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Long Social Distancing

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Abstract:

Many working-age Americans plan to continue some forms of social distancing after the COVID-19 pandemic ends. We uncover this long social distancing phenomenon in our monthly Survey of Working Arrangements and Attitudes. It is stronger among older persons, the less educated, and those who live with or care for persons at high risk from infectious diseases. Regression models fit to individual-level data suggest that social distancing lowered labor force participation by 2.4 percentage points in 2022, 1.2 points on an earnings-weighted basis. These effects are highly concentrated among persons with long COVID experiences or daily interactions with at-risk persons. When combined with simple equilibrium models, our results imply that the participation drag reduced U.S. output by $205 billion in 2022, shrank the college wage premium by 2.1 percentage points, and modestly steepened the cross-sectional age-wage profile. The socialdistancing drag on participation diminished by an estimated 1.6 percentage points from February 2022 to April 2023. Drawing on self-assessed causal effects in a separate analysis, infection worries lowered participation by an estimated one percentage point as of late 2022.

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1. Introduction

The COVID-19 pandemic drove an enormous uptake in social distancing behaviors. The pandemic also intensified concerns about the infection risks that come with face-to-face encounters in public places, including the workplace. These behaviors and concerns – and their influence on labor supply – emerge clearly in data from our Survey of Working Arrangements and Attitudes (SWAA), which goes to thousands of working-age Americans each month. The SWAA yields data on demographics, earnings, labor force status, social distancing intentions, concerns about infection risks, and more. We use SWAA data to characterize social distancing intentions and to estimate their effects on labor force participation, potential output, and the age-education structure of wages. We also relate social distancing intentions and their labor supply effects to long COVID experiences. In separate analyses that rely on self-assessments of own behaviors, we quantify the effects of infection worries on labor force participation.

As of 2022, 12% of SWAA respondents say they will continue social distancing after the pandemic ends. Another 44% say they will engage in limited forms of social distancing such as avoiding subways, crowded elevators, taxis, ride-hailing services and indoor restaurant dining. We refer to this phenomenon as "long social distancing," because it persists after distancing mandates ended and despite a steep drop in COVID deaths. Social distancing intentions are stronger among the less educated, low earners, persons who have close friends or family with long COVID experience, and those who live with or care for persons at high risk from infectious diseases. Strong social distancing roughly doubles from the early 20s to the early 60s. Beyond age 30, it is more common among women than men. Along several dimensions – education, earnings, industry, and occupation – strong social distancing is more common when remote work opportunities are fewer. Social distancing intentions also correlate with infection concerns. For example, among persons who point to infection worries as the main reason for being out of the labor force in the survey reference week, only 16% plan a "complete return to pre-COVID activities" after the pandemic ends. Among non-participants who do not cite infection worries, 42% plan a complete return.

To assess the economic effects of long social distancing, we estimate regression models that relate labor force status to social distancing intentions. We start with a simple specification that treats all demographic groups as equally responsive to social distancing intentions. Interpreted causally, the regression results say that social distancing reduces labor force participation. The estimated effects are statistically significant, and their magnitudes increase monotonically with the strength of individual-level social distancing intentions.

While this simple specification offers a transparent starting point, the equal-responsiveness assumption is too restrictive. Better educated persons are more likely to hold jobs that are amenable to remote work, and less likely to hold jobs that require many face-to-face interactions with customers and coworkers.[1] Thus, it is easier for the highly educated to practice at least limited social distancing while remaining employed. In addition, because of their higher earnings, well-educated persons can more readily avoid commuting modes that involve a high volume of close encounters with others. When we let the effects of social distancing intentions on labor force participation vary by education in our regression models, we find the largest effects by far for persons who did not attend college, moderate effects for persons with some college, and small and statistically insignificant effects for those who finished college.

If social distancing intentions are exogenous with respect to individual-level labor force status, our fitted regressions yield causal effects of those intentions. Accordingly, we use our regression models to quantify outcomes in a counterfactual scenario where each person fully returns to pre-COVID activities. That is, we turn off any reported intentions to continue social distancing and calculate model-implied outcomes. Relative to this counterfactual, social distancing intentions reduce the participation rate by 2.4 percentage points in 2022, and by 1.2 points when weighting individuals by prior-year earnings in the regression. This social-distancing drag on participation falls after spring 2022, reaching 1.6 percentage points in April 2023.

Digging deeper, we investigate how the social-distancing drag on labor force participation varies with pertinent aspects of individual-level experiences and circumstances. In this regard, we consider four groups: those with long COVID experience, those who have close friends or family with long COVID experience, those who live with or care for someone who is "more vulnerable than the general population to COVID-19 or other infectious diseases," and the other one-half of respondents who meet none of these conditions. For this last and relatively unscathed group, the estimated social distancing drag is near zero and statistically insignificant. For the other three groups, the estimated drag is large and highly significant. Thus, the social-distancing drag on

[1] See, for example, Adams-Prassl et al. (2020), Bartik et al. (2020), Barrero et al. (2021b), Dingel and Neiman (2020), and Mongey, Pilossoph and Weinberg (2021).

participation is highly concentrated among persons who have first- and close second-hand experience with long COVID, and among those who interact daily with at-risk persons.

We combine these findings with simple equilibrium models to estimate the impact of social distancing on (potential) output and the wage structure. To quantify the output effect, we adopt an efficiency-units formulation for labor and posit a standard aggregate production function with a labor input elasticity of two-thirds. Plugging the estimated earnings-weighted participation drag into the production function, social distancing reduced potential output by 0.8 percent in 2022. This effect translates to an annual GDP loss of $205 billion at 2022 prices. Our empirical results also imply that social distancing behaviors reduced the relative supply of non-college workers by 2.9 percentage points in 2022. Inserting this relative supply shift into a standard labor demand model, we estimate that social distancing shrank the college wage premium by 2.1 percentage points. In a richer analysis, we estimate the social-distancing drag on labor supply for eight distinct age-education groups, feed the results into the competitive equilibrium model of Card and Lemieux (2001), and derive the wage-structure effects. The results say that long social distancing shrank the college wage premium and modestly steepened the age-wage profile, more so for non-college than college-educated workers.

We also use self-assessments to estimate how much infection worries depress participation. Specifically, we ask persons outside the labor force in the survey reference week: "What is the <u>main reason</u> you are ***not currently working and not seeking work?***" Respondents see nine response options, including "I worry about catching COVID or other infectious diseases." A follow-up question asks about the secondary reason. To estimate the impact of infection worries on the participation rate using these data, we assign values of 1.0 and 0.5, respectively, to persons who select infection worries as the main and secondary reason. We assign 0 to everyone else. Aggregating over persons, this approach yields an estimated labor force drag due to infection worries of 1.0 percentage points in the period from October 2022 to January 2023, 0.4 points on an earnings-weighted basis. This effect is less than half the size of the contemporaneous social-distancing drag on participation, which suggests that many people engage in social distancing behaviors for reasons other than infection worries.

The self-assessment approach to causal inference relies neither on assumption-heavy structural models nor assertions about exogenous variation in the data. Instead, the identifying assumption is that respondents accurately report the reasons for their own behaviors. We think the self-assessment approach belongs in the tool kit of economists, because standard approaches to ascertaining causal effects involve their own challenges, limitations, and costs.[2] Under the self-assessment approach, the identification challenge centers on how to use surveys to elicit accurate explanations for own behaviors.[3] Obviously, but importantly, that is quite unlike the challenge of finding and using exogenous variation in quasi-experimental settings or the challenge of creating suitable random variation in field experiments.

Our findings broadly align with other evidence of less willingness to work after the pandemic struck. Using data from the Survey of Consumer Expectations and Current Population Survey (CPS), Faberman et al. (2022) find that fears of catching COVID contribute to a reduced willingness to work in 2020 and 2021, and that such fears play a larger role for women, older persons, and those with less education. Abraham and Rendell (forthcoming) consider a question in the Household Pulse Survey (HPS) that is similar in design to our question about self-assessed explanations for non-participation, but narrower in scope. Their Figure 5 says that concerns about "getting or spreading the coronavirus" lowered the participation rate by three-quarters of a percentage point in 2022. Using employment and job vacancy data, Forsythe et al. (2022) infer that the pandemic reduced the appeal of service jobs with little scope for social distancing.

Other research considers the labor supply effects of "long COVID," shorthand for the fatigue, cognitive dysfunction and other debilitating health conditions that some people experience after an active COVID infection. According to HPS data, 15% of American adults experienced long COVID symptoms as of July 2022.[4] Bach (2022), Cutler (2022), Sheiner and Salwati (2022) and Goda and Soltas (2023) deploy various empirical designs and data sources to assess the labor market effects of long COVID. All four studies conclude that it has depressed labor supply, but they differ as to how much. We contribute to this literature in two ways. First, we show how personal and vicarious experiences (through family and close friends) with long COVID relate to social distancing intentions. Second, we find evidence that long COVID among family and close

[2] For another example of the self-assessment approach to the estimation of causal effects, see the analysis in Barrero et al. (2021a) of how better internet access would affect U.S. labor productivity and output. For a broader discussion of the approach, see Stancheva (2022).
[3] Indeed, critics noted the potential for our original self-assessment question to overstate the impact of infection worries on labor force participation. We took the criticism to heart, redesigned the question, and confirmed that our new formulation yields a smaller impact. We continue to report some results based on the original question formulation, because the data cover a longer time period and larger sample.
[4] https://www.cdc.gov/nchs/covid19/pulse/long-covid.htm#technical_notes, accessed 28 August 2022.

friends lowers own participation. This indirect effect of long COVID is distinct from the direct health effects that are the focus of previous research.

Our study also relates to a literature on how personal experiences and exposure to major shocks shape individual beliefs and economic decisions. Malmendier and Nagel (2011), for example, develop evidence that past exposure to bad stock market outcomes depresses stock market participation and shrinks the equity portfolio shares of those who do participate. Malmendier and Wachter (2022) review the broader literature. In this regard, we note that confirmed COVID-19 cases number nearly 100 million in the United States as of September 2022, and deaths attributed to COVID exceed one million. In addition, public health authorities mounted an extensive, sustained campaign to persuade Americans to get vaccinated against the SARS-CoV-2 virus, wear masks, and engage in social distancing behaviors. In this light, it seems likely that the pandemic experience led to more social distancing and heightened concerns about infection risks that, in turn, reduced labor force participation. Our evidence strongly supports this view.

The next section provides additional motivation for our study. Section 3 describes the Survey of Working Arrangements and Attitudes, and Section 4 uses SWAA data to characterize the long social distancing phenomenon. Section 5 estimates the effects of social distancing intentions and infection worries on labor force participation. Section 6 quantifies the implications of social distancing for aggregate output and the wage structure. Section 7 concludes.

2. The COVID-19 Experience, Risk Perceptions, and Behaviors

The SARS-CoV-2 pandemic killed more than a million Americans as of September 2022. U.S. hospital admissions to treat COVID-19 number about six million, and confirmed COVID cases number nearly one hundred million.[5] Americans with a family member or close friend who died from COVID-19 or required hospitalization to treat the disease probably number in the tens of millions. All of this happened in just two and one-half years. In light of these facts, we hypothesize that personal and vicarious experiences with COVID-19 made infection risks more salient, encouraged social distancing behaviors, and affected labor force participation.

[5] The figures for COVID deaths and confirmed cases are from the Johns Hopkins Coronavirus Resource Center at https://coronavirus.jhu.edu/region/united-states, accessed 28 September 2022. The data on hospitalizations are from Our World in Data at https://ourworldindata.org/covid-hospitalizations, accessed 28 September 2022. We sum the daily data on new hospitalizations in the previous seven days to treat active COVID infections from 21 July 2020 to 26 September 2022, which yields a figure of 5.5 million.

Previous research supports this view. As an example, Dryhurst et al. (2020) investigate COVID-related risk perceptions in a survey of nearly 7,000 persons across ten countries from mid-March to mid-April 2020. Their "COVID-19 risk perception index" captures the respondent's perceived risk of contracting COVID in the next six months, the perceived seriousness of the illness, and their virus-related worries with regard to friends, family, and others. Looking across persons, their index rises with both (a) personal experience with COVID-19 and (b) hearing about the disease from family and friends conditional on personal knowledge of the government's strategy for dealing with the pandemic, confidence in the understanding of scientists, trust in government, trust in medical professionals, perceived efficacy of actions taken to mitigate COVID risks, and other factors. As Dryhurst et al. stress (page 1001), "experience with the virus stands out across all countries, such that people who have had personal and direct experience perceive significantly higher risk." They also find that "preventative health behaviors" (e.g., social distancing, mask wearing) increase with their risk perceptions index. Among the two-thirds of their sample that worked before the pandemic, 18 percent no longer worked four-to-six months after hospital discharge, and 19 percent had made a health-related occupational change.

Schneider et al. (2022) study the relationship of health-protective behaviors to COVID-19 risk perceptions in a series of cross-sectional surveys in the United Kingdom from March 2020 to January 2021. Looking across persons, the adoption of mask wearing and social distancing behaviors rises with risk perceptions, and the relationship becomes stronger in later survey waves. As in Dryhurst et al., risk perceptions rise with personal experience with COVID conditional on a large set of other factors. Finally, Schneider et al. find that "psychological factors are more predictive of risk perception than an objective measure of situational severity, i.e. the number of confirmed COVID-19 cases at the time of data collection." Many other studies also find that (most) individuals undertake more self-protective behaviors when they perceive greater health-related risks. Examples include Brewer et al. (2004, Lyme disease), Brewer et al. (2007, meta study of vaccine take up), Weinstein et al. (2007, influenza), Sadique et al. (2007, influenza), Bruine de Bruin and Bennett (2020, COVID), and Wise et al. (2020, COVID).

In addition, there is now abundant evidence that many people experience impaired health for weeks, months or longer after the end of an acute COVID illness. Lingering symptoms include fatigue, dyspnea, pain, insomnia, headaches, loss of taste or smell, organ damage, memory impairment, and reduced cognitive function. One well-cited study of 1,077 persons in the United

Kingdom who were hospitalized for COVID-19 and discharged in 2020 finds that only 29 percent felt "fully recovered" four-to-six months after discharge (Evans et al., 2021, page 11). In a meta study of the broader literature, Groff et al. (2021) find that more than half of COVID-19 survivors experienced symptoms six months after recovery. The most common symptoms "involved functional mobility impairments, pulmonary abnormalities, and mental health disorders." People who live with post-infection symptoms receive daily, sometimes constant, reminders that their health is adversely affected by a previous bout with COVID. These reminders keep COVID-related risks top of mind, and they may increase the salience of other infection risks as well.

There is also evidence that perceived own risks of developing a life-threatening health condition are greater when family members have had the condition. For example, persons with a family history of lung cancer perceive a two- or three-fold greater risk of developing the disease than others (Chen and Kaphingst, 2011). Women with a family history of breast cancer perceive a higher personal risk of breast cancer and are more likely to screen for the condition (Katapodi et al., 2009). Experimental studies find that exposure to (information about) one type of risk, when it generates a strong emotional response, raises the perceived likelihood of other, unrelated risks. See, for example, Johnson and Tversky (1983) and Lee et al. (2010).

Since early in the pandemic, public health authorities have undertaken extensive, sustained campaigns to inform the population about COVID-related risks and to encourage (and often mandate) social distancing and other protective behaviors.[6] It would be surprising if these extraordinary communication and persuasion efforts did not leave a lasting imprint on COVID-related risk perceptions and on the behavioral responses of at least some people. Indeed, previous research finds that strong fear appeals by public health authorities yield high levels of perceived risk in the population, more health-protective behaviors, and greater expressed intentions to engage in such behaviors. See the meta study by Witte and Allen (2000) and the review of experimental studies in Sheeran, Harris and Epton (2014). Athey et al. (2022) conduct a large-scale evaluation of public information campaigns and find that they influenced self-reported beliefs.

Media sources amplified the messaging efforts of public health authorities. Sacerdote, Seghal and Cook (2020) show that coverage of COVID-related developments in the top 15 U.S. media

[6] See, for example, the "COVID-19 Public Education Campaign," which the U.S. Department of Health and Human Services describes as a "national initiative to increase public confidence in and uptake of COVID-19 vaccines while reinforcing basic prevention measures such as mask wearing and social distancing." https://wecandothis.hhs.gov/about, accessed 28 August 2022.

sources (by readership and viewership) was overwhelmingly negative in the first months of 2020, and much more negative than the scientific literature and major media sources outside the United States. They also find that major U.S. media devote more attention to the positive effects of mask wearing and social distancing than major non-U.S. media. Ash et al. (forthcoming), Bursztyn et al. (2020) Simonov et al. (2020) all find that the tone of media coverage affects the propensity to engage in social distancing behaviors.

To sum up, personal experiences with COVID-19, COVID-related deaths and hospitalizations among family and friends, the high incidence of persistent symptoms among those who recover from COVID, the extraordinary campaign by public health officials to highlight COVID risks and underscore the need for preventative health measures, and media amplification of official messaging all operate to make infection risks more salient and to encourage social distancing behaviors. These developments motivate the hypotheses that increased social distancing and greater infection worries since the onset of the pandemic have reduced labor force participation. We investigate these hypotheses in Section 5.

There is some prior evidence that exposure to one type of risk can raise the perceived likelihood of other risks, but the existing literature appears to be thin in this regard. We are unaware of research that investigates the extent to which personal and vicarious experiences with one type of negative health shock affect the salience or perceived likelihood of other health risks. In particular, we know of no research that assesses whether negative COVID-19 experiences raise the perceived likelihood of influenza, pneumonia or other infectious diseases. There also appears to be little research on the persistence of risk perception reactions and behavioral responses to experiences with infectious diseases and to public health campaigns and media messaging about infection risks and preventative behaviors. Sections 4 and 5 provide evidence that social distancing and labor force participation responses persist for many months or more for a sizable share of the population.

