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Where Are the Missing Workers?

Katharine Abraham and Lea Rendell (University of Maryland)

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Where Are the Missing Workers?

Katharine G. Abraham
University of Maryland,
IZA and NBER

Lea Rendell
University of Maryland

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I. Introduction

The U.S. labor force participation rate has been trending downwards since the beginning of the 21st century (Abraham and Kearney 2020), falling from 67.3 percent in January 2000 to 63.3 percent in January 2020 or on average about 0.2 percentage points per year. At the start of the pandemic, however, participation plummeted, dropping more than 3 percentage points over just two months, as the labor force fell by more than 8.2 million people. As can be seen in Figure 1, which shows the seasonally adjusted participation rate as published by the Bureau of Labor Statistics (BLS) for the period from January 2019 forward, about half of that initial drop was quickly regained, but the participation rate remained stuck near 61.5 percent for more than a year. Following a period of growth in the second half of 2021, participation again appears to have stagnated, this time a percentage point below its February 2020 level.¹ Average weekly hours of work as measured in the CPS also fell sharply at the onset of the pandemic and remain below their immediate pre-pandemic levels. Even after seasonal adjustment, weekly hours are noisy and, for that reason, the right-hand panel of Figure 1 plots a centered 3-month average series rather than the monthly numbers. As of January 2020, the last month for which the 3-month average was unaffected by the pandemic, workers responding to the CPS reported working an average of 37.5 hours per week; by November 2022, the last month for which we can compute the centered 3-month average using data through December 2022, this had fallen to 36.9 hours per week, a drop of 0.6 hours.

¹ For technical reasons (discussed later) related to how the BLS incorporates new information about the size and composition of the population into Current Population Survey (CPS) estimates, the true participation rate shortfall may be 0.2 to 0.3 percentage point larger than the published estimates shown in the figure suggest.

Figure 1: Labor Force Participation and Average Weekly Hours, Seasonally Adjusted, January 2019 to December 2022 (Participation) and November 2022 (Hours)

A: Labor Force Participation



**B: Average Weekly Hours
(3 month centered moving average)**



Source: Bureau of Labor Statistics and authors' calculations.

Note: Seasonally adjusted labor force participation as published by the BLS. Hours data downloaded from IPUMS database (Flood et al. 2022). Series seasonally adjusted using X-12 seasonal adjustment command in Eviews applying multiplicative X-11 method and auto X-12 seasonal and trend filter, then averaged over 3 months.

The next section of the paper explores more systematically what has happened to labor force participation and hours of work since the start of the pandemic. Excess mortality and reductions in immigration associated with the pandemic also have affected the size of the labor force through their effects on the size of the population (Powell 2022, Hobijn and Şahin 2022), but our focus in this paper is on what has happened to the willingness of those who are here to supply their labor to the market. Over the post-pandemic period, population aging has put downward pressure on the labor force participation rate, while rising educational attainment has worked in the opposite direction. By our estimates, a post-pandemic decline in participation of about 0.5 percentage point remains after accounting for these demographic changes. The post-pandemic decline in average hours per week has reduced aggregate hours worked per adult

member of the population as much as the decline in participation, but demographic changes explain none of the decline.

Even prior to the pandemic, participation among younger and prime age adults generally had been trending downwards. In contrast, older adults' participation had been rising. Another way to think about the overall post-pandemic changes in participation and hours is to ask how we would have expected them to change had the long-term trends within detailed age-by-education groups continued. We estimate that a post-pandemic decline in participation of about 0.3 percentage point remains after accounting for both demographic changes and an assumed continuation of pre-pandemic within-group trends. In contrast, very little of the post-pandemic decline in average weekly hours is explained by these factors.

