social distancing policies. Moreover, our simple approach can be extended to individual economic indicators in any microdata that records occupation. An obvious example would be individual level data on wealth and asset portfolios beyond what is available in the PSID, such as the microdata underlying the *Survey of Consumer Finance* (SCF) which is available to researchers at the Federal Reserve Board.

References

Chodorow-Reich, Gabriel, "The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-9 Financial Crisis," *The Quarterly Journal of Economics*, 2014, *129* (1), 1–59.

Dingel, Jonathan and Brent Neiman, "How Many Jobs Can Be Done At Home?," BFI White Paper, Becker Friedman Institute 2020.

Heathcote, Jonathan, Fabrizio Perri, and Giovanni L. Violante, "Unequal We Stand: An Empirical Analysis of Economic Inequality in the United States: 1967-2006," *Review of Economic Dynamics*, January 2010, *13* (1), 15–51.

Kaplan, Greg and Giovanni L. Violante, "A Model of the Consumption Response to Fiscal Stimulus Payments," *Econometrica*, July 2014, *82* (4), 1199–1239.

_ , _ , and Justin Weidner, "The Wealthy Hand-to-Mouth," *Brookings Papers on Economic Activity*, 2014, *45* (1 (Spring), 77–153.

Leibovici, Fernando, Ana Maria Santacrue, and Matthew Famiglietti, "Social Distancing and Contact-Intensive Occupations," Technical Report, St. Louis Federal Reserve Bank - On the Economy Blog March 2020.

Tomer, Adie and Joseph W. Kane, "How to protect essential workers during COVID-19," Brookings Report, Brookings Institute March 2020.

Appendix

A Additional figures and tables

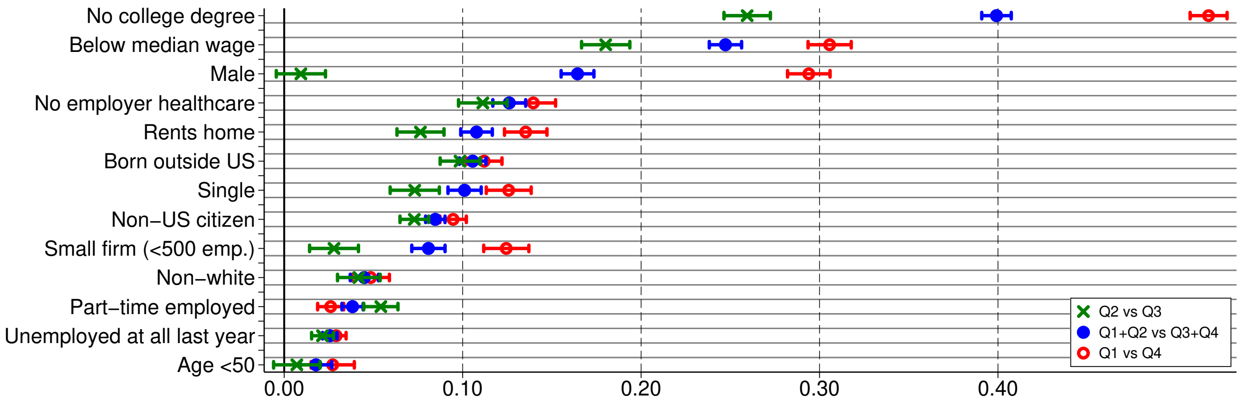

Figure A1: Comparing different groups of occupations on the Work-from-home measure

Notes This figure extends Figure 3. The blue markers replicate Figure 3. In constructing the estimates plotted in green, we set $LWFH_j = 0$ for the second quartile of our continuous measure $\overline{z}_j$, and $LWFH_j = 1$ for the third quartile of $\overline{z}_j$. In constructing the estimates plotted in red, we set $LWFH_j = 0$ for the first quartile of $\overline{z}_j$, and $LWFH_j = 1$ for the fourth quartile of $\overline{z}_j$.