3. The Survey of Working Arrangements and Attitudes (SWAA)

We have fielded a Survey of Working Arrangements and Attitudes (SWAA) of our own design since May 2020. Each month, we sample thousands of U.S. residents who are 20 to 64 years of age. We ask about demographics, labor force status, industry and occupation of the current or most recent job, working arrangements, social distancing intentions, infection worries, and more. To cost-effectively survey persons with recent work experience, we initially limited the SWAA to persons who meet a prior-earnings requirement. As our funding grew, we relaxed and then eliminated this requirement.[7] Because social distancing intentions and infection worries exert a stronger participation drag for low earners, the prior-earnings requirement reduces the magnitude of our estimated drag effects, as we confirm below.

To implement the SWAA, we contract with market research firms like IncQuery. The market research firm provides a platform to program the survey questions and intermediates with other firms (e.g., Lucid) that offer access to pre-recruited panels of prospective survey participants. When a survey wave goes to field, the market research firm issues email invitations to prospective respondents and continues until reaching the desired number and mix of participants. Email recipients are selected based on their location within the United States and their (imperfectly known) demographic characteristics. The email message states the estimated survey completion time, but does not describe the topic, and includes a link to an online questionnaire. Respondents who complete the survey receive cash, vouchers or award points, which they can donate. We do not contact respondents ourselves, do not collect personally identifiable information, and have no way to re-contact them. See Aksoy et al. (2022) for a fuller discussion of this survey technology and evidence of its widespread use in commercial applications.

Before proceeding to our empirical analysis, we drop "speeders" with survey completion times so short as to suggest a lack of careful attention to questions and response options. After dropping speeders (about 16 percent of the sample), median survey completion times range from 7 to 12 minutes across waves, which vary in number and complexity of questions. We then reweight the SWAA data to match CPS population shares in cells defined by the cross product of age groups, sex, education groups, and earnings groups.[8] The aim is to construct a sample that is representative of our target population.

[7] Initially, sample inclusion required earnings of at least $20,000 in 2019. From April to September 2021, we transitioned to a lower threshold of $10,000 in 2019. From January to March 2022, we transitioned to a threshold of $10,000 in 2021. We then phased out the prior-earnings requirement over the next few months, eliminating it altogether from June 2022 onwards.

[8] Appendix Figure A.1 reports the age, education, and earnings groups. We construct weights as follows: From May 2020 to March 2021, we pool over months and compute fixed cell-level weights so that the reweighted age-sex-education-earnings distribution in the SWAA matches the 2010 to 2019 CPS distribution. From April 2021 onwards, we use a rolling six-month approach. In month *t*, we compute the share of observations in each cell from *t-5* to *t*. We set the weights for month *t* by up- or down-weighting the SWAA cells so as to match the cell-level 2010 to 2019 CPS population shares. We cap the weights, so that no SWAA cell gets upweighted by more than five times its proportion in the raw SWAA data.

Our core analysis samples also drop respondents who fail any of the three attention check questions shown in appendix Figure A.2. These questions aim to identify respondents who fail to read questions carefully. For "What color is grass?... Make sure that you select purple…" we keep respondents who choose purple or green. For "In how many cities with more than 500,000 inhabitants have you lived?... Irrespective of your answer please insert the number 33," we drop respondents who do not report 33. For "What is 3 + 4?" we drop respondents who give any response other than 7. An additional 12% of respondents (after dropping speeders) fail one or more attention check questions.[9]

Despite our best efforts to construct a representative sample for the target SWAA population, non-random selection on unobservables could still bias our estimates of labor supply responsiveness to social distancing intentions and infection worries. To assess this concern, we fielded an HPS question about the "main reason for not working for pay or profit" in the August 2022 SWAA. We then compare HPS and SWAA responses to the HPS question. Because the HPS does not ask about earnings, we use household income data to create an HPS sample that crudely approximates the individual earnings requirement in the contemporaneous SWAA samples.

As reported in Appendix Table A.1, 1.9 percent of the resulting HPS sample gave "I was concerned about getting or spreading the coronavirus" as the reason for not working. 2.6 percent of the SWAA sample gave this reason. The difference is statistically insignificant but consistent with a modest tilt in the SWAA sample towards persons who don't work because of COVID-19 concerns. However, another 3.2 percent of the HPS sample gave their reason for not working as "I was sick with coronavirus symptoms or caring for someone who was sick with coronavirus symptoms." Only 1.6 percent of the SWAA sample gave this reason. Someone who is sick with the coronavirus, or caring for someone who is, could reasonably select either response option shown in Table A.1. Doing the arithmetic, 5.1 percent of the HPS sample gave one of the two responses related to coronavirus fears, as compared to 4.2 percent of the SWAA sample. This comparison gives no indication that the SWAA sample suffers from a form of selection that would overstate the impact of infection worries on labor force participation. Thus, we see these

[9] We first included attention-check questions in late 2021 and did not include "What is 3 + 4?" till March 2022. Thus, we cannot make use of these questions in the parts of our empirical analysis that extend back to 2020. Fortunately, our main results are not very sensitive to the exclusion of persons who fail attention-check questions in the more recent data.

comparisons as reassuring about the representativeness of the SWAA sample for our purposes. That said, we recognize that this analysis does not prove the absence of selection bias, given the imperfect nature of our HPS-SWAA sample comparisons, the ambiguity of the HPS response options, and the possibility that the HPS itself suffers from selection problems.

For more information about the SWAA, we refer interested readers to Barrero, Bloom, and Davis (2021b) and www.wfhresearch.com. The monthly SWAA survey instruments are available at www.WFHresearch.com/survey-design-and-question-repository/, and the SWAA micro data are accessible to interested researchers at https://wfhresearch.com/data. For description and analysis of data from a closely related many-country survey, see Aksoy et al. (2022).

4. The Long Social Distancing Phenomenon

We quantify and characterize social distancing intentions using a SWAA question first fielded in July 2020. The version in effect since June 2022 reads as follows:

> ***As the COVID-19 pandemic ends,*** which of the following would best fit your views on social distancing?
> - Complete return to pre-COVID activities
> - Substantial return to pre-COVID activities, but I would still be wary of things like riding the subway or getting into a crowded elevator
> - Partial return to pre-COVID activities, but I would be wary of many activities like eating out or using Uber, Lyft, or other ride hailing services
> - No return to pre-COVID activities, as I will continue to social distance

Over time, we modified the initial clause in this question to keep the focus on a post-pandemic future. From October 2021 to May 2022, the question began with *"**Once the COVID-19 pandemic has ended**… "* and continued with a nearly identical set of response options, as shown in Appendix Figure A.3.[10] From March to September 2021, we began with *"**Once most of the population has been vaccinated against COVID** … "*, because the prevailing view then held that sufficiently high vaccination rates would produce herd immunity and halt the pandemic. In January and February 2021, the question began *"**If a COVID vaccine becomes widely available** … "*, and in December 2020 it began *"**If a COVID vaccine is approved and made widely available** … "* Earlier waves began *"**If a COVID vaccine is discovered and made widely available** … "*

Figure 1 shows the distribution of responses to this question from February 2022 to January 2023. 12% of respondents intend "No return to pre-COVID activities, as I will continue to social

[10] In June 2022, we randomized over the older and newer versions of the question.

distance," and 44% intend either a "Substantial" or "Partial" return. Only 44% say they plan a "Complete return." We refer to intentions to continue at least some forms of social distancing after the pandemic as "long social distancing."

It's natural to hypothesize that social distancing intentions weakened over time in reaction to the roll-out of SARS-COV-2 vaccines, the spread of (partial) immunity due to recovery from previous COVID illnesses, better treatments for the disease, and declining COVID death rates. To assess this hypothesis, Figure 2 plots COVID death counts over time alongside selected responses to our question about social distancing intentions.[11] Persons planning a full return to pre-COVID activities rose from 26% of SWAA respondents in July 2020 to more than 50% in March and April 2023, providing some support for the hypothesis. The full-return share dips when COVID death counts surged in the Winter of 2020-21, late Summer 2021, and January 2022 but exhibits little near-term response to the roughly 75 percent drop in COVID deaths after early 2022. Thus, there is only a weak time-series relationship between "situational severity" and the working-age population share that fully returns to pre-COVID activities. The share that intends "no return to pre-COVID activities" is even stickier and remains above 10% through January 2023. In the descriptive characterizations to follow, we focus on this strong form of social distancing. Our analysis in Sections 5 and 6 uses the full range of expressed social distancing intentions.

As shown in Figure 3, the incidence of strong-form social distancing falls sharply with education and earnings. It rises with age, roughly doubling from the early 20s to the early 60s. It is similar for men and women in their 20s but higher for women at older ages (Figure A.4). These patterns make sense. People with less education and lower earnings have a higher incidence of pre-existing health conditions that place them at greater risk of death or serious illness from COVID and other infectious diseases. They also tend to hold jobs that place them at greater risk of infection (e.g., Mongey, Pilossoph and Weinberg, 2021). Older people are also at greater risk from COVID-19, a pattern that became evident and widely reported early in the course of the pandemic. Compared to men, women are more likely to be primary care givers for children (some of whom are too young for vaccination) and the elderly (who are highly vulnerable to COVID and other infectious diseases). Their greater care-giving responsibilities may lead women to practice more social distancing as part of precautionary efforts to protect those in their care.

[11] The count of hospitalizations to treat COVID-19 exhibits a time-series path that is very similar to the path of deaths attributed to COVID, as shown in an earlier draft.

Social distancing intentions also vary with partisan affiliation. Aggregating over the sub-groups reported in Figure 4, only 9.6% of Republicans intend to practice strong social distancing after the pandemic, as compared to 11.4% of Democrats and 14.3% of those who identify with a small party or no party. This pattern aligns with other evidence on how political leanings relate to social distancing behaviors and perceived COVID risks. For example, Allcott et al. (2020) find that Republicans were less likely to engage in social distancing behaviors during the pandemic. They also provide suggestive evidence that partisan differences in news consumption sources partly account for differences in social distancing behaviors and COVID-related risk perceptions. Likewise, Pennycook et al. (2021) find that COVID-related risk perceptions and risk-avoidance behaviors during the pandemic correlate with political leanings.

The appendix documents other cross-sectional patterns. Strong-form social distancing intentions are more common among people who work (or most recently worked) in industries and occupations that present higher infection risks because the jobs are not amenable to work from home, because they require a high volume of face-to-face encounters with others, or both. For example, the incidence of strong-form social distancing is about 13% in Leisure & Hospitality and in Retail/Wholesale Trade but only 8% in the Information sector (Figure A.6). It is 16% in Transportation-related occupations but only 8% in Management, Business & Financial occupations (Figure A.7). Among persons who are outside the labor force in the survey reference week, the strong form of social distancing is much more common among persons who point to infection worries as a reason for non-participation than among those who do not (Table A.2).

Finally, we investigate how social distancing intentions relate to personal and vicarious experiences with COVID and to living with or caring for someone "who would be more vulnerable than the general population to COVID-19 or other infectious diseases." To do so, we use the data on social distancing intentions to construct an index for how fully the respondent plans to return to pre-COVID activities. We regress the individual-level index values on indicators for COVID-related experiences and circumstances and report the results in Table 1. Persons who had COVID plan a fuller return to pre-COVID activities. The marginal effect of "Had COVID?" is highly statistically significant and sizable relative to the mean (71) and standard deviation (34) of the dependent variable. Thus, surviving COVID appears to reduce (a) the perceived risk of contracting COVID (again), (b) the expected adverse health consequences of another COVID illness, or both (a) and (b). Personal experience with long COVID shrinks this "survival effect" on labor force participation. Respondents with close friends or family who had long COVID also plan a less complete return to pre-COVID activities. This result suggests that watching other (close) persons suffer from long COVID discourages a return to pre-COVID-activities. Living with or caring for persons who are more vulnerable to COVID and other infectious diseases also discourages a return to pre-COVID activities.

In summary, the SWAA data reveal several noteworthy patterns in social distancing intentions. First, most respondents plan (as of 2022) to continue some forms of social distancing after the pandemic ends. Second, the rate of strong-form social distancing intentions rises with age and falls sharply with education and earnings. It is similar for men and women in their 20s, but higher for women at older ages. Third, strong-form incidence is greater for those who work in industries and occupations that offer less scope for remote work and require more face-to-face encounters. Fourth, social distancing intentions are stronger for those who point to infection worries to explain why they are not working. Fifth, social distancing intentions are weaker among those who survived COVID. Sixth, conditional on surviving COVID, personal and vicarious experiences with long COVID lead to more social distancing. Finally, social distancing intentions are stronger among those who live with or care for persons who are more vulnerable to infectious disease. These cross-sectional patterns indicate that social distancing intentions are more than cheap talk. In particular, persons who face greater health risks from COVID and other infectious diseases by virtue of their ages or jobs plan to engage in more social distancing, as do those who express greater worries about infection risks and those who interact on a daily basis with persons who are more vulnerable to infection.

5. The Impact of Social Distancing and Infection Worries on Labor Force Participation

We have established that ma working-age Americans express intentions to continue at least limited forms of social distancing after the pandemic, and that roughly one-tenth intend to continue strong social distancing. We now investigate how these intentions affect labor force participation. We also investigate how infection worries contribute to non-participation using separate data on self-assessed causal effects.

A. Social Distancing Intentions and Participation

Our assessment of how social distancing intentions affect labor force participation relies on regression-based quantifications of a counterfactual scenario. Table 2 reports a bare-bones regression specification that relates participation to social distancing intentions and illustrates how we quantify the implied effects. We regress $100 \times \mathbf{1}(\text{Not working and not looking for work})_{it}$ for person i in month t on his or her social distancing intentions. Column (1) reports the fitted regression in SWAA data from February 2022 to January 2023. Relative to those who plan a "complete return to pre-COVID activities," persons who plan "No return" are 14.4 (0.8) percentage points more likely to be out of the labor force, a huge effect. Those who plan a "partial return" are 3.7 (0.6) points more likely to be outside the labor force, and those who plan a "substantial return" are 0.5 (0.4) points more likely.

Next, we multiply the sample share in each category of social distancing intentions by the corresponding regression coefficient to obtain the implied drag on participation relative to "complete return." Then we sum the resulting products in column (3) to obtain a total effect on labor force participation of minus 2.4 percentage points.[12] If the regression is correctly specified and social distancing intentions are exogenous with respect to participation, this procedure yields an estimate for the causal effect of social distancing intentions on the participation rate relative to a counterfactual scenario that turns off those intentions. The earnings-weighted drag on labor force participation is only half as large at 1.2 percentage points, because the social-distancing effects are much stronger among those with lower earnings.[13] When we drop the prior-earnings requirement in column (4), the estimated participation drag is somewhat larger.

As discussed in the introduction, the equal-responsiveness assumption embedded in the Table 2 specification is overly restrictive. Table 3 relaxes this assumption by letting the coefficients on social distancing intentions vary freely across age and education groups.[14] As reported in Panel A, the marginal effects of social distancing rise with age. Recall from Figure 3 that the strength of social distancing intentions also rises with age. The estimated "total drag" on participation rises with age for both reasons. The total drag is small and statistically insignificant for people in their 20s, moderate in size but statistically significant for people in their 30s, larger for people in their 40s, and larger yet for those who are 50-64 years old. For this last group, our

[12] Adding controls for survey wave, sex, age categories, and education categories improves the regression goodness-of-fit but has very little impact on the overall estimated effect of social distancing intentions.
[13] For earnings-weighted outcomes here and elsewhere in the paper, we set individual-level earnings to the mid-point of the bin-level intervals in Figure A.1. For the top bin (>$500,000), we set earnings to $1 million. This bin accounts for only one-half of one percent of SWAA observations after reweighting.
[14] For the "No College" group in Panel B, we allow separate intercepts for those who did and did not finish high school.

results say that long social distancing reduced labor force participation by five percentage points in the period from February 2022 to January 2023.

We also find large differences across education groups in the marginal and total effects of social distancing on labor force participation. The total effects are statistically insignificant for those with a four-year college degree and for those with a more advanced degree. For those with some college, the total participation drag is large and statistically significant. For those who did not attend college, the estimated total drag on participation is even larger at 4.5 percentage points. These results also throw light on why our estimates for the earnings-weighted drag on participation are so much smaller than the equal-weighted estimates.

The appendix considers a finer partition of the sample into eight distinct groups: four age groups for "High School" workers (including those who did not finish high school) and four age groups for "College" workers (including those with some college and those with an advanced degree). Table A.3 reports the results and provides evidence that the relative supply shift away from older workers is stronger for High School workers than for College workers. The table also shows that the estimated labor force drag is greater for High School workers in each age group. Later, we will combine the Table A.3 results with a model of labor market equilibrium to estimate the effects of social distancing intentions on the age-education structure of wages.

B. The Role of COVID-Related Experiences and Situations

We now consider some evidence on how COVID-related experiences and daily interactions with health-vulnerable persons relate to labor force participation – directly and through their interactions with social distancing intentions. To do so, we first use the regressions behind Table A.3 to construct an impact index that summarizes how much social distancing intentions deter participation. This index allows for heterogeneity across age-education groups in the marginal effects of social distancing intentions.[15] We then regress individual-level non-participation status on the social distancing impact index, our indicators for personal and vicarious COVID experiences, our indicator for living with or caring for vulnerable persons, and interactions of the impact index with these indicator variables.