Relative to the changes projected based on changes in age and education and on the continuation of pre-existing trends, the post-pandemic shortfalls in participation and hours have not been uniform across the population. Participation among adults under age 65 has dropped for those without a college degree but fallen less or even risen among the college educated. Among adults age 65 and older, there were *larger* unanticipated participation rate declines among the college educated than among those with less education, though in this case both groups' participation rates fell significantly. Participation net of demographic and trend influences has fallen for White non-Hispanics, held roughly constant for Hispanics, and actually risen for Black non-Hispanics. The unanticipated declines in hours have been somewhat larger for men than for women.

Various hypotheses have been offered for why participation and hours have not yet fully rebounded following the pandemic. We explore (and in some cases extend) available evidence related to several widely cited explanations, including that improvements in households' balance

sheets attributable to federal safety net spending or to the rising stock market and increases in housing prices have had a dampening effect on labor supply; that fear of COVID continues to slow the return of workers to the labor market; and that long COVID has led to lower participation and shortened hours of work. We conclude that, although they have contributed to improvements in household balance sheets, neither federal transfers to households during the pandemic nor rising asset prices have had a substantial continuing effect on overall labor supply. Rising house prices, however, could have made it possible for some older homeowners adversely affected by other shocks to retire earlier than they otherwise might have done. Some prior studies have estimated very large effects of COVID fears or ill health due to long COVID on participation. Although we do not find the largest estimated effects to be plausible, we conclude that, together, fear of COVID and lingering COVID health effects explain much if not all of the shortfall in anticipated participation. Insofar as working even a shortened in-person work schedule would involve potential COVID exposure, fear of COVID seems unlikely to explain the decline in hours that we document. Long COVID may explain some but not all of the hours decline, leading us to speculate that a reevaluation of the balance between work and other activities also may be a part of the explanation.

II. What Has Happened to Labor Supply in the Post-Pandemic Labor Market?

The question we seek to answer is why, despite the recent strength in the labor market, neither participation nor hours has fully recovered to pre-pandemic levels. We look first at the raw changes in participation and hours during the nearly three years since the start of the pandemic, then examine series from which we net out the effects of demographic changes and, for a second counterfactual, also net out the effects of pre-existing trends. Most of our analysis

makes use of 12-month moving averages that smooth short-term fluctuations in the underlying data series. Participation and hours both are measured using data from the Current Population Survey (CPS); the underlying microdata were downloaded from the IPUMS database (Flood et al. 2022).

Developing a Benchmark for Assessing Post-Pandemic Participation and Hours

Prior to the start of the pandemic, the labor market had been experiencing a long-running cyclical recovery, with unemployment having reached lows not seen since the late 1960s. Had the labor market been less strong at the end of 2022 than in early 2020, the post-pandemic shortfall in participation and hours plausibly could have been attributed to labor demand conditions. In fact, however, available data suggest that the labor market was at least as tight at the end of 2022 as it had been in early 2020.

Macroeconomic modelers commonly use a measure based on the unemployment rate to capture the effects of labor market conditions on participation. The seasonally adjusted unemployment rate stood at 3.5 percent in both February 2020 and December 2022. Participation responds to tightening labor markets with a lag (Hobijn and Şahin 2022), but both at the start and at the end of our period, unemployment had been at or below 4.0 percent for a year or more. If anything, the elevated levels of both job vacancies and quits prevailing at the end of 2022 suggest a tighter labor market than implied by the unemployment rate (Domash and Summers 2022). In the remainder of the paper, we mostly treat cyclical conditions at the endpoints of the period we are studying as equivalent, but if the labor market was indeed tighter in December 2022 than in February 2020, our calculations may understate the true cyclically-adjusted post-pandemic shortfall in participation and hours. Whether the December 2022 labor market is

tighter than that prevailing in February 2020 or merely just as tight, its strength supports interpreting observed shortfalls in participation and hours as driven by labor supply rather than labor demand.