[15] To construct the index, we regress labor force non-participation status on social distancing intentions (as in Table 2) for each age-education group in Table A.3. We allow separate intercepts for did and did not finish high school in the non-college regressions and for 1-3 years of college, 4-year college degree and graduate degree in the college regressions. Using these regressions, we set the individual-level index value to the coefficient on his or her social distancing intentions (to zero, if the individual intends a "full return" to pre-COVID activities). The mean and standard deviation of the resulting index are 2.1 and 4.2, respectively.

Table 4 reports the results. Column (1) shows that the impact index is highly significant, which is unsurprising in light of earlier results. Columns (2) and (3) show that individuals who had (and survived) COVD actually participate in the labor force at higher rates than others. Personal experience with long COVID has no significant marginal effect. Column (4) reports results for a specification that includes the impact index and all four indicator variables. When we control for the impact index, the direct effect of long COVID on non-participation shrinks by about one-third. However, people who live with or care for vulnerable persons are more likely to stay out of the labor force, conditional on the impact index and their personal and vicarious COVID experiences. The impact index itself remains highly statistically significant, and the coefficient is nearly unchanged from column (1).

Lastly, column (5) considers a richer specification that interacts each indicator variable with the social distancing impact index and includes all of the main effects. This specification reveals evidence that the negative marginal impact of social distancing intentions on labor force participation is greater for those with long COVID experience, those who have close friends and family with long COVID experience, and those who live with or care for vulnerable persons. The main effect on the "vulnerable persons" indicator shrinks but remains statistically significant at the ten percent confidence level. Oddly, the main effect on vicarious experiences with long COVID is large and negative in this expanded specification. We recognize that Table 4 is unlikely to fully capture the heterogeneity in individual-level responses to similar pandemic-related experiences. For example, Table 3 suggests that the effects of the experiential and situational variables vary with age, education and other factors. Given the size of our sample with data on these variables, we leave a deeper investigation of this heterogeneity to future work.

In Table 5, we take a different approach to assessing the role of COVID-related experiences and daily contact with health-vulnerable persons. In particular, we estimate the social-distancing drag on participation separately for subsamples that differ with respect to these experiences and situations. The results are striking. When we restrict attention to the 52% of respondents who have no personal or vicarious experience with long COVID, and who do not live with or care for vulnerable persons, the estimated social-distancing drag on participation is small, negative and statistically insignificant, as reported in column (2). When we consider subsamples with long COVID experience, or who live with or care for vulnerable persons, the estimated social-distancing drag ranges from six to eight percentage points and is highly significant. These results tell that the negative effects of social distancing intentions on labor force participation arise entirely from people who have personal and vicarious experience with long COVID or who live with or care for persons who are more vulnerable to infection risks.

In closing this section, we gather some conclusions. First, our social distancing measures capture important forces associated with reduced labor force participation. Second, the marginal and total effects of social distancing intentions on labor force participation fall sharply with education and rise strongly with age. Third, the explanatory power of social distancing survives when controlling for indicators of personal and vicarious COVID experiences and an indicator for living with or caring for someone who is vulnerable to infectious diseases. Fourth, social distancing intentions exert a larger drag on labor force participation among persons who had more intense COVID-related experiences and among those who care for or live with vulnerable persons. In fact, we find no drag on participation for persons who lack long COVID experiences and do not live with or care for health-vulnerable persons.

A natural interpretation of the third result is that people differ in how they react to similar experiences and circumstances. For example, some COVID survivors may react with a sense of relief or with perceptions of newly-acquired partial immunity that lead to less social distancing and greater labor force participation. Other COVID survivors may react with an intensified aversion to situations that bring infection risks and, as a result, a reduced willingness to work. Thus, our social distancing measures can more effectively capture the impact of COVID-related experiences than direct measures of experience. In addition, some people practice social distancing because, for them, daily close encounters with others are uncomfortable or anxiety-inducing experiences. Anecdotal accounts suggest that, after a period of semi-isolation, some people find it stressful to re-engage with high-volume social interactions and work life. And some people, having experienced a more socially-distanced lifestyle during the pandemic, may discover that they like it that way. Our social distancing measures can also capture these behavioral reactions, which can contribute to reduced labor force participation.

C. Infection Worries and Participation

Since October 2022, we have put the following question to SWAA respondents who are outside the labor force in the survey reference week:

What is the ***main reason*** you are ***not currently working and not seeking work?***

a) I am retired
b) I am a full-time student

c) I worry about catching COVID or other infectious diseases
d) I would lose social assistance benefits (e.g. Medicaid, disability payments, food stamps, etc.)
e) My health makes it hard to work
f) Child-care responsibilities
g) Other caregiving responsibilities – e.g., caring for a parent or partner
h) I don't need to work, and I prefer not to
i) Other reason (please specify): [Free-form text input]

We randomize the ordering of response options, except or placing "Other reason (please specify)" last. We then ask, "What is the ***second most important reason*** you are ***not currently working and not seeking work?"*** Response options are the same except for dropping the main reason and adding "None" at the end of the response options. We deliberately frame these questions in terms of "catching COVID or other infectious diseases" to allow for the possibility that the pandemic experience increased the salience of all work-related infection risks.

These questions elicit the respondent's own assessment of whether infection worries explain their non-participation status. We summarize the responses and quantify their implications in Table 6, drawing on data from October 2022 to January 2023 and reporting results for two samples: all persons 20-64 years of age, and a sample that excludes persons who earned less than $10,000 in the prior calendar year. In the "all persons" sample, 1.1% of non-participants identify infection worries as the main reason for not working and not seeking work, and another 4.6% point to them as the second most important reason. These values translate to 0.3% and 1.3%, respectively, of everyone from age 20 to age 64 – including labor force participants.

To quantify the associated drag on labor force participation, we attribute non-participation status to infection worries with a weight of one for persons who say those worries are the main reason for not working and not seeking work, and with a weight of one-half for those who say infection worries are the second most important reason. We attribute a zero role to infection worries for everyone else. Aggregating over persons, the implied labor force drag due to infection worries in the full sample is 1.0 (0.07) percentage points on an equal-weighted basis and 0.4 (0.04) points on an earnings-weighted basis.

Originally, starting in February 2022, we used a different formulation of the self-assessment question. In particular, if the respondent was outside the labor force in the survey reference week, we asked:

Are worries about catching COVID or other infectious diseases a factor in your decision not to seek work at this time?

- *Yes, the **main reason***
- *Yes, a **secondary reason***
- *No*

We randomized the ordering of response options.[16] This question went to all non-participants from February to September 2022 and to half of them, randomly selected, from October 2022 onwards. (The other half received the formulation above with many response options.) When we use the responses to this question, following the same approach as before, we obtain a larger labor force participation drag associated with infection worries, as detailed in Table A.4. Specifically, using data from October 2022 to January 2023, this formulation yields an estimated labor force drag of 1.7 percentage points, 1.2 points on an earnings-weighted basis.

Our original self-assessment question suffers from a design weakness, as critics have pointed out. In particular, the response options don't explicitly mention other potential reasons for not seeking work. That design feature could encourage respondents to focus on infection worries to the exclusion of other factors, or prompt respondents to exaggerate the role of infection worries because they believe that's what the survey designers want to hear. In either case, this aspect of the question design can upwardly bias the estimated drag associated with infection worries. We think this criticism is well taken, and that our newer question design is superior. We still report results based on our original question formulation, because the data cover a longer time period.

We also draw on HPS data for a question that goes to all respondents who are not working in the survey reference week. That question reads as follows:

What is your main reason for not working for pay or profit? *Select only one answer.* I did not work because:

- I did not want to be employed at this time
- I am/was sick with coronavirus symptoms or caring for someone who was sick with coronavirus symptoms (including long-term effects of coronavirus)
- I am/was caring for children not in school or daycare
- I am/was caring for an elderly person
- I was concerned about getting or spreading the coronavirus

[16] From February to May 2022, we randomized over the two "Yes" options but always placed "No" last. Starting in June, we did the same for half the sample and fully randomized the ordering for the other half. The data for June and July reveal evidence that always placing "No" last imparts an upward bias to the estimated labor force drag due to infection worries, so we continued randomizing the placing of "No."

- I am/was sick or disabled (not coronavirus related)
- I am retired
- I am/was laid off or furloughed
- My employer closed temporarily
- My employer went out of business
- I did not have transportation to work
- Other reason, please specify

Using the response data, we compute the fraction of working-age persons who are not working in the survey reference week ***and*** say that concerns "about getting or spreading the coronavirus" is the main reason. The resulting estimate for the participation drag using HPS data from October 2022 to January 2023 is 0.6 (0.02) percentage points. This estimated drag effect is 60% as large as the SWAA-based estimate in column (7) of Table 6.

There are several potential sources of this difference between the SWAA-based estimate of the labor force drag associated with infection worries and the HPS-based estimate of the drag associated with concerns about getting or spreading the coronavirus. One factor that matters greatly is the treatment of secondary reasons for not working. Recall that the SWAA asks about the main and second most important reasons, while the HPS asks only about the main reason. If we lower the weighting factor on respondents who point to infection worries as the second most important reason from 0.5 to 0.25, the resulting SWAA-based drag estimate is 0.6 percentage points, nearly identical to the HPS-based estimate. If we restrict attention to the "main reason" responses in the SWAA, the implied labor force drag estimate is 0.3 percentage points, only half as large as the HPS-based estimate.[17] Thus, the weights assigned to secondary reasons have a big impact on the resulting estimate of the labor force drag.

It's also clear from this discussion that the treatment of secondary reasons is not the only important source of the difference between the SWAA-based and HPS-based drag estimates. In this regard, several other factors warrant attention: First, 0.8 (0.02) percent of working-age HPS respondents say they are not working in the survey reference week, because "I am/was sick with coronavirus symptoms or caring for someone who was sick with coronavirus symptoms …" Some unknown share of this 0.8 percent has an active COVID infection or cares for someone with an active COVID infection. Presumably, those respondents also stay away from their worksites to avoid getting or spreading the coronavirus. Suppose, for example, that the unknown share is one-

[17] We obtain the 0.3 value directly from column (7) in the top row of Table 5.

half. Adding that share to those who say concerns about getting or spreading the coronavirus is the main reason for not working yields a labor force drag estimate of 1.0 percentage points.

Second, the HPS question goes to all non-working persons, including those who are unemployed or on furlough in the survey reference week. That survey feature pushes up the HPS-based drag estimate relative to the SWAA-based estimate.[18] Third, the SWAA asks about the role of infection worries, whereas the HPS asks specifically about concerns related to getting or spreading the coronavirus. This narrower framing around coronavirus risks pushes down the HPS-based drag estimate relative to the SWAA-based estimate. Finally, the HPS and SWAA samples could be unrepresentative, and differently so, in ways that affect the drag estimates.[19]

In closing this section, we draw two broad conclusions. First, there is powerful statistical evidence that infection worries continue to exert a material drag on labor force participation as of late 2022. This conclusion emerges from self-assessments of own behaviors among those who are not working. It holds across multiple question designs and two independently developed surveys. Second, we are unable to confidently pinpoint the precise magnitude of the participation drag exerted by infection worries. The issue is not sampling variability. Rather, the key challenges pertain to question design and how to weight secondary reasons for non-participation status. According to our preferred SWAA-based estimate (from column (7) in Table 6), infection worries lowered the participation rate by 1.0 percentage points in late 2022. Coincidentally, HPS data also yield an estimated drag of 1.0 points when we factor in persons who say they are not working because "I am/was sick with coronavirus symptoms or caring for someone who was sick with coronavirus symptoms …" with a weight of one-half.

D. Labor Force Drag Estimates Over Time

Figure 5 gathers statistics for the four participation drag estimates discussed above and plots them over time.[20] We show each series for the maximal period covered by our data. The

[18] We can identify a subset of unemployed persons in the HPS who point to concerns about getting or spreading the coronavirus as the main reason for not working. When we drop these respondents from the numerator in the HPS-based labor force drag estimate, it does not materially affect the result.

[19] The HPS relies on a probability-based sample drawn from the Census Bureau's Master Address File. However, the sample response rate is only about ten percent. Thus, as with the SWAA, unrepresentative samples can influence the labor force drag estimates.

[20] Figures A.8 and A.9 compare the estimated drag associated with social distancing intentions and with infection worries across groups defined by sex, age, education, earnings, living arrangements, and more. Despite the level differences observed in Figure 5, the group-level results are highly correlated in the

HPS-based estimate associated with concerns about getting or spreading the coronavirus covers the longest period. It falls from 2.4 percentage points in June-July 2020 to 0.3 points in April 2023. Using our original self-assessment question, the SWAA-based estimate for the drag associated with infection worries follows a roughly parallel slide for the overlapping period, falling from 2.4 points in February 2022 to 1.1 points in April 2023. The SWAA-based estimate for the drag associated with social distancing intentions falls from 3.1 points in February 2022 to 1.6 points in April 2023. All three statistics – based on different concepts, estimation methods, and surveys – say the drag on participation fell sharply from February 2022 to April 2023: 1.1 points according to the HPS-based statistic, 1.3 points according to the SWAA-based measure of infection worries, and 1.5 points according to the estimated effect of social distancing intentions.

The estimated drag associated with social distancing intentions may appear puzzling in its movements over time and in its high levels. In this regard, we offer four observations.[21] First, as indicated by the data on COVID deaths shown in Figure 2 (and by data on hospitalizations to treat COVID), the cumulative number of Americans with close personal or vicarious encounters with COVID grew rapidly from August 2021 to February 2022, perhaps doubling from the start to the end of this period. Based on the evidence in Table 5, this development substantially raises the social-distancing drag on participation. For example, if one-fifth of the working-age population transitions from "No Long COVID Experience and No Care of Vulnerable Persons" to personal or vicarious experience with long COVID, it raises the social-distancing drag on participation by about 1.4 percentage points, according to the results in Table 5.[22] That helps understand the large rise in the social-distancing drag on participation during late 2021 and early 2022.

Second, the post-pandemic future that respondents envision in reaction to our social distancing question has surely evolved over time. In early 2021, for example, there was optimism

cross section. This strong congruence in the cross section is reassuring, given that the various statistics displayed in Figure 5 reflect different methods, question designs, and identifying assumptions.

[21] Two technical factors are also worth mentioning. First, as discussed in Section 3, we relaxed the prior-year earnings requirement from April to September 2021. While underway, and other things equal, this change in our sampling criteria imparts an upward drift in the estimated drag, as seen by comparing columns (3) and (4) in Table 2. Second, as described in Section 4, we occasionally modified the initial clause in our question about social distancing intentions. However, the timing of these modifications does not coincide with any of the largest month-to-month changes in the estimated social-distancing drag. Thus, it seems unlikely that these question modifications matter much.

[22] We compute this figure as one-fifth of the average "Estimated drag on labor force participation" in columns (3) and (4) in Table 5, treating the value for column (2) as a zero effect.

that vaccines and naturally acquired immunity would bring an end to the pandemic and consign COVID-19 to history. At the time, it was reasonable to expect the baseline level of infection risks in a post-pandemic world to approximate that of 2019. Later, however, the highly mutable nature of the SARS-CoV-2 virus became apparent, and we learned that neither vaccines nor recovery from COVID-19 conferred immunity. Accordingly, the post-pandemic future evoked by our question then involved a higher level of baseline risks. As that evolution in perceptions unfolded, it likely led to upward revisions in social distancing intentions and an increase in their marginal drag effects. Third, and cutting the other way, some people may have soured on social distancing with the passage of time and as negative psychological effects accumulated. Fourth, despite the explicit attention to the pandemic in our question design, some respondents may express social distancing intentions that are not rooted in the pandemic itself. If so, that would not bias the estimated participation drag associated with social distancing intentions, but it would lead us to overstate the extent to which the drag is a pandemic-induced phenomenon.

We cannot fully disentangle these influences on the participation drag associated with social distancing intentions, given our currently available data. We can point to some lessons for survey design. First, it is useful to ask directly about experiences, attitudes, situations, and perceptions. Tables 4, 5, and 6 illustrate the value of the data generated by such questions. Second, it would be helpful in future work to take a more sequential approach that first asks about social distancing behaviors and then probes into underlying motivations and reasons for those behaviors. That way, we could better understand the reasons for social distancing, more fully explore how the labor market effects of social distancing are mediated by the underlying reasons and experiences, and more confidently assess the extent to which the pandemic drove social distancing and its knock-on effects in the labor market. Tables 4 and 5 are helpful in these respects, but there is room for improvement in the design of our questions.

To close this section, we compare the estimates in Figure 5 to recent changes in the labor force participation rate and take note of other influences on participation. According to the U.S. Bureau of Labor Statistics, the participation rate fell 0.9 percentage points from 2019 to 2022 for all persons 20 and older and also for persons 25 to 54 year of age.[23] As Abraham and Rendell (forthcoming) discuss, the manner in which the BLS introduced new population controls in January 2022 (based on the 2020 Census) understates the participation rate decline by about 0.3

[23] See the BLS series CIVPART and LNS113000060, respectively, which we retrieved from FRED.

percentage points. Thus, it appears that the actual U.S. participation rate fell by about 1.2 percentage points from 2019 to 2022. This is a large drop, as are the labor force drag estimates summarized in Tables 2 and 6 and depicted in Figure 5.

Population aging was another force for declining participation rates from 2019 to 2022, and rising educational attainment was a force in the opposite direction. Abraham and Rendell assess these demographic forces and conclude that their overall contribution was to reduce the participation rate by about 0.5 points from 2019 to 2022. As their analysis and discussion of related research make clear, alternative reasonable assumptions and counterfactuals give rise to widely ranging assessments for the contribution of demographic shifts to changes in the participation rate. Turning to another possible factor, some observers conjecture that disruptions in schooling and childcare services during the early stages of the pandemic have had persistent negative effects on participation rates among persons with school-age children, especially mothers. However, Furman et al. (2021) and Goldin (2022) find little support for this conjecture.

Other forces put upward pressures on the participation rate in 2022 relative to 2019. For example, U.S. labor markets were unusually tight in 2021 and 2022 (Domash and Summers, 2022), and probably tighter in 2022 than in 2019. Tight labor markets tend to raise the participation rate (Hobijn and Şahin, 2021). In addition, the pandemic catalyzed a large, lasting shift to remote work (Barrero et al., 2021b). This shift expanded labor market opportunities for people with mobility impairments, including those who can't commute five days a week but could manage one or two days; people who live in remote and left-behind places with a limited set of nearby job opportunities; people who face joint-location constraints that limit their job options; and people who prefer to work from home to be physically present with their children or for other reasons. New options to work remotely can draw some of these people into the labor force, raising the participation rate. Jaumotte et al. (2023, Figure 14) find that countries with higher work-from-home rates in 2021 also tended to have more positive deviations from trend participation rates. Aside from this suggestive evidence, we are unaware of research that seek to quantify the overall impact of new remote-work options on labor force participation, but it seems potentially large.

In short, several forces have put upward and downward pressures on U.S. labor force participation rates since the pandemic struck. Many of these forces and their effects on participation are difficult to quantify with confidence. Some of these forces are quite unusual from an historical perspective – including the social distancing intentions and infection worries that are the focus of our analysis. We think it will take several years and many studies to reach a full understanding of recent and ongoing developments in the labor force participation rate.

6. Some Economic Implications

A. Long Social Distancing Reduces Output

We combine our estimates of the social-distancing drag on labor force participation with a simple equilibrium model to quantify the implied effects on potential output. To do so, we adopt an efficiency-units formulation of the aggregate labor input and posit a standard aggregate production function that exhibits constant returns to scale and a labor input elasticity of two-thirds. In computing labor efficiency units, we weight persons (and groups of persons) by earnings, which accounts for variation in hours worked per employed person. Implicitly, this weighting method also assumes that people are paid their marginal value products, at least on average. That assumption is surely an approximation, but it is a useful one in this context.

Using this theoretical framework, we quantify the social-distancing effect on potential output using our estimate of its overall impact on the earnings-weighted labor force participation rate. The specific calculation for the percentage impact is

$$\text{Potential Output Loss} = 100\left(\frac{2}{3}\right)\ln(1 - \text{Labor Force Drag}). \qquad (1)$$

Plugging in the earnings-weighted labor force drag estimate of 1.2 percent points from column (4) in Table 2 implies a loss in potential output of 0.8%. Thus, we conclude that social distancing intentions reduced potential output in the U.S. economy by 0.8% in 2022 relative to a counterfactual with no social-distancing drag on participation. Because U.S. labor markets were so tight in 2022, it is reasonable to supplement our potential output calculation with a full-employment assumption. With that extra assumption, this analysis further implies that social distancing reduced actual U.S. output by 0.8% in 2022. This is a material effect, corresponding to an annual GDP flow of $205 billion at 2022 prices.

B. Long Social Distancing Shrinks the College Wage Premium

Next, we assess the impact of long social distancing on the college wage premium. To do so, we combine our labor force drag estimates by education group with a standard labor demand model. In particular, we posit a CES technology defined over two labor types and treat relative wages as the outcome of a competitive equilibrium. See Katz and Murphy (1992, Section VI) for a well-known application of this framework to the evolution of the U.S. college wage premium.

They use the framework to quantify how much rising educational levels moderated the impact of increased demand for better-educated workers on the college wage premium. We use it to assess how much social-distancing intentions reduced the college wage premium.

Let *C* and *HS* index college-equivalent and other workers, respectively. The college wage premium responds to a shift in the relative supply of college-equivalent workers according to

$$\Delta \ln\left(\frac{w^C}{w^{HS}}\right) = -\left(\frac{1}{\sigma}\right)\Delta \ln\left(\frac{L^C}{L^{HS}}\right), \tag{2}$$

where $\Delta \ln\left(\frac{L^C}{L^{HS}}\right)$ is the relative supply shift, σ is the elasticity of substitution between college-equivalent and other workers in the production technology, and the equation gives the model-implied change in the college wage premium. Katz and Murphy (1992) adopt $\sigma = 1.41$ as their preferred estimate for the substitution elasticity. Other studies also conclude that a value in the neighborhood of 1.5 is appropriate for the elasticity of substitution between college-educated and other workers. See Ciccone and Peri (2005), for example.

To operationalize (2), we use estimated labor force drag effects to obtain the supply shifts by education group. Social distancing intentions reduced participation of the *HS* group by an estimated 4.4 percentage points in 2022.[24] For the College group, we consider a sample that pools over persons with some college, a four-year college degree and a graduate degree and implement the approach in Table 2. We allow separate intercepts for each education group in the regression specification and obtain an estimated drag of 1.6 points. Putting these pieces together in (2) yields $\Delta \ln\left(\frac{w^C}{w^{HS}}\right) = -\left(\frac{1}{1.41}\right)\ln\left(\frac{1-0.016}{1-0.044}\right) = -\left(\frac{1}{1.41}\right)(0.029) = -0.021.$ In words, social distancing raised the relative supply of college-equivalent workers by 2.9 percentage points in 2022, which shrank the college wage premium by 2.1 percentage points.

By design, this analysis captures a single channel through which the pandemic affects the wage structure. It is not meant to offer a full account of pandemic-related influences on the college wage premium. It also rests on a substitution elasticity value that earlier research uses to explain year-to-year and medium-run changes in the college wage premium. The COVID-19 pandemic was a surprise event that drove an abrupt fall in the relative supply of non-college workers. Perhaps the possibilities for substitution between more and less educated workers in the near-term

[24] We obtain this value as in Table 3.B and using data from January to December 2022. It differs slightly from the estimate for the HS group reported in Table 3.B, because that table uses data from February 2022 to January 2023.

aftermath of the pandemic were more limited than reflected in a 1.41 elasticity value. If so, the implied effects on the college wage premium would be greater than suggested by our calculation.

Using CPS data, Autor et al. (2023) document a remarkable compression in the U.S. wage distribution in the wake of the COVID-19 pandemic, including a decline in the college wage premium. They stress the role of tight labor markets, especially among non-college workers, as a key force behind the compression of the wage structure. Our analysis says that the social-distancing drag on labor force participation operated with much greater force on non-college workers. If our assessment is correct in this respect, then social distancing contributed to the rising tightness of labor markets for non-college workers that Autor et al. feature in their analysis.

Unlike us, Autor et al. interpret the data through the lens of a model with imperfect competition in the labor market. They develop evidence that tighter labor markets for non-college workers in the wake of the pandemic improved their bargaining positions with employers and reduced the size of their wage markdowns relative to a competitive benchmark. If their analysis is correct in this respect, our quantification exercise above may understate the impact of social distancing on the college wage premium, because it captures only the competitive-equilibrium effects on wages and not any effects that work through changes in wage markdowns.

The pandemic also operated on the wage structure in other ways. For example, it reduced the amenity value of low-pay jobs that require many face-to-face encounters (jobs held disproportionately by less educated workers), and it raised the amenity value of jobs that offer new-found opportunities for remote work (held disproportionately by highly educated workers). See Barrero et al. (2022) for a fuller discussion of this point and evidence that wages have responded to pandemic-induced changes in the amenity value of work.

C. How Long Social Distancing Affects the Age-Education Structure of Wages

We now consider a richer model that lets us quantify how social distancing has affected the age-education structure of wages. Following Card and Lemieux (2011), we posit a nested CES aggregate production function,

$$y_t = \left(\theta_h \, H^{\rho} + \theta_c \, C^{\rho}\right)^{1/\rho}, \tag{3}$$

with sub aggregates for high-school and college-equivalent workers given by, respectively,

$$H = \left[\sum_j \alpha_j \; H_j^{\eta}\right]^{1/\eta} \text{ and } C = \left[\sum_j \beta_j \; C_j^{\eta}\right]^{1/\eta}, \tag{4}$$

where H_j and C_j are corresponding labor inputs for age-group *j*. Here, $\rho = 1 - 1/\sigma^E$, where σ^E is the elasticity of substitution between the two education categories. Similarly, $\eta = 1 - 1/\sigma^A$, where η is the partial elasticity of substitution σ^A across age groups in a given education category. The α_j and β_j are group-specific efficiency parameters, which we set to mirror relative hourly wages by age group in each education category as of 2022.

In competitive equilibrium, this production function specification implies that group-level labor supply shifts alter the wage structure according to

$$\Delta \ln\left(w_j^H\right) = \left[\frac{1}{\sigma^A} - \frac{1}{\sigma^E}\right] \Delta \ln(H) - \left(\frac{1}{\sigma^A}\right) \Delta \ln\left(H_j\right) \tag{5}$$

$$\Delta \ln\left(w_j^C\right) = \left[\frac{1}{\sigma^A} - \frac{1}{\sigma^E}\right] \Delta \ln(C) - \left(\frac{1}{\sigma^A}\right) \Delta \ln\left(C_j\right), \tag{6}$$

where Δ denotes the shift associated with social distancing.[25] We set the $\Delta \ln\left(H_j\right)$ and $\Delta \ln\left(C_j\right)$ values in (5) and (6) to the corresponding labor force drag estimates reported in Table A.3. The implied shifts for the aggregated education categories follow from (4):

$$\Delta \ln(H) = (1/\eta) \ln\left\{ \left[\sum_j \alpha_j \; H_j^\eta\right] \Big/ \left[\sum_j \alpha_j \; \widetilde{H}_j^\eta\right] \right\} \tag{7}$$

$$\Delta \ln(C) = (1/\eta) \ln\left\{ \left[\sum_j \alpha_j \; C_j^\eta\right] \Big/ \left[\sum_j \alpha_j \; \tilde{C}_j^\eta\right] \right\}, \tag{8}$$

where H_j and C_j are the observed group-specific labor inputs as of 2022, and $\widetilde{H}_j$ and $\tilde{C}_j$ are the counterfactual input values that would have prevailed with no social distancing – i.e., with a "complete return to pre-COVID activities" by all working-age persons. In calculating the H_j and C_j values, we adjust for differences in average hours worked per person by age group. As before, we set $\sigma^E = 1.41$. Following Card and Lemieux, we set $\sigma^A = 5$.

Inspecting equations (5) to (8), social distancing alters the age structure of wages for a given education category only insofar as the percentage drag on participation differs across age groups. Since our empirical investigation says that the social-distancing drag on participation rises with age, we anticipate that social distancing steepens the age-wage profile. Equations (5) to (8) provide a basis for calculating how much. When the percentage drag on participation is uniform across age groups within each education category, equations (5) to (8) collapse to (2).

[25] See Card and Lemieux (2001) for the derivations underlying (5) and (6), which mirror their equations (14).

Figure 6 displays the wage-structure implications that emerge when we combine this equilibrium model with our group-level participation drag estimates in Table A.3. We find that social distancing shrank the college wage premium in every education group, more so for older workers. As anticipated, the social-distancing drag on participation also steepens the cross-sectional age-wage profile. However, the effects on the age-wage structure are modest in size, especially for college workers. The largest effect of this sort arises when comparing non-college workers 50-64 to their educational counterparts 20-29 years of age. The relative supply drop associated with social distancing for the older group raised their relative hourly wages by 1.2 log points, according to this analysis. For college-equivalent workers, the corresponding old-young relative wage effect is only two-thirds as large. As before, these results aim to quantify the effects of the social-distancing participation drag on the wage structure. Nothing in this analysis denies a role for other pandemic-related influences on the wage structure.

D. Will Social Distancing Continue to Discourage Participation?

Extrapolating from Figure 5 suggests that the participation drag exerted by social distancing intentions and infection worries will continue to subside in 2023 and beyond. That would help raise U.S. participation rates and potential output, welcome news for the economy. It would also act to partly undo the remarkable compression of wage differentials from 2019 to 2022. That said, even as of late 2022, roughly one-tenth of working-age persons continue to express strong social distancing intentions in the SWAA data. Thus, it seems unlikely that the social-distancing drag on participation will vanish completely in the near future.

There are other reasons to anticipate a waning of the drag on labor force participation. First, the pandemic drew attention to indoor air quality and its impact on infection risks at the workplace. Better ventilation and other steps to improve air quality may draw some people back into the labor force. Improving indoor air quality is costly and can require a complex set of changes, especially in existing buildings and worksites (U.S. Environmental Protection Agency, 2022). So, gains on this front are likely to be incremental, unfolding over many years. Second, the pandemic catalyzed a large, lasting increase in the opportunities to work from home (Barrero et al., 2021b, and Aksoy et al., 2022). As people with strong social distancing desires continue to find and sort into jobs that accommodate those desires, it may draw them into the labor force and help keep them engaged.

However, it's not hard to envision gloomier futures. Jones et al. (2008) document the emergence of 335 new infectious diseases in human populations from 1940 to 2004, with a rising incidence over time. Bernstein et al. (2022) present evidence that "Novel viral outbreaks appear at an irregular but increasing rate" from 1912 to 2020. Other research highlights the role of agricultural intensification and expansion, environmental change, and greater associations between humans and wildlife disease reservoirs as forces that drive the emergence of zoonotic viruses.[26] None of these forces abate any time soon. Urbanization and long-distance travel make it possible for new disease outbreaks to spread rapidly and become global pandemics.

If the SARS-CoV-2 virus mutates in a manner that brings another large surge in COVID-19 deaths and hospitalizations, or if some other virus produces a lethal pandemic, we can anticipate another wave of long social distancing that suppresses labor force participation for months and years. In this regard, our analysis (especially Tables 4 and 5) suggests that any labor force drag exerted by another pandemic event would last longer than the pandemic itself.

7. Concluding Remarks

As of 2022, more than ten percent of Americans with recent work experience say they will continue social distancing after the COVID-19 pandemic ends. Another 45 percent say they will do so in limited ways. We uncover this long social distancing phenomenon in our monthly Survey of Working Arrangements and Attitudes. It is stronger among older persons, the less educated, those who earn less, those who live with or care for persons who are more vulnerable to infectious diseases, and among those who work in occupations and industries that require many face-to-face encounters. Social distancing intentions lowered the labor force participation rate by an estimated 2.4 percentage points in 2022, 1.2 points on an earnings-weighted basis. This participation drag is concentrated among non-college workers. The labor force drag is smaller for persons with some college, and smaller yet and statistically insignificant for the college-educated. Daily contact with health-vulnerable persons and long COVID experiences lead to larger drags on participation.

When combined with simple equilibrium models, our results imply that the social-distancing drag on participation reduced U.S. output by $205 billion in 2022, shrank the college wage premium by 2.1 percentage points, and modestly steepened the cross-sectional age-wage profile – more so for non-college workers. According to our time-series evidence, the social-distancing drag on labor force participation diminished by 1.6 percentage points from February 2022 to April 2023, generating a sizable upward impulse to potential output and employment. We

[26] See, for example, Dobson et al. (2020), Gibb et al. (2020), and Carlson et al. (2022)

also find that social distancing intentions overlap with, but are broader than, infection worries. Drawing on self-assessed causal effects in a separate analysis, we estimate that infection worries lowered participation by one percentage point as of late 2022. Our estimates for the labor force drag associated with infection worries diminished by 1.3 percentage points from February 2022 to April 2023, reinforcing the view that the economy benefited from a sizable upward impulse to potential output and employment over this period.

Our study illustrates how surveys can be used to elicit behavioral intentions and self-assessed causal effects at the individual level, and how those expressed intentions and self-assessments help explain labor market outcomes. It also illustrates how to combine the empirical results at the individual level with equilibrium models to quantify aggregate implications. We hope our study inspires more research in a similar vein.

The idea of asking people about their intentions and the reasons for their behaviors is not a new one. Indeed, Freeman (1989) remarks that John Dunlop, his undergraduate professor and doctoral advisor at Harvard in the 1960s, encouraged researchers to speak with labor and management to obtain insights about the operation of markets. Freeman continues, “Getting the opinions of the subjects of our research is about the only advantage we have over physicists. Quarks and gluons do not talk about what they do or why, not even to Richard Feynman.” That line resonates with us, and we think economists have under invested in the use of surveys and structured interviews to elicit behavioral intentions and self-assessed causal effects. There are exceptions, to be sure. Bewley’s book (1999) on the sources of downward wage rigidity is a prominent example, but one that stands out for its unusual methods as well as its insights. Of course, the use of surveys to elicit behavioral intentions and self-assessed causal effects is subject to many challenges, pitfalls, and limitations. That’s true of all methods economists have at their disposal to assess causal effects.