Even absent the pandemic, changing population demographics over the past three years, most especially the aging of the population and ongoing increases in educational attainment at given ages, would have affected participation and possibly hours. Because participation rates drop off significantly at older ages, it has long been anticipated that the aging of the Baby Boom would put downward pressure on the participation rate. In addition to becoming older, however, the population also has been becoming more educated. At every age, more educated individuals have higher participation rates than those with lower levels of education.² Any evaluation of how the pandemic has affected participation thus needs to take these demographic changes into account (see, for example, D. Aaronson et al. 2012, S. Aaronson et al. 2006, S. Aaronson et al. 2014, Montes 2018 and Hornstein and Kudlyak 2019). Average weekly hours vary less with age and education than participation, but also should be adjusted for these same demographic factors.

Some analyses of post-pandemic labor force participation have set a benchmark that incorporates a continuation of subgroup participation trends during the years immediately preceding the pandemic. As unemployment fell and the labor market tightened during this period, within-group participation rates generally were rising. Extrapolating those short-term trends generates a benchmark against which the number of “missing workers” is very large. Given the significant cyclical upswing in participation that already had occurred by the

² Among men age 60-64, for example, an average of just 48.7 percent of those with less than a high school education were in the labor force over the 12 months ending in February 2020, compared to 59.7 percent of those with a high school diploma, 62.7 percent of those with some college and 73.7 percent of those with at least a Bachelor’s degree. Women in the same age band had participation rates of 29.9 percent, 47.5 percent, 52.6 percent and 61.8 percent across the four educational groups. Sizable differences in participation rates by education can be seen within other five-year age groups.

beginning of 2020, however, we view a continuation of the immediate pre-pandemic participation trends as an unrealistic counterfactual.³ That said, there have been notable longer-term trends in participation that might well have continued absent the pandemic. Participation among young adults (16-24 years old) and prime age adults (25-54 years old) generally has fallen since about 2000; in contrast, participation among older adults (55 years old and older) generally has risen (Abraham and Kearney 2020). Different analysts have modeled these trends in different ways. The ten-year labor force projections developed by the Bureau of Labor Statistics, for example, extrapolate pre-existing participation trends for specific subgroups (Bureau of Labor Statistics n.d.). Others have directly estimated participation rate models for demographic sub-groups that contain cyclical, structural and cohort variables (see, for example, D. Aaronson et al. 2012, S. Aaronson et al. 2006, S. Aaronson et al. 2014 and Montes 2018). Even among models of the same general sort, different analysts have made different choices about exactly what variables to include in the model, how the cohort effects are specified, and other model features. Despite the difference in approaches—and some notable differences in the estimated trend or natural rate of labor force participation—there is broad agreement about the combined effects of demographic changes and other factors on the overall trend in labor force participation.