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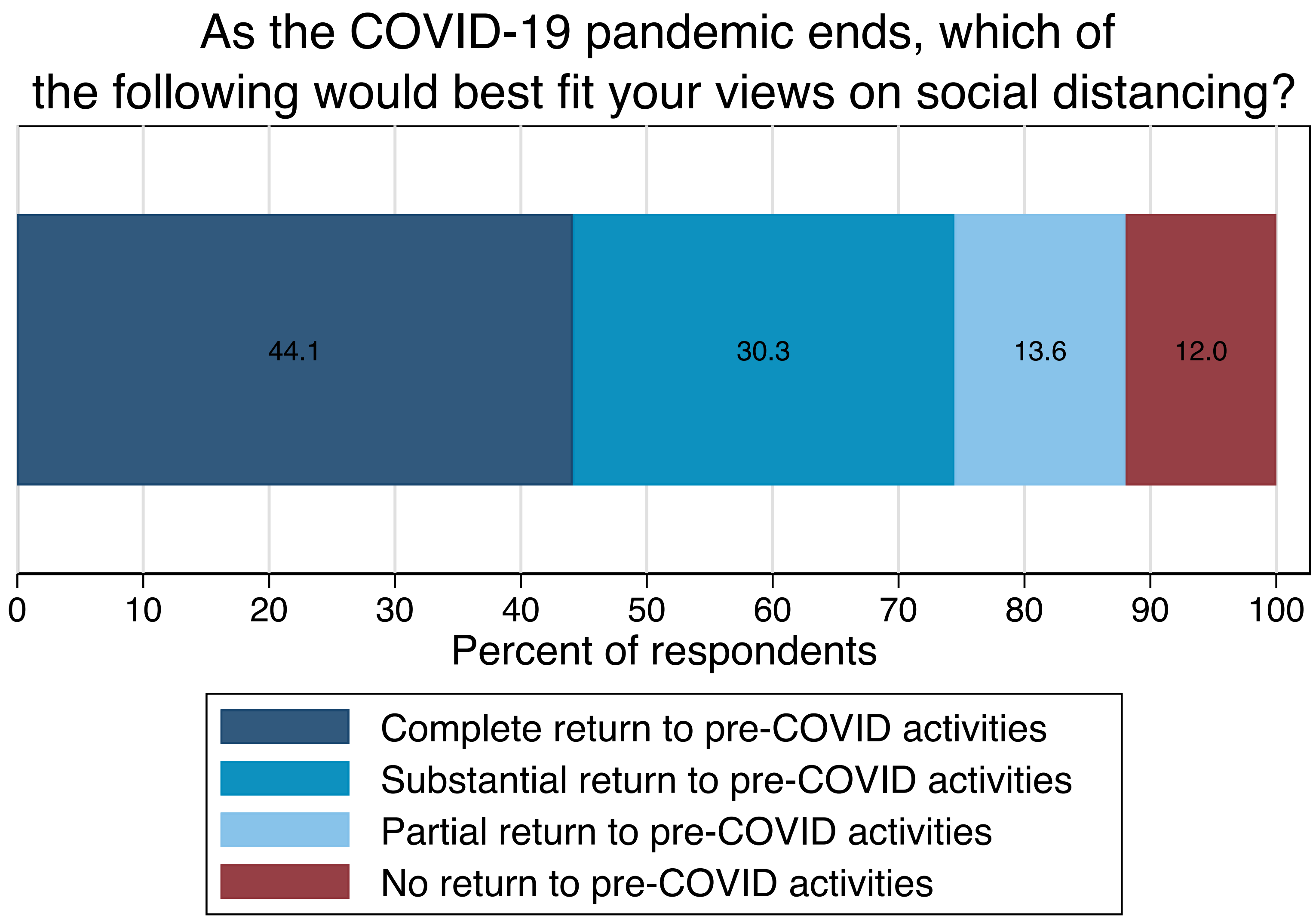
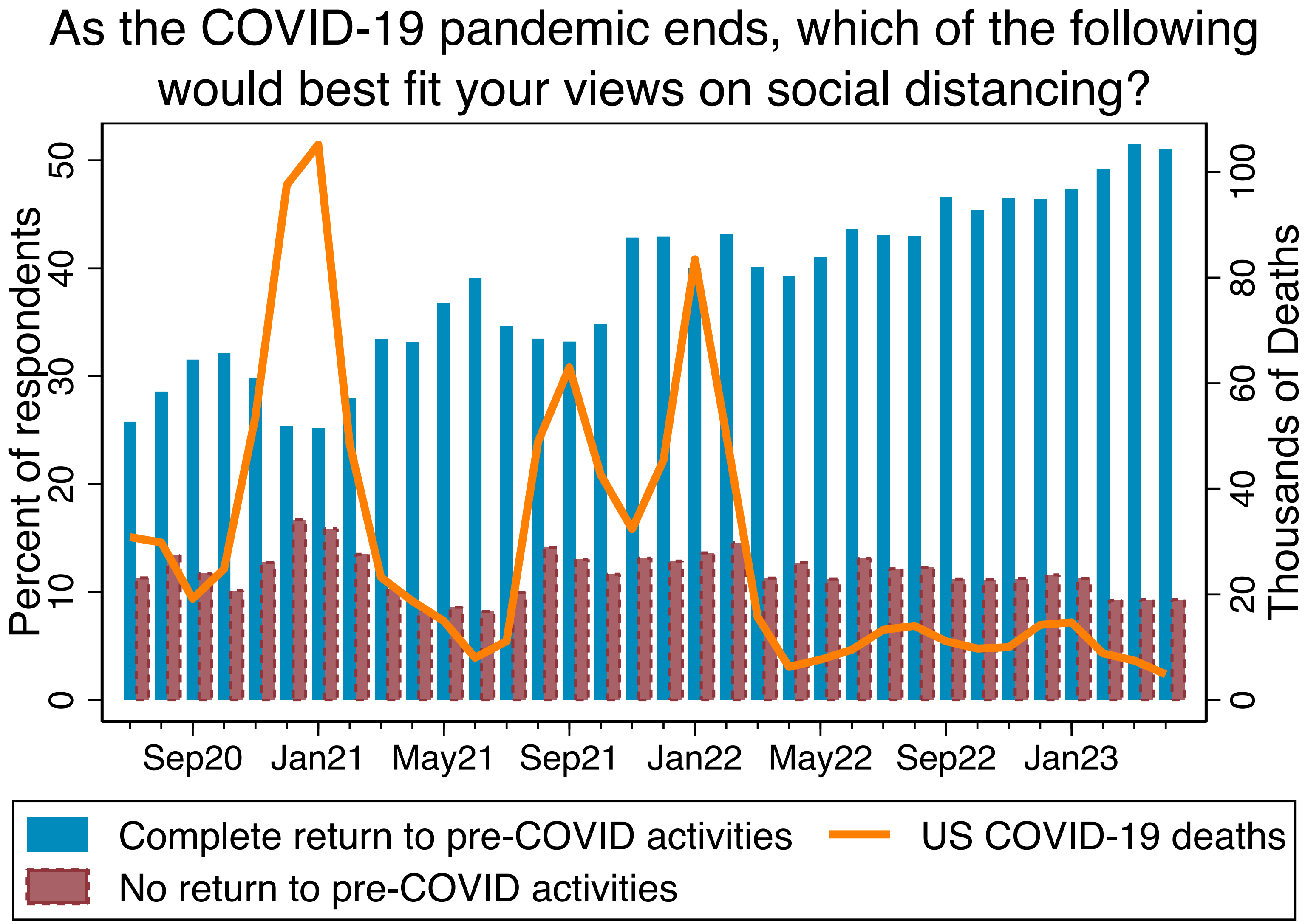
Figure 1. Social Distancing Intentions, February 2022 to January 2023



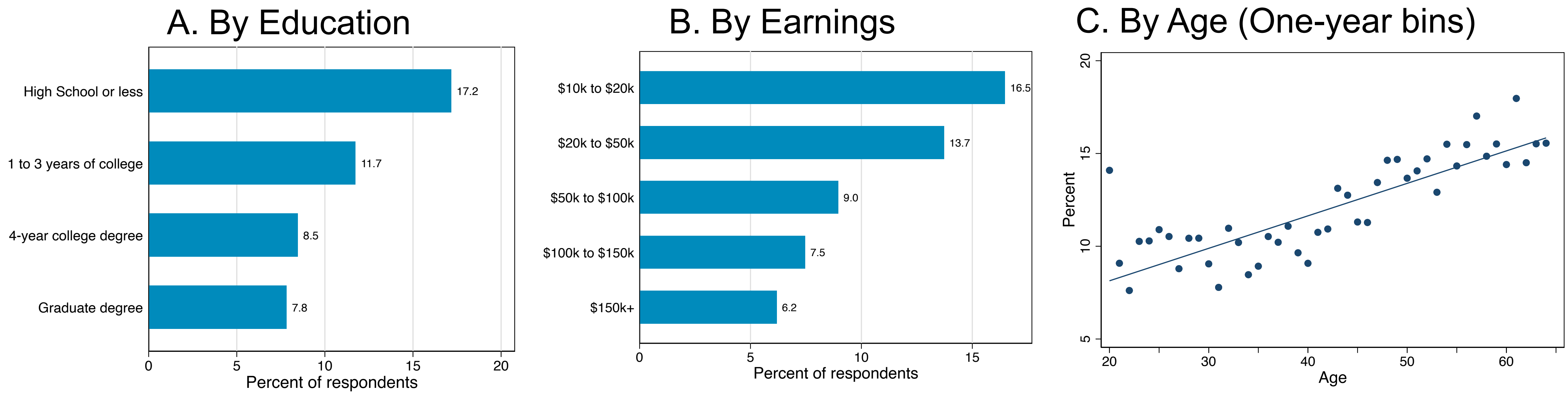
Notes: The chart title states the survey question as fielded from July 2022 onwards. From February to June 2022, the question differs slightly and reads as follows: "***Once the COVID-19 pandemic has ended,…".*** The tabulations reflect SWAA samples of US residents, 20 to 64, with prior-year earnings of at least $10,000 or, for one-half of respondents in February 2022 and one-quarter in March 2022, earnings of at least $10,000 in 2019. N = 62,751.

Figure 2. Social Distancing Intentions and COVID Deaths, July 2020 to April 2023



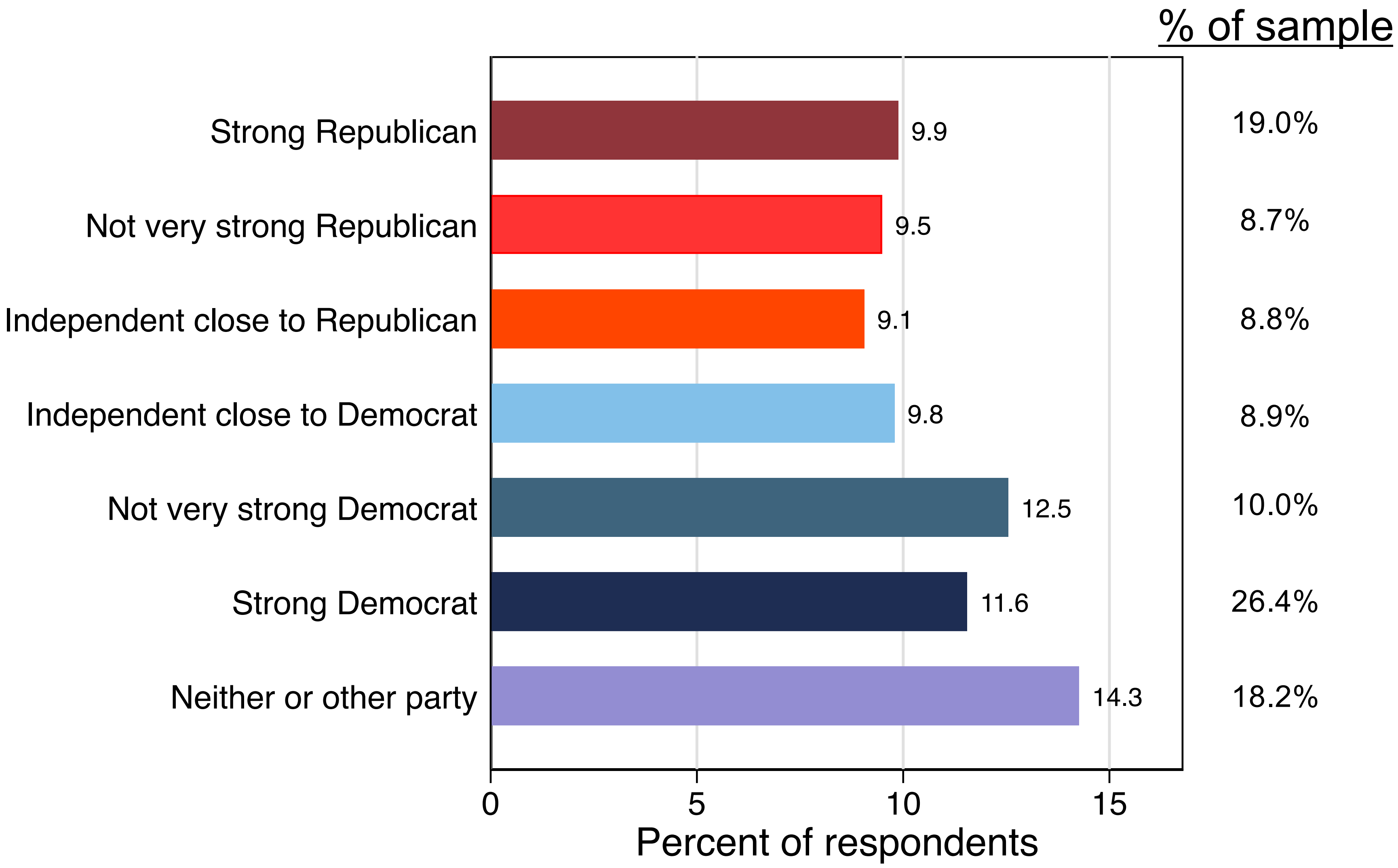
Notes: The chart title states the survey question as fielded from July 2022 onwards. The opening clause differs in earlier waves as follows: "If a COVID vaccine is discovered and made widely available" (July-November 2020); "If a COVID vaccine is approved and made widely available" (December 2020); "If a COVID vaccine becomes widely available" (January- February 2021); "Once ***most of the population has been vaccinated*** against COVID" (March-September 2021); and "***Once the COVID-19 pandemic has ended"*** (October 2021 to June 2022). The SWAA samples used in this chart cover US residents, aged 20 to 64, who meet a prior earnings requirement, as described in the text. N = 148,548 for SWAA data. The data on US COVID-19 deaths are from the US Centers for Disease Control (CDC).

Figure 3. Strong-Form Social Distancing Falls with Education and Earnings, and It Rises with Age



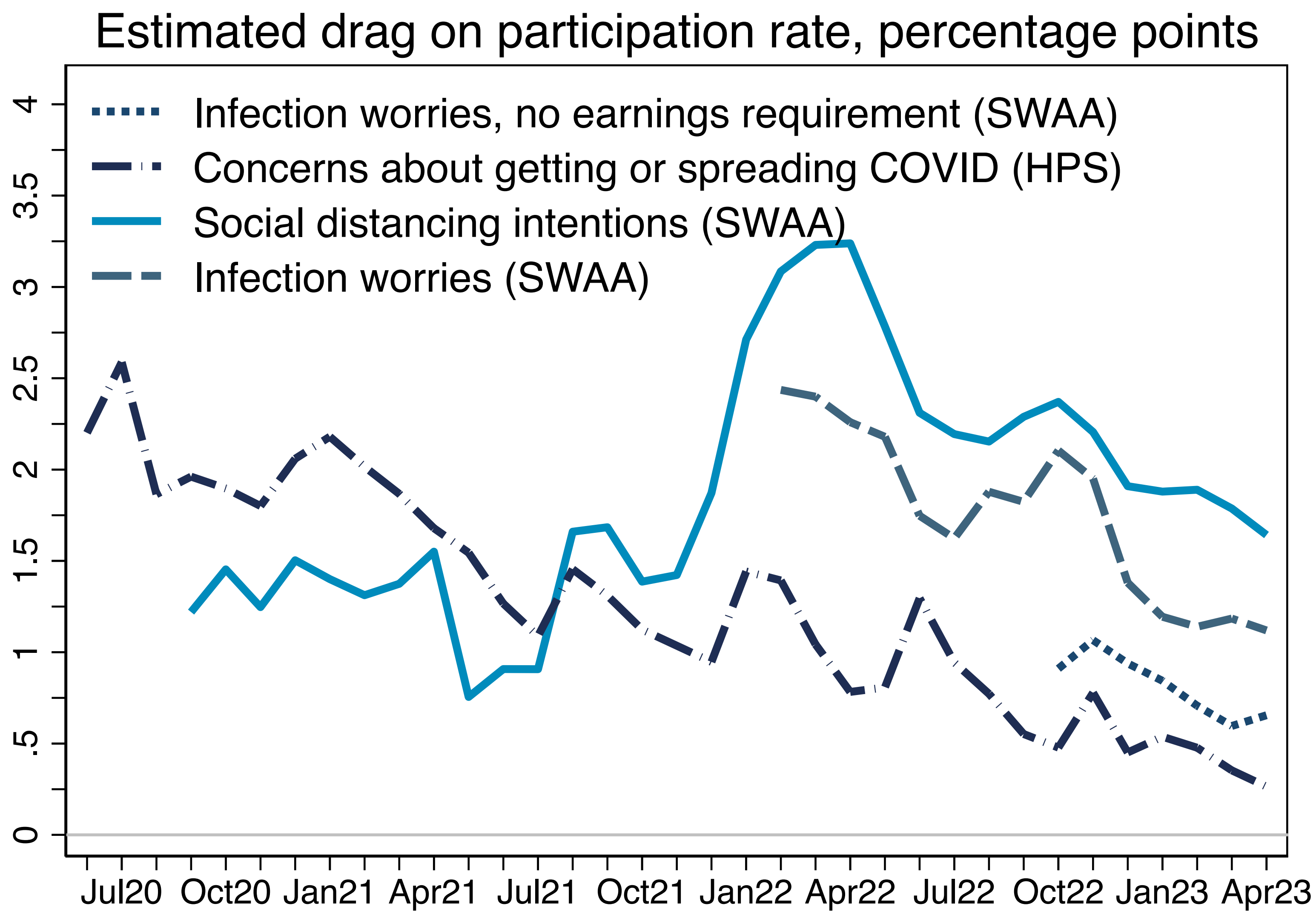
Notes: These charts make use of SWAA data from February 2022 to January 2023 and cover US residents, 20 to 64, who satisfy the prior-year earnings requirement described in the notes to Figure 1. The sample is also the same as in Figure 1. See Figure A.4 for a breakdown by sex and age and Figure A.5 for a more granular set of earnings bins. N = 62,751.

Figure 4. Strong-Form Social Distancing by Partisan Affiliation



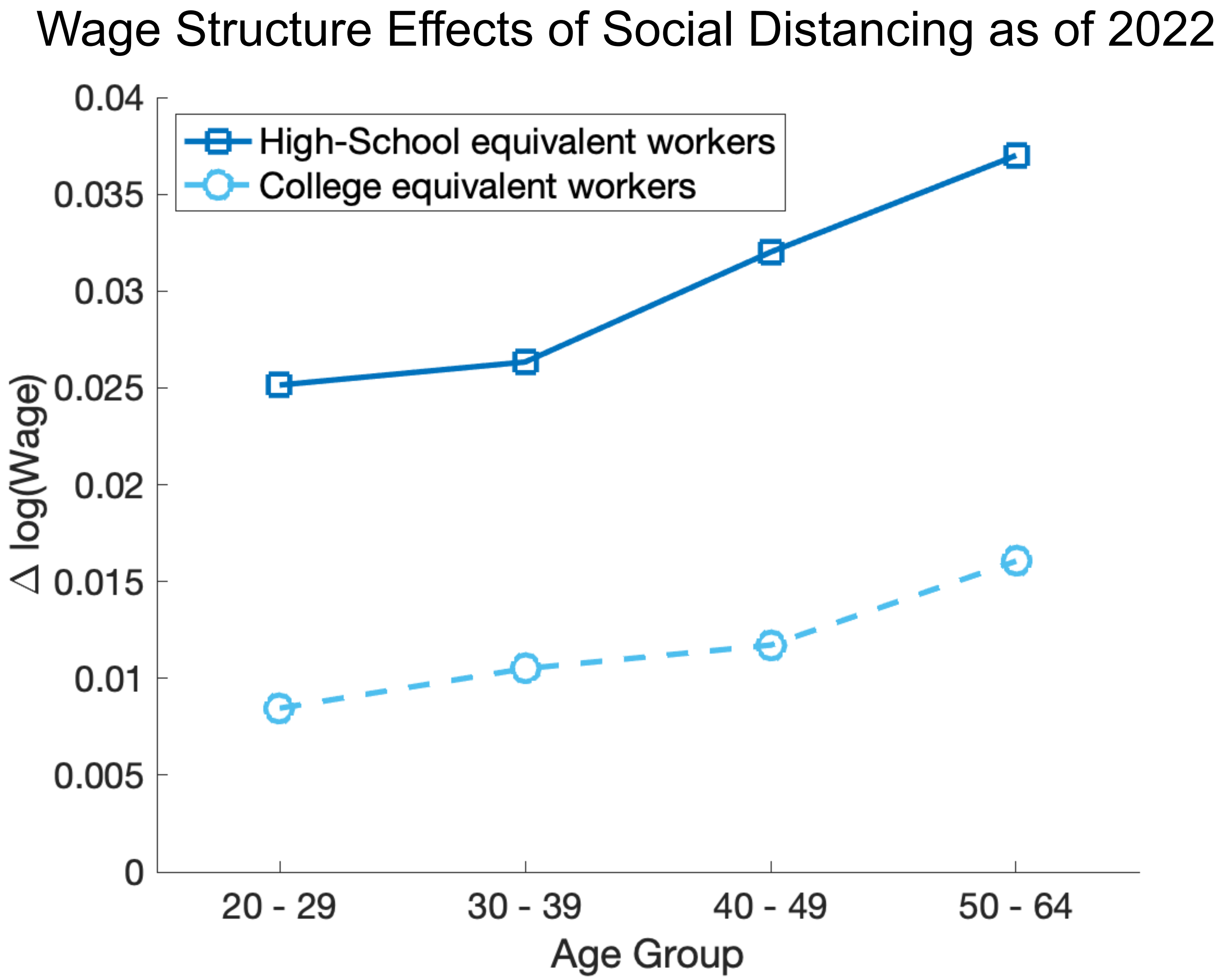
Notes: This chart make use of SWAA data from February 2022 to January 2023. The sample is the same as in Figures 1 and 3, except for excluding respondents who prefer not to answer. N = 60,544.

Figure 5. Estimated Labor Force Drag Effects, June 2020 to April 2023



Notes: The solid blue line shows the labor force drag associated with social distancing intentions, following the calculations in Table 2 and pooling over the most recent three months of data to construct each monthly estimate. The dashed line shows the drag due to infection worries in SWAA data, using our original self-assessment question and following the calculations in Table A.4. The dotted line shows the drag due to infection worries in SWAA data, using our new self-assessment question with many response options and following the calculations in Table . The dotted line shows a three-month moving average (two months at end points). The dash-dot-dash line shows the drag due to concerns about "getting or spreading COVID," according to the Household Pulse Survey (HPS). For all four series, we show equal-weighted labor force drag estimates. N=148,548 (social distancing intentions); N=61,698 (infection worries, original question); N=22,944 (infection worries, new question and no prior-earnings requirement); N=2,733,170 (concerns about getting or spreading COVID).

Figure 6. Social Distancing Effects on Labor Supply Raise the Relative Wages of Older and Less Educated Workers



Notes: We combine estimated drag effects with the labor market equilibrium model of Card and Lemieux (2001) to derive social distancing effects on the wage structure. To do so, we first regress non-participation status on social distancing intentions for each age-education group – i.e., eight separate regressions. Each regression yields a group-level drag effect. We then compute the labor supply shifts implied by the group-level drag effects and measured hours. Finally, we insert the labor supply shifts into the equilibrium model to obtain the implied effects on the age-education structure of mean log wages. When implementing this last step, we set the elasticity of substitution across age groups within an education category to 5 (following Card and Lemieux) and the elasticity between education groups to 1.41 (following Katz and Murphy, 1992). See the text for additional details.

Table 1. How Social Distancing Intentions Relate to COVID Experiences and Living with or Caring for Vulnerable Persons

Dependent variable: Index of Return to Pre-COVID Activities (100 = full return, 66.7 = substantial return, 33.3 = partial return, 0 = no return)					
	(1)	(2)	(3)	(4)	(5)
1(Had COVID)	5.0***	5.8***			6.4***
	(0.7)	(0.8)			(0.8)
1(Had Long COVID)		-2.8**			-0.8
		(1.1)			(1.2)
1(Close Friends/Family Had Long COVID)			-2.0**		-2.3***
			(0.8)		(0.9)
1(Live/Care for Someone Vulnerable)				-4.0***	-4.5***
				(0.8)	(0.9)
Constant	66.7***	66.7***	69.6***	70.2***	68.1***
	(0.5)	(0.5)	(0.5)	(0.5)	(0.6)
Observations	21,695	21,695	21,695	21,695	21,695
R-squared	0.01	0.01	0.00	0.00	0.01

Notes: We construct individual-level values for the Return Index using our question about social distancing intentions. See Figure 1 for a statement of the question and the response options. The mean value of the Return Index is 69.0 and the standard deviation is 34.7. We set “Had COVID” to 1 if the respondent says yes to "Have you had a positive diagnosis for COVID-19?” or "Despite not having tested positive for COVID-19, do you believe you have been infected at some point?" We set “Had Long COVID” to 1 if the respondent says yes to "Did you have any symptoms lasting 3 months or longer that you did not have prior to having coronavirus or COVID-19?” We use responses to "Have any close friends or family members of yours experienced symptoms lasting 3 months or longer that they did not have prior to a COVID infection?" and “Do you live with or care for someone who would be more vulnerable than the general population to COVID-19 or other infectious diseases?” in the same way. The sample period runs from October 2022 to January 2023. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2. Our Regression Approach to Quantifying the Effects of Social Distancing Intentions on Labor Force Participation

Question: *Once the COVID-19 pandemic has ended, which of the following would best fit your views on social distancing?*

Sample Period: February 2022 to January 2023 **Dependent variable: 100 x 1(Not working and not looking for work)**	**(1) Regression coefficient**	**(2) Percent of sample**	**(3) Implied drag on LF participation rate (ppts)**	**(4) Implied drag on LF participation rate (ppts), no earnings requirement**
Complete return to pre-COVID activities (baseline)	-	44.1	0	0
Substantial return to pre-COVID activities (e.g. avoid subway, crowded elevators)	0.5	30.3	0.1	-0.1
	(0.4)		(0.1)	(0.2)
Partial return to pre-COVID activities (e.g. avoid eating out, taxi/ride-share)	3.7	13.6	0.5	0.5
	(0.6)		(0.1)	(0.1)
No return to pre-COVID activities	14.4	12.0	1.7	2.3
	(0.8)		(0.1)	(0.1)
	Total drag: Equal-Weighted		**2.4 (0.2)**	**2.7 (0.4)**
	Earnings-Weighted		**1.2 (0.2)**	**1.4 (0.2)**
Observations	62,751		62,751	57,206
R-squared	0.02			

Notes: Column (1) reports regression coefficients on the indicated level of social distancing intentions, and column (2) reports the sample percentage at each level. Column (3) is computed as (1) times (2) divided by 100. Column (4) reports the results of an analogous calculation for a sample with no prior earnings requirement. We use the row entries in columns (3) and (4) to compute the "Total Drag" in an equal-weighted and earnings-weighted manner (using prior-year earnings). We use SWAA data from February 2022 to January 2023. Robust standard errors in parentheses for the regression coefficients. We compute the standard errors in columns (3) and (4) via the Delta method using the joint variance-covariance matrix of the regression coefficients and the percent at each social distancing level.

Table 3. Estimated Effects of Social Distancing Intentions on Labor Force Participation by Age and by Education

A. By Age Group	**Ages 20 to 29**	**Ages 30 to 39**	**Ages 40 to 49**	**Ages 50 to 64**
Substantial return to pre-COVID activities (e.g. avoid subway, crowded elevators)	0.4	-0.3	0.5	3.5***
	(0.8)	(0.5)	(0.7)	(1.0)
Partial return to pre-COVID activities (e.g. avoid eating out, taxi/ride-share)	-0.4	1.9***	2.9***	9.4***
	(0.9)	(0.7)	(1.0)	(1.4)
No return to pre-COVID activities	2.7**	9.4***	13.3***	18.5***
	(1.3)	(1.4)	(1.4)	(1.4)
Implied drag on labor force participation rate, percentage points	0.4 (0.4)	1.1 (0.3)	2.1 (0.3)	5.0 (0.5)
B. By Education Group	**No college**	**1 to 3 years of college**	**4-year college degree**	**Graduate degree**
Substantial return to pre-COVID activities (e.g. avoid subway, crowded elevators)	2.9***	2.3***	-1.3**	-0.5
	(1.0)	(0.8)	(0.6)	(0.8)
Partial return to pre-COVID activities (e.g. avoid eating out, taxi/ride-share)	6.5***	4.2***	1.1	1.7
	(1.4)	(1.0)	(0.9)	(1.3)
No return to pre-COVID activities	17.1***	12.3***	8.3***	10.2***
	(1.4)	(1.2)	(1.4)	(2.1)
Implied drag on labor force participation rate, percentage points	4.5 (0.5)	2.7 (0.4)	0.4 (0.3)	0.8 (0.5)

Notes: For each indicated age and education category, we regress 100 x 1(Not working and not looking for work) on responses to "Once the COVID-19 pandemic has ended, which of the following would best fit your views on social distancing?" The omitted social distancing group is "Complete return to pre-COVID activities." In the "No college" regression, we allow distinct intercepts for did and did not finish high school. Otherwise, the regression specification is the same as in Table 2. So is the sample period, which runs from February 2022 to January 2023. The first three rows in each panel report regression coefficients on the indicated extent of social distancing. The last row reports the implied drag on the labor force participation rate, following the equal-weighted calculations in Table 1. See the notes to Table 1 regarding the calculation of standard errors.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4. Social Distancing Intentions, COVID Experiences, Interactions with Vulnerable Persons, and Labor Force Participation

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	**100 x 1(Not working and not looking for work)**				
Social distancing impact index (mean = 2.5, standard deviation = 4.7)	1.9***			1.8***	1.4***
	(0.1)			(0.1)	(0.2)
x 1(Had COVID)					-0.4
					(0.3)
x 1(Had Long COVID)					1.5***
					(0.4)
x 1(Close Friends/Family Had Long COVID)					0.6**
					(0.3)
x 1(Live/Care for Someone Vulnerable)					0.8***
					(0.3)
1(Had COVID)		-3.3***	-3.2***	-2.1*	-1.4
		(1.0)	(1.1)	(1.1)	(1.3)
1(Had Long COVID)			-0.4	-2.0	-5.0***
			(1.7)	(1.7)	(1.8)
1(Close Friends/Family Had Long COVID)				0.6	-1.1
				(1.2)	(1.4)
1(Live/Care for Someone Vulnerable)				4.2***	2.2*
				(1.2)	(1.4)
Constant	22.3***	28.6***	28.6***	22.2***	23.3***
	(0.6)	(0.7)	(0.7)	(0.8)	(0.8)
Observations	21,695	21,695	21,695	21,695	21,695
R-squared	0.04	0.00	0.00	0.04	0.05

Notes: We regress 100 x 1(Not working and not looking for work) on an index for the social-distancing drag on participation and the indicated experiential and situational variables. The sample covers the September to December 2022 waves. It excludes persons who fail any of the attention check questions. We classify a person as having had COVID if they say yes to either of the following questions: "Have you had a positive diagnosis for COVID-19?" "Despite not having tested positive for COVID-19, do you believe you have been infected at some point?" We report robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Social Distancing Intentions Exert a Greater Labor Force Drag on Persons More Strongly Impacted by COVID

	(1)	(2)	(2)	(4)	(5)
	Dependent Variable: 100 x 1(Not working and not looking for work)				
	Full sample	No Long COVID experience and No Care of Vulnerable Person	Had Long COVID	Close Friends or Family Had Long COVID	Lives with or Cares for Vulnerable Person
Substantial return to pre-COVID activities (e.g. avoid subway, crowded elevators)	0.3	-4.5***	7.1**	4.1*	9.3***
	(1.2)	(1.6)	(3.0)	(2.1)	(2.2)
Partial return to pre-COVID activities (e.g. avoid eating out, taxi/ride-share)	3.3**	-2.9	17.3***	10.9***	9.0***
	(1.6)	(2.2)	(4.5)	(3.0)	(2.9)
No return to pre-COVID activities	16.5***	8.8***	34.3***	26.3***	30.1***
	(1.8)	(2.3)	(5.2)	(3.3)	(3.3)
Estimated drag on labor force participation rate, percentage points	2.6 (0.6)	-0.3 (0.7)	8.3 (1.5)	6.0 (1.1)	8.2 (1.2)
Observations (Sample Period: September – December 2022)	21,695	11,389	3,423	6,975	6,519
R-squared	0.02	0.01	0.06	0.03	0.04

Notes: This table applies the same regression approach as Table 2. We implement the subsample selections as follows: For column (3), we include persons who respond yes to "Did you have any symptoms lasting 3 months or longer that you did not have prior to having coronavirus or COVID-19?" For column (4), we include persons who respond yes to "Have any close friends or family members of yours experienced symptoms lasting 3 months or longer that they did not have prior to a COVID infection?" For column (5), we include persons who respond yes to "Do you live with or care for someone who would be more vulnerable than the general population to COVID-19 or other infectious diseases?" For column (2), we include persons who respond no to all three questions. The sample covers the period in which we asked these questions and excludes respondents who failed any attention check questions. See Table 2 for explanations of how we calculate the labor force drag estimates and standard errors. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Using Self-Assessments to Estimate the Labor Force Drag Due to Infection Worries

Question: What is the main reason [second most important reason] you are not currently working and not seeking work?	(1) Percent of Those Currently Out of the Labor Force	(2)	(3) Percent of full sample	(4)	(5) Contribution of infection worries to LF drag	(6) Implied Drag on LF Participation Rate (ppts)	(7)
Exclude persons with prior-year earnings < $10,000? →	**Yes**	**No**	**Yes**	**No**		**Yes**	**No**
Main reason is: "I worry about catching COVID or other infectious diseases"	1.3	1.1	0.2	0.3	1	0.2 (0.04)	0.3 (0.05)
Secondary reason is: "I worry about catching COVID or other infectious diseases"	4.5	4.6	0.6	1.3	0.5	0.3 (0.04)	0.7 (0.05)
Other main and second reasons	94.1	94.3	12.6	26.7	0	0.0	0.0
Respondents who are currently employed or unemployed	-	-	86.7	71.7	0	0	0
					Total drag: Equal-Weighted	**0.5 (0.05)**	**1.0 (0.07)**
					Earnings-Weighted	**0.3 (0.04)**	**0.4 (0.04)**
Observations	**1,156**	**1,909**	**11,798**	**13,085**		**11,798**	**13,085**

Notes: The first four columns report values for respondents who point to infection worries as the main or secondary reason for not working and not seeking work in the survey week – as a percent of persons outside the labor force in Columns 1 and 2, and as a percent of all persons in Columns 3 and 4. The comparisons between columns 1 and 2, and 3 and 4, highlight the impact of limiting the sample to persons with at least $10,000 in prior-year earnings (the baseline sample). Column 5 assigns numerical values to the indicated responses. Columns 6 and 7 compute the implied drag on the labor force participation rate, as in Table 4. We use SWAA data from October 2022 to January 2023 to implement the calculations.