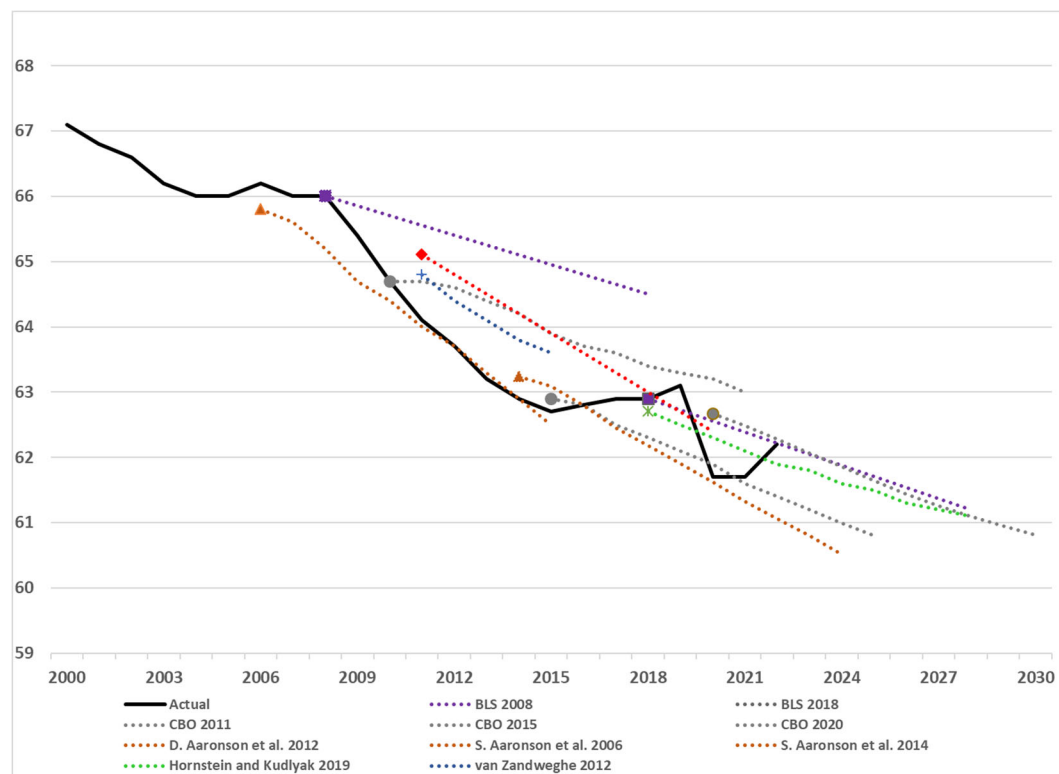
This can be seen in Figure 2, adapted from a recent paper by Hobijn and Şahin (2022).⁴ Both across models and across different vintages of the same model, there are significant differences in the level of the trend participation rate. In every case, however, the models imply that the overall participation rate has been trending downwards. The majority of the decline is

³ Hobijn and Şahin (2022) make a similar point.

⁴ We thank Hobijn and Şahin for sharing the data underlying their chart with us. Our chart includes a slightly different set of previous projections than were included in their chart, but otherwise is similar to their original

attributed to changes in the demographic composition of the population, but all of the projections also reflect the influence of other factors in some fashion. In the models for which a projection spanning all or part of the period from January 2020 through January 2023 is reported, the projected annual declines in overall participation for the covered portion of that period are between 0.2 and 0.3 percentage point per year. The adjustments we make to account for changes in demographic mix and, in some calculations, pre-existing within-group trends, described below, are consistent with these projections.

Figure 2: Actual and Projected Trend of Natural Labor Force Participation Rates, 2000-2028



Source: Adapted from Hobijn and Şahin (2022). BLS projections available at <https://www.bls.gov/emp/> and CBO forecasts at <https://www.cbo.gov/data/budget-economic-data>. See also D. Aaronson et al. (2012), S. Aaronson et al. (2006), S. Aaronson et al. (2013), Hornstein and Kudlyak (2019) and van Zandweghe (2012).

Note: Markers show vintage of projection or forecast.

One other technical factor that should be mentioned in the context of evaluating the post-pandemic change in labor force participation is the Bureau of Labor Statistics' introduction of new population controls for the CPS in January 2022. New population controls are introduced in the CPS each year to reflect updates in population estimates, but the January 2022 controls were notable because they incorporated the information from the 2020 Census. Those data revealed a population that is younger than previous estimates had indicated. Had the December 2021 labor force participation rate been estimated using the new population controls, it would have been 0.3 percentage point higher. Rather than a one-time jump in participation, this higher participation rate should be thought of as reflecting uncaptured demographic changes that have occurred gradually since the prior Census in 2010. The implication is that labor force participation in February 2020 was higher than the official estimates suggest. Because the BLS does not revise the historical CPS estimates when new population controls are introduced, the decline in overall labor force participation between February 2020 and December 2022 thus looks smaller than it really has been.⁵ Rather than being about a percentage point lower in at the end of 2022 than in February 2020, the participation rate may have been 1.2 or 1.3 percentage points lower.