Appendix Tables and Figures
(Intended as online material)

Table A.1. Comparison of SWAA and HPS Responses to the HPS Question about the Main Reason for Not Working

What is your main reason for not working for pay or profit?	Household Pulse Survey	Survey of Working Arrangements and Attitudes	
Sample Period	29 Jun. – 11 Jul., 27 Jul. – 8 Aug., 14 – 18 Sep., 2022	12 – 25 Jul., 11 – 18 Aug. , 13 – 24 Sep. 2022	
	Percent of respondents	Respondents who pass attention check questions	All respondents
		Percent	
I was concerned about getting or spreading the coronavirus	1.9	2.6	2.5
	(0.1)	(0.4)	(0.4)
I am/was sick with coronavirus symptoms or caring for someone who was sick with coronavirus symptoms	3.2	1.6	1.4
	(0.2)	(0.3)	(0.3)
Observations	**12,532**	**1,539**	**1,850**

Notes: This table shows selected responses to the stated question in the Household Pulse Survey (HPS) and in the SWAA for similar sample periods. The response options are 1) I did not want to be employed at this time; 2) I am/was sick with coronavirus symptoms or caring for someone who was sick with coronavirus symptoms; 3) I am/was caring for children not in school or daycare; 4) I am/was caring for an elderly person; 5) I was concerned about getting or spreading the coronavirus; 6) I am/was sick (not coronavirus related) or disabled; 7) I am retired; 8) I am/was laid off or furloughed due to coronavirus pandemic; 9) My employer closed temporarily due to the coronavirus pandemic; 10) My employer went out of business due to the coronavirus pandemic; 11) I do/did not have transportation to work; 12) Other reason, please specify. In the SWAA, we combine options 9 and 10 into a single option saying "My employer went out of business due to the coronavirus pandemic" and we reclassify responses of "Other reason" depending on the description provided. The SWAA sample restricts attention to people who report not working and not seeking work. For the HPS, we drop persons with household income per adult below $25,000 (for 1-person households) or $17,500 (for 2- or 3-adult households). The SWAA sample excludes persons who earned less than $10,000 in 2021. We drop persons who applied for or received unemployment benefits in 2022, and those who report job loss in the household during the four weeks before the survey.

Table A.2. The Joint Distribution of Social Distancing Intentions and Infection Worries as a Reason for Not Working

Panel A. Using the Original Self-assessment Question

	(1)	(2)	(3)	(4)
	Type of return to pre-COVID activities			
Worries about catching COVID or other infectious diseases a factor in your decision not to seek work	**Complete**	**Substantial**	**Partial**	**None**
Yes, the main reason	1.4	2.2	1.9	3.2
	(0.2)	(0.2)	(0.2)	(0.2)
Yes, a secondary reason	1.8	4.7	3.2	2.8
	(0.2)	(0.3)	(0.2)	(0.2)
No	32.5	18.8	9.6	17.7
	(0.7)	(0.6)	(0.4)	(0.5)
Observations		4,991		

Notes: This table shows the joint distribution of responses to the following questions in the February 2022 to January 2023 waves of the SWAA: *Are worries about catching COVID or other infectious diseases a factor in your decision not to seek work at this time?* And, *Once the COVID-19 pandemic has ended, which of the following would best fit your views on social distancing?* The sample includes respondents who are currently not working and not seeking work. Each cell shows the percent of respondents who chose responses given by the respective row and column of the matrix. Standard errors in parentheses.

Panel B. Using Self-Assessment Question with Many Response Options, Sample with No Prior-Earnings Requirement

	(1)	(2)	(3)	(4)
	Type of return to pre-COVID activities			
Main and second most important reason for not working and not seeking work is worry about catching COVID or other infectious diseases	**Complete**	**Substantial**	**Partial**	**None**
Main reason	0.3	0.3	0.2	0.3
	(0.1)	(0.1)	(0.1)	(0.1)
Second most important reason	0.5	1.5	1.1	1.5
	(0.2)	(0.3)	(0.2)	(0.3)
Not the main or second most important reason	39.7	25.6	12.8	16.2
	(1.1)	(1.0)	(0.8)	(0.8)
Observations	1,909			

Notes: This table shows the joint distribution of responses to the following questions in the October 2022 to January 2023 waves of the SWAA: *What is the main reason [second most important reason] you are not currently working and not seeking work? Once the COVID-19 pandemic has ended, which of the following would best fit your views on social distancing?* The sample covers respondents who are currently not working and not seeking work. Each cell shows the percent of respondents who chose responses given by the respective row and column of the matrix. Standard errors in parentheses.

Table A.3. Estimated Participation Drag Due to Social Distancing for Eight Distinct Age-by-Education Groups

	LF Participation Drag Due to Social Distancing Intentions, percentage points			
	20 to 29	**30 to 39**	**40 to 49**	**50 to 64**
High School Workers	1.3	1.9	4.9	7.5
	(0.7)	(0.7)	(0.8)	(1.0)
College Workers	-0.2	0.8	1.4	3.7
	(0.5)	(0.3)	(0.3)	(0.5)

Notes: We use SWAA data from January to December 2022, consider respondents who meet the prior-earnings requirement, and partition the sample into eight distinct groups: the four indicated age groups for "High School" workers (including those who did not finish high school) and the four age groups for "College" workers (including those with some college and those with an advanced degree). We separately estimate the labor force participation drag due to social distancing intentions for each of the eight groups following the method illustrated in Table 2. We allow distinct intercepts for those who did and did not finish high school in each regression for "High School" workers. We allow distinct intercepts for those with some college, a four-year degree, and an advanced degree in each regression for "College" workers. Robust standard errors in parentheses.

Table A.4. Using the Original Formulation of the Self-Assessment Question to Estimate the Labor Force Drag Due to Infection Worries

	(1)	(2)	(3)	(4)
Question: Are worries about catching COVID or other infectious diseases a factor in your decision not to seek work at this time?	**Percent of those currently outside the labor force**	**Percent of sample**	**Contribution of infection worries to labor force drag**	**Implied drag on LF participation rate (ppts)**
Yes, the main reason	7.6	0.9	100	0.9 (0.1)
Yes, a secondary reason	11.7	1.4	50	0.7 (0.1)
No	80.7	10.0	0	0.0 (-)
Respondents who are currently employed or unemployed	-	87.6	-	-
			Total drag: Equal-Weighted	**1.7 (0.1)**
			Earnings-Weighted	**1.2 (0.1)**
Observations	**1,109**	**11,885**		

Notes: Column 1 reports the question response distribution among persons who are out of the labor force (not working and not seeking work). Column 2 reports the response distribution in the full sample. Column 3 assigns numerical values to each response option. Column 4 is the product of the value in Column 2 and the value in Column 3. We sum these entries in Column 4 to obtain the estimated equal-weighted "Total drag" on the labor force participation rate associated with "worries about catching COVID or other infectious diseases." We obtain the earning-weighted total drag in the same way except for weighting individuals by their prior-year earnings. We use SWAA data from October 2022 to January 2023 to implement the calculations.

Figure A.1. Age, Education, and Earnings Groups Used in Constructing Cell-Level Weights in the SWAA

Age Groups: 20-29, 30-30, 40-49, 50-64.

Education Groups: Less than high school (HS), HS graduation, 1-3 years of college, 4-year college degree, Master's or Professional Degree, PhD.

Earnings Groups: From May 2020 to March 2021, we use the following annual earnings groups: $20-50K, $50-100K, 100-150K, and $150K+. Starting in April 2021, we add a group for $10-20K. For the sample that does not impose an earnings requirement, which covers January to February 2022, and June 2022 and later months, we add groups for less than $5K and $5-10K.

We sort individuals into earnings groups based on their responses to the type of question at the right, which shows the exact version we fielded from June to December 2022.

Approximately how much did you ***earn by working in 2021, on a before-tax basis***?

Q_income_2021 | *Multiple choice | Required | Vertical | Single-select*

a) Less than $5,000 [TAG: 4]
b) $5,000 to $10,000 [TAG: 7.5]
c) $10,000 to $19,999 [TAG: 15]
d) $20,000 to $29,999 [TAG: 25]
e) $30,000 to $39,999 [TAG: 35]
f) $40,000 to $49,999 [TAG: 45]
g) $50,000 to $59,999 [TAG: 55]
h) $60,000 to $69,999 [TAG: 65]
i) $70,000 to $79,999 [TAG: 75]
j) $80,000 to $99,999 [TAG: 90]
k) $100,000 to $124,999 [TAG: 113]
l) $125,000 to 149,999 [TAG: 138]
m) $150,000 to $199,999 [TAG: 175]
n) $200,000 to $499,999 [TAG: 225]
o) $500,000+ [TAG: 500]

Figure A.2. Attention Check Questions

A. Asked from November 2021

What color is grass?

The fresh, uncut grass, not leaves or hay. Make sure that you select purple as an answer so we know you are paying attention.

- Magenta
- Green
- Purple
- Brown
- Black
- White
- Blue

Continue

B. Asked from December 2021

In how many big cities with more than 500.000 inhabitants have you lived?

Please note that **this question only serves the purpose to check your attention.**

Irrespective of your answer, please insert the number 33.

Continue

C. Asked from March 2022

What is 3 + 4?

Continue

Figure A.3. SWAA Question on Social Distancing Intentions, Version Asked from October 2021 to May 2022

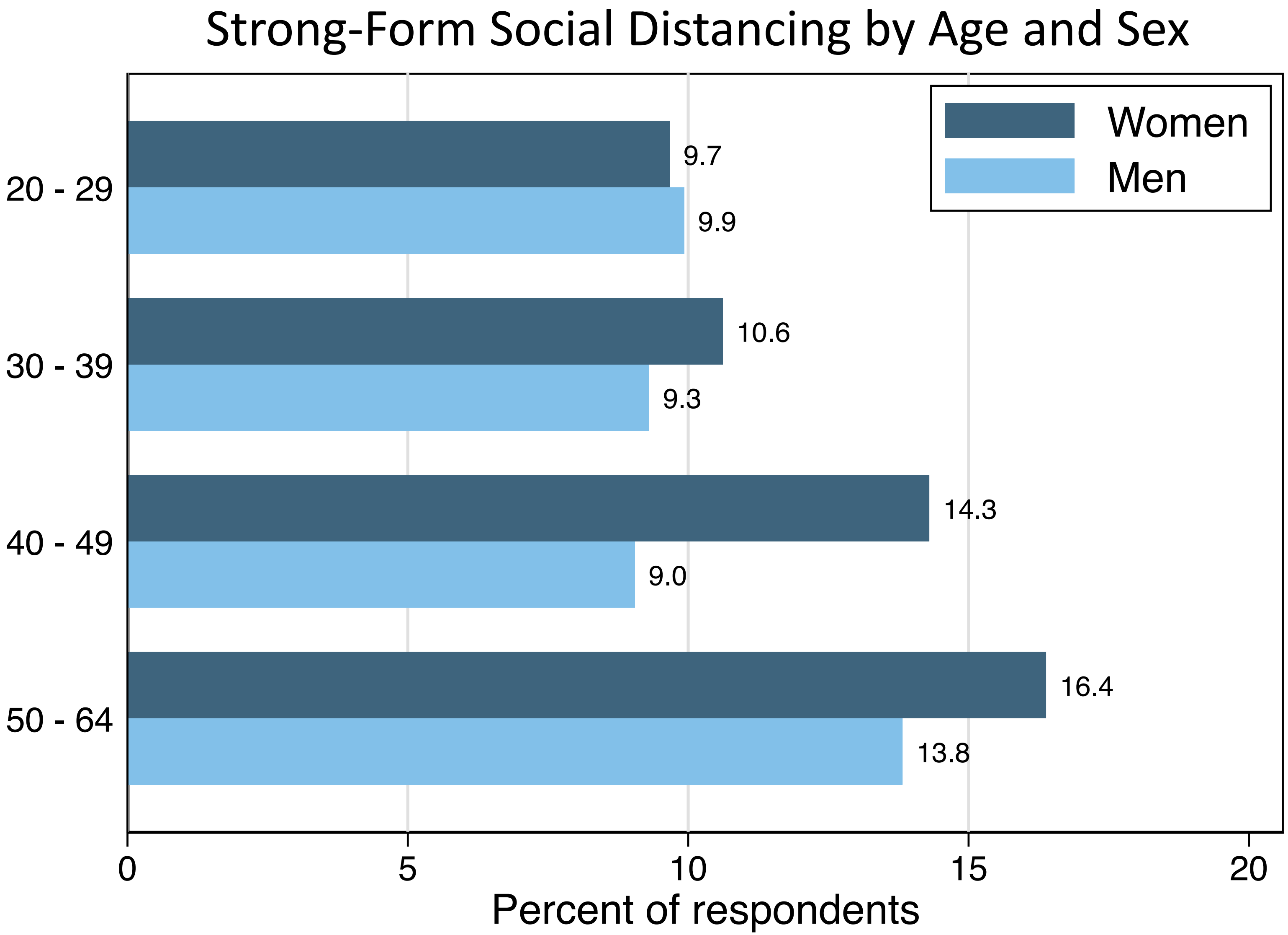
Once the COVID-19 pandemic has ended, which of the following would best fit your views on social distancing?

- ○ Complete return to pre-COVID activities
- ○ Substantial return to pre-COVID activities, but I would still be wary of things like riding the subway or getting into a crowded elevator
- ○ Partial return to pre-COVID activities, but I would be wary of many activities like eating out or using ride-share taxis
- ○ No return to pre-COVID activities, as I will continue to social distance

Continue

Note: In June 2022, we randomized over this question and the version stated at the outset of Section 3 in the main text, with 50 percent of the sample receiving each version.

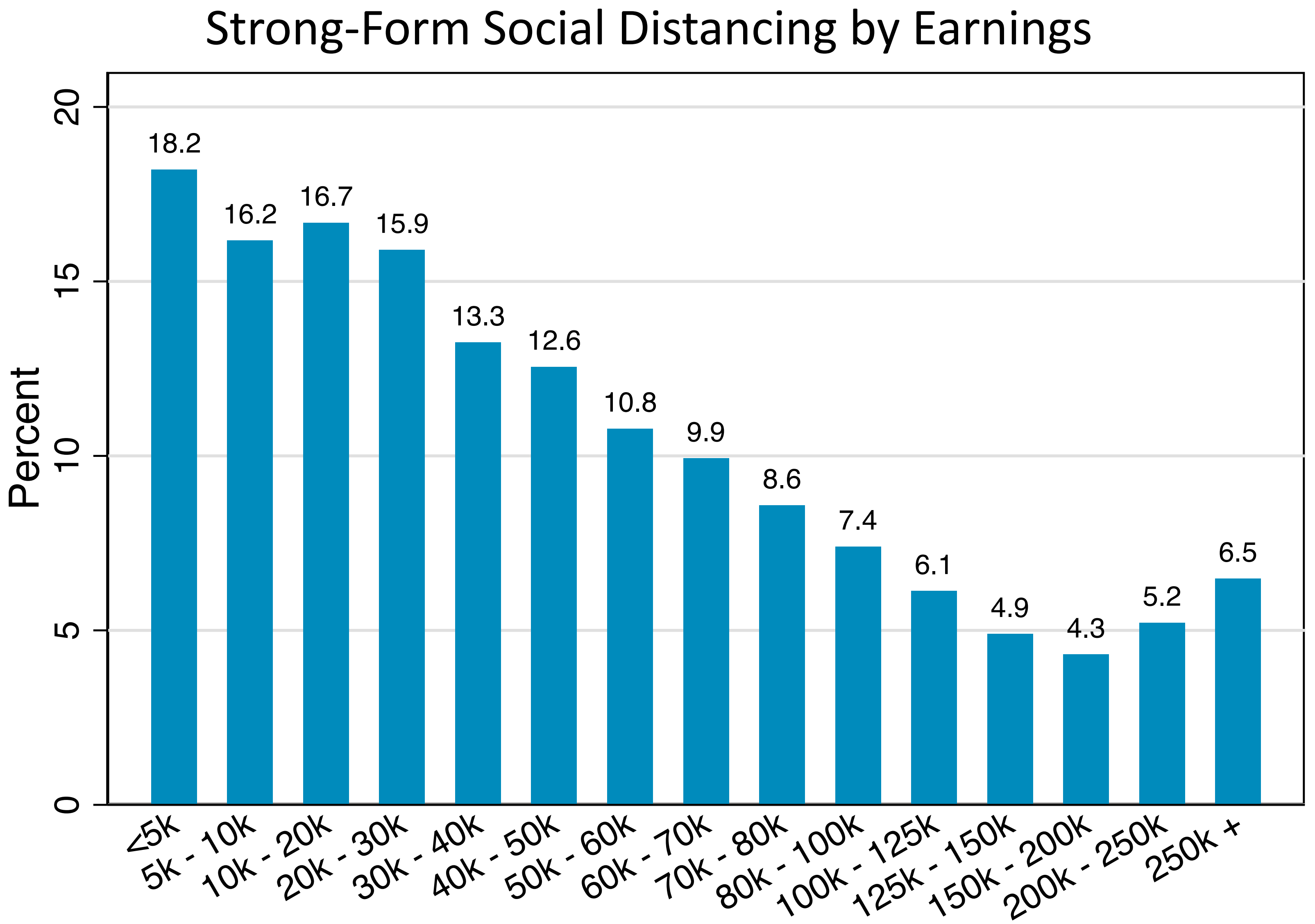
Figure A.4. Strong-Form Social Distancing Is Higher for Women in All But the Youngest Age Group



Notes: The sample includes respondents from the February 2022 to January 2023 waves of the SWAA who meet a prior-earnings requirement, as detailed in the notes to Figure 1.

N = 62,751.

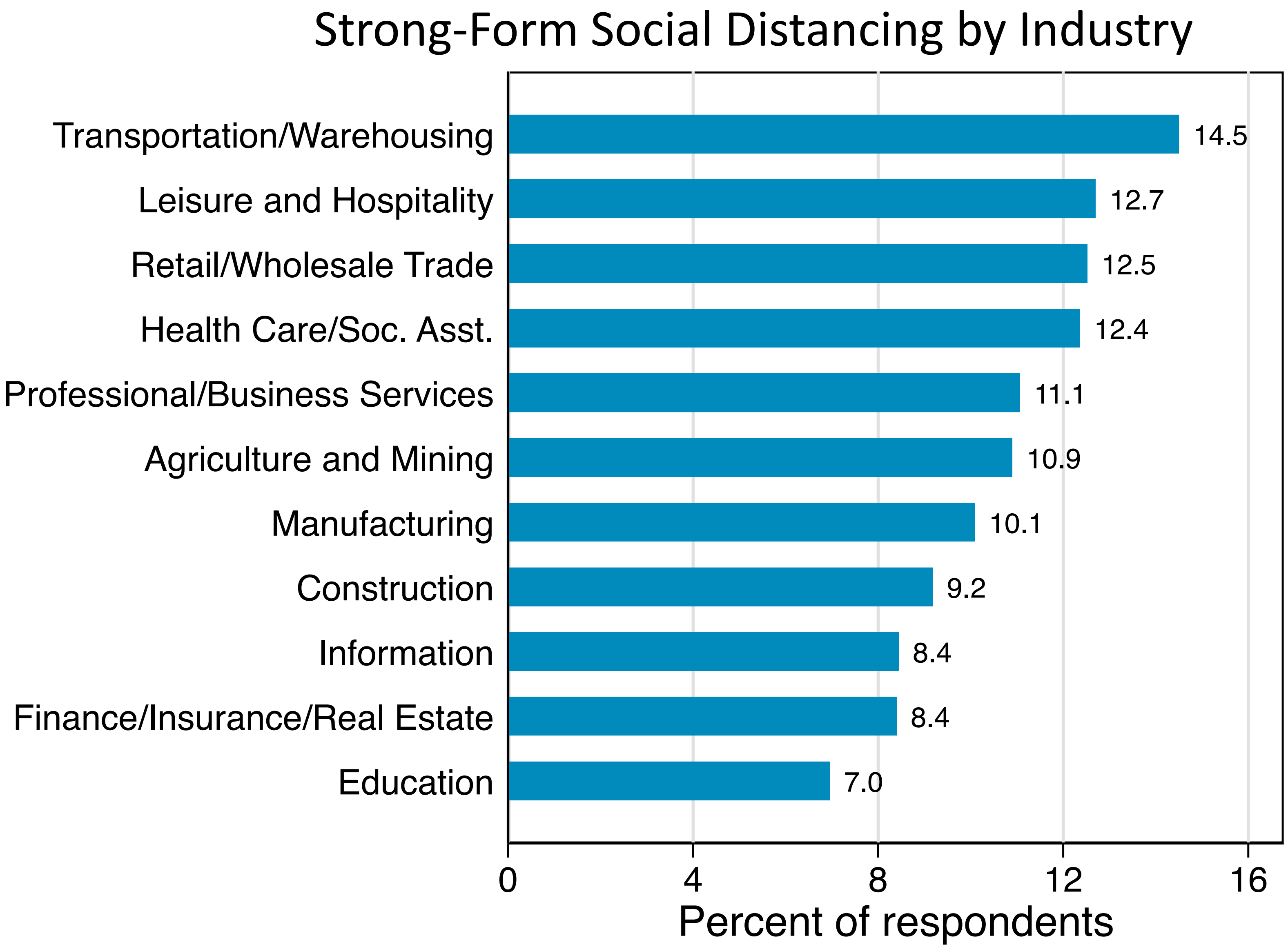
Figure A.5. Strong-Form Social Distancing Falls with Earnings



Notes: The sample includes respondents from the February 2022 to January 2023 survey waves and does not impose a prior-earnings requirement. We report equal-weighted means for each earnings bucket.

N = 57,206.

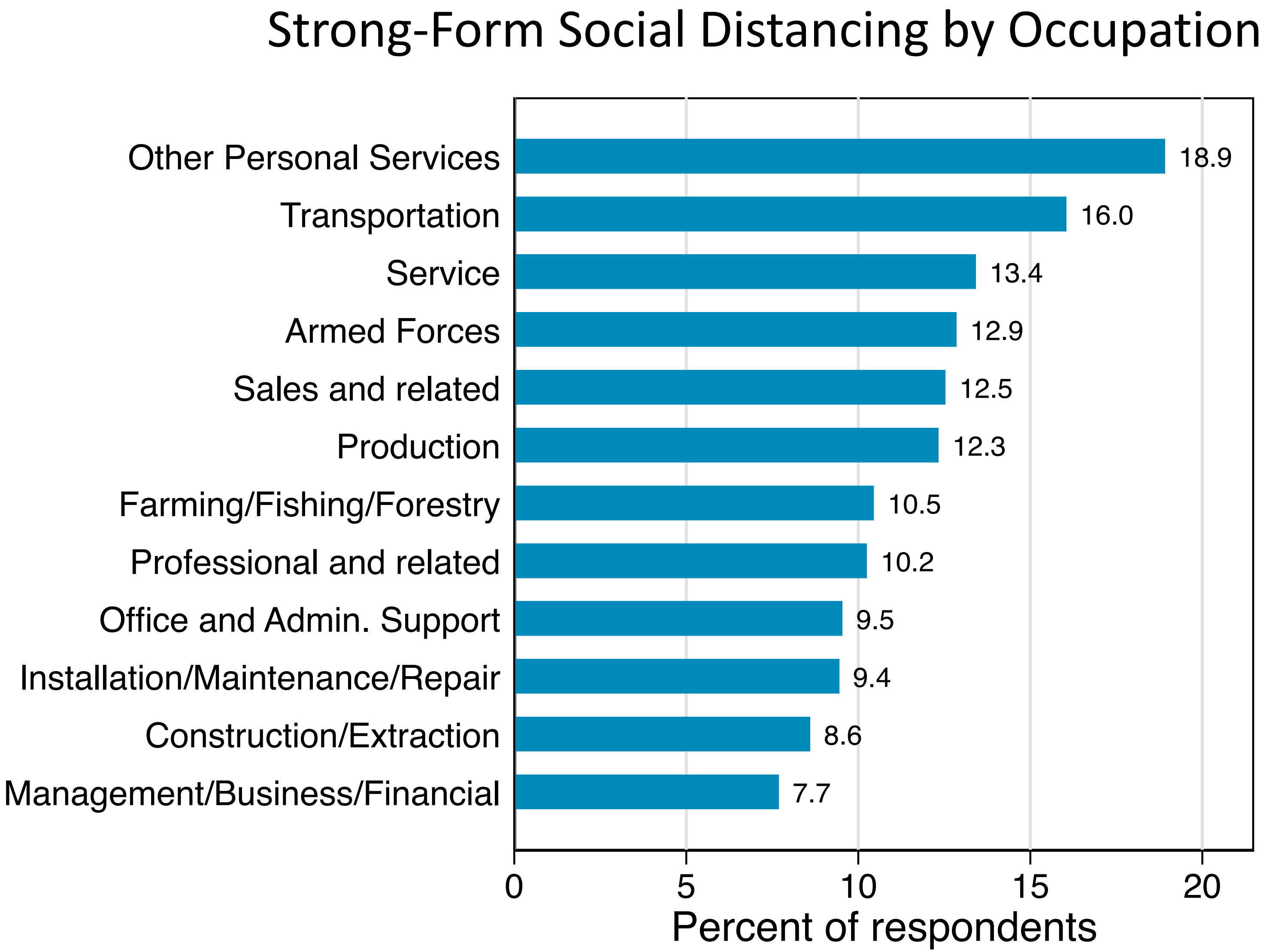
Figure A.6 Strong-Form Social Distancing by Industry



Notes: The sample includes respondents from the February 2022 to January 2023 survey waves who meet a prior-earnings requirement, as detailed in the notes to Figure 1.

N = 55,687.

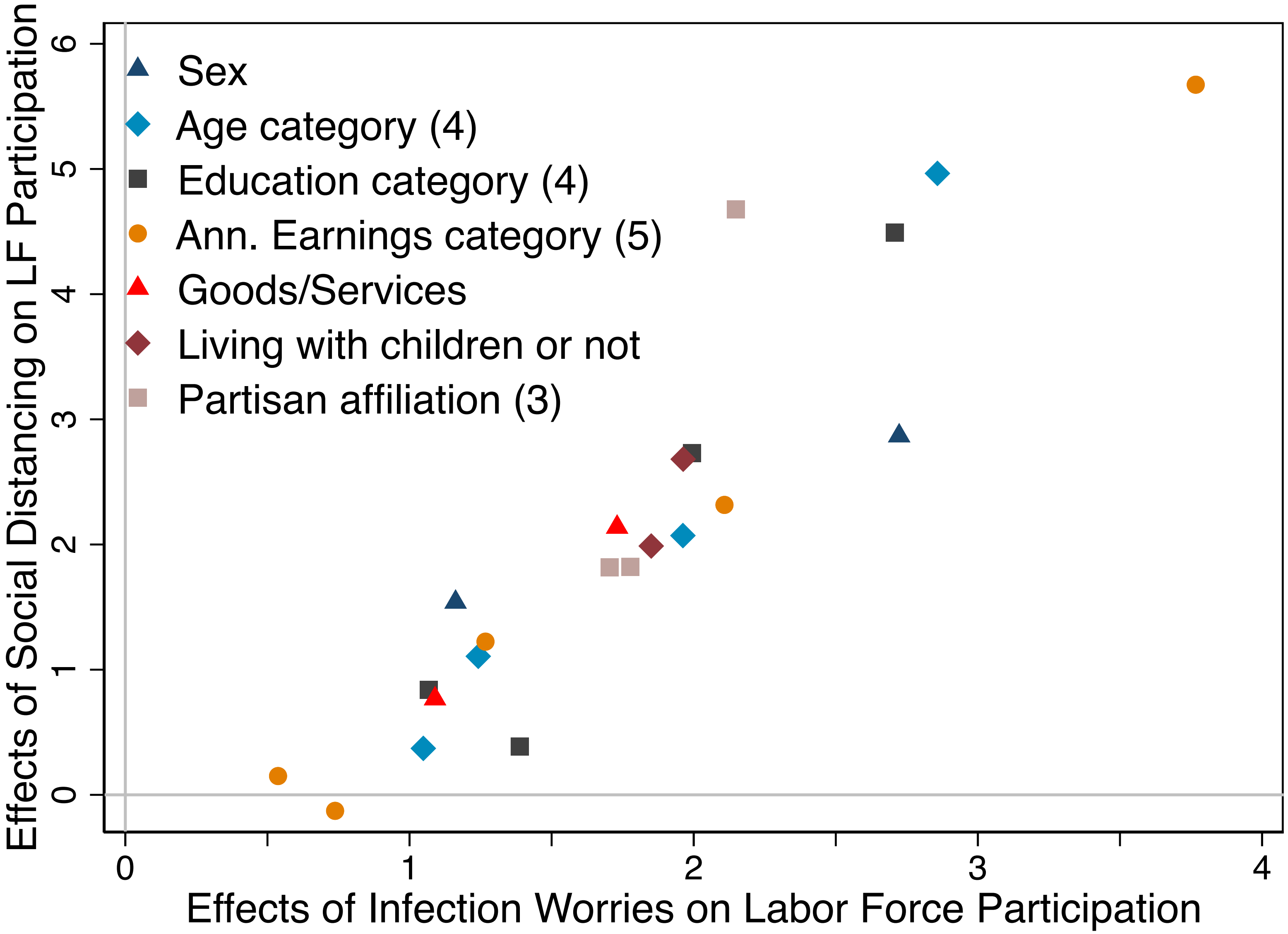
Figure A.7. Strong-form Social Distancing by Occupation



Notes: The sample includes respondents from the February to July 2022 survey waves who meet a prior-earnings requirement, as detailed in he notes to Figure 1.

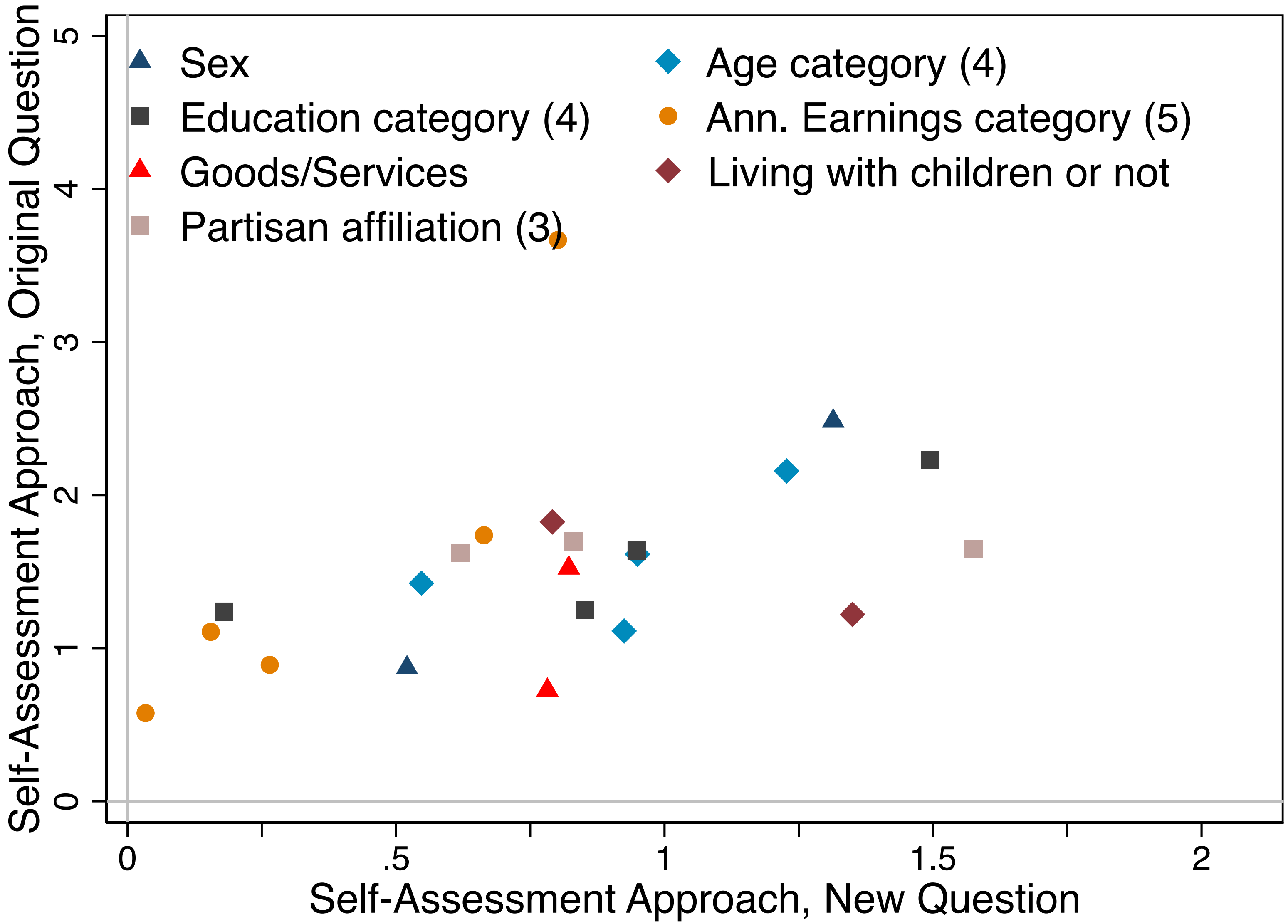
N = 59,740.

Figure A.8. Social Distancing Intentions and Infection Worries Yield Similar Patterns of Labor Force Drag Across Groups



Note: To estimate the labor force effects of social distancing, we regress 100 x **1**(Not working and not seeking work) on social distancing intentions by group and implement the equal-weighted calculations illustrated in Table 2. The specifications include no other controls except in the "No College" regression, which allows distinct intercepts for did and did not finish high school. To estimate the labor force effects of infection worries, we exploit data from our original question on "worries about catching COVID or other infectious diseases" to compute group-level means, implementing the equal-weighted calculations illustrated in Table A.4. The samples used in this chart cover the period from February 2022 to January 2023. All estimated effects are expressed as a percent of the group-specific labor force.

Figure A.9. Two Different Formulations of the Self-Assessment Question Yield Similar Patterns of Labor Force Drag Across Groups



Note: Values on the vertical scale are simple group-level means for the labor force drag due to infection worries based on our original self-assessment question. We compute these means as in Table A.4. on a sample that excludes persons with prior-year earnings of less than $10,000. Values on the horizontal scale are the corresponding group-level means based on the new self-assessment question. We compute these means as in Table 6 on a sample that does not impose a prior-year earnings requirement. All calculations use data from October 2022 to January 2023. All estimated effects are expressed as a percent of the group-specific labor force.