We do not account explicitly for the effects of the new population controls in the numbers we report below. Our primary interest, however, lies with participation rate changes net of changes in the demographic mix of the population and, in some cases, pre-existing within-group trends. Because these estimates fix the demographic composition of the population, they are not affected by the issues with changing population controls in the same way as the raw participation rate estimates. As we will discuss shortly, hours vary less with age than

⁵ Montes, Smith and Dajon (2022) make this same point in the context of discussing the post-pandemic growth in the share of the population that is retired, which is understated if the change in population controls is not taken into account. .

participation and, based on our calculations, are relatively insensitive to changes in demographic mix. This means that even the raw average hours series should be relatively insensitive to changes in the population controls.

Adjusting Participation and Hours for Demographics and Pre-Existing Group-Specific Trends

We would like to know how much of the participation and hours shortfalls we have been discussing reflects factors whose effects should have been anticipated prior to the onset of the pandemic. Subtracting out the influence of those factors should give us a clearer picture of the impact of the pandemic and its aftermath. With the goal of identifying the effect that the pandemic has had on these outcomes, we begin by removing the effects of changes in demographic mix from the data and then adjust in addition for the potential effects of pre-existing within-group participation rate trends.

Disaggregating across any mutually exclusive set of population subgroups, the change in the labor force participation rate between any two periods can be written as:

$$(1) \Delta(LFPR)_{t_0, t_1} = \sum_i s_{i, t_0} \Delta(LFPR)_{i, t_0, t_1} + \sum_i (LFPR)_{i, t_0} \Delta s_{i, t_0, t_1} + \sum_i \Delta s_{i, t_0, t_1} \Delta(LFPR)_{i, t_0, t_1}$$

where LFPR is the labor force participation rate, s is a specific group's share of the overall population, i indexes the different mutually exclusive groups, and t_0 and t_1 are the start and end of the time period over which the change is measured. The change in average hours can be expressed similarly:

$$(2) \Delta(AVEHRS)_{t_0, t_1} = \sum_i e_{i, t_0} \Delta(AVEHRS)_{i, t_0, t_1} + \sum_i (AVEHRS)_{i, t_0} \Delta e_{i, t_0, t_1} + \sum_i \Delta e_{i, t_0, t_1} \Delta(AVEHRS)_{i, t_0, t_1}$$

where AVEHRS is average weekly hours worked and e is a specific group's share of overall employment. The first term in these equations captures the effects of within-group changes in participation or hours, holding population or employment shares fixed. A series constructed based on that term tells us how much participation and hours have changed net of the effects of changes in demographic mix. The second term captures the effect of changes in group shares, holding each group's initial participation rate or average hours constant. Note that this may include changes in measured population mix attributable to the arrival of new information as well as true changes in group shares. The third term summarizes any potential interaction effects. Although these can be important in some contexts, they are consistently negligible for the decompositions we report.

The decomposition just described treats each group's initial period participation rate or hours as the relevant benchmark for evaluating subsequent within-group changes. We also might want to know how much participation and hours have changed after additionally netting out the effects of any pre-existing within-group trends, on the grounds that persistent trends may reflect factors that can be expected to have a continuing influence. Equations (1) and (2) can be modified to do this. Equation (1) becomes:

$$(1a) \quad \Delta(LFPR)_{t_0, t_1} = \sum_i s_{i, t_0} [\Delta(LFPR)_{i, t_0, t_1} - TREND_{i, t_0, t_1}] + \sum_i [(LFPR)_{i, t_0} \Delta s_{i, t_0, t_1} + s_{i, t_0} TREND_{i, t_0, t_1}] \\ + \sum_i \Delta s_{i, t_0, t_1} \Delta(LFPR)_{i, t_0, t_1}$$

and equation (2) becomes:

$$(2a) \Delta(AVEHRS)_{i,t_0,t_1} = \sum_i e_{i,t_0} [\Delta(AVEHRS)_{i,t_0,t_1} - TREND_{i,t_0,t_1}] + \sum_i [(\Delta(AVEHRS)_{i,t_0,t_1} \Delta e_{i,t_0,t_1} + e_{i,t_0} TREND_{i,t_0,t_1})] + \sum_i \Delta e_{i,t_0,t_1} \Delta(AVEHRS)_{i,t_0,t_1}$$

In (1a) and (2a), TREND is the estimated pre-existing long-term within-group trend for group i extrapolated over the time period of interest. The first term in these expressions is now the unanticipated change in participation or hours after netting out the effects of both demographic changes and pre-existing within-group trends. The second term is the change that should have been anticipated based on the combination of those factors. The third term is unchanged and, as before, represents potential interaction effects.

To better understand the factors that have influenced participation and hours since the start of the pandemic, we begin with age-adjusted series constructed as specified by the initial terms in equations (1) and (2) with the groups defined by age. For these calculations, we fix the shares of the population or of employment in each of 13 detailed age groups (16-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74 and 75 plus). Within-age-group participation and hours are allowed to change as they actually did. This series thus answers the question of how much participation and hours would have changed had the age composition of the population been fixed. To avoid difficulties associated with the seasonal adjustment of some of the underlying detailed data series, our estimates are based on 12-month moving averages.

Next, we construct series that fix the age-by education composition of the population or employment, as appropriate. For these series, we start with the same age groups as were used for the age-adjusted series. Because those age 16-24 are still in the process of completing their education and the decision whether to remain in school is itself an endogenous outcome, we do

not hold educational attainment constant within the 16-19 year old or 20-24 year old age groups. For those age 25 and older, we fix the shares within each detailed age group in each of the following four educational attainment categories—less than a high school education, high school or the equivalent, some college, or a Bachelor’s degree or higher.⁶ Again, within-group participation and hours are allowed to change as they actually did and the estimates are based on 12-month moving averages.

Finally, starting with the age-by-education-adjusted series, we construct series that additionally net out the effects of within-group trends, as shown in the first terms of equations (1a) and (2a). For this purpose, the pre-existing trend in each of the detailed age groups (for those under age 25) or age-by-education groups (for those age 25 and older) is estimated using annual data for the period from 2000 through 2019.

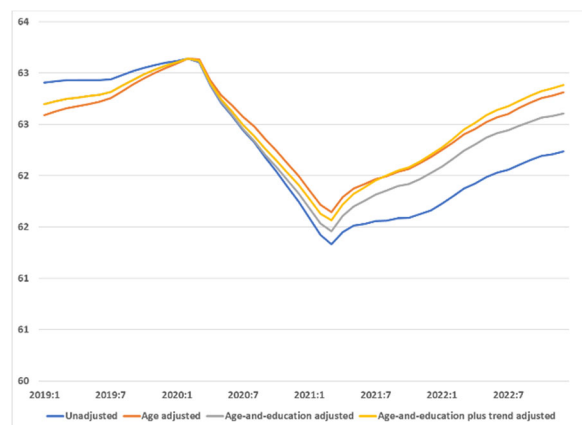
The effects of making these adjustments can be seen in Figure 3. As shown in the figure’s left-hand panel, in February 2020, the 12-month moving average labor force participation rate was 63.1 percent. On an unadjusted basis, by December 2022, moving average participation was 62.2 percent, approximately 0.9 percentage point lower. Had the Bureau of Labor Statistics known sooner how the age distribution of the population was changing following the 2010 Census and incorporated that knowledge into the estimates, the estimated February 2020 participation rate likely would have been a bit higher and the raw post-February 2020 participation decline correspondingly a bit larger. This does not apply, however, to series that hold the age- or age-and-education mix of the population constant as they were in February 2020. On an age-adjusted basis, the 12-month moving average participation rate in December

⁶ Among those age 16-24, participation rates and hours of work are markedly higher for those who are out of school than for those who are still enrolled. Because the shares of 16-19 year olds and 20-24 year olds who are out of school has risen, holding constant the shares who are in versus out of school would leave slightly more of the change in participation to be explained by within-group changes as opposed to changes in population demographics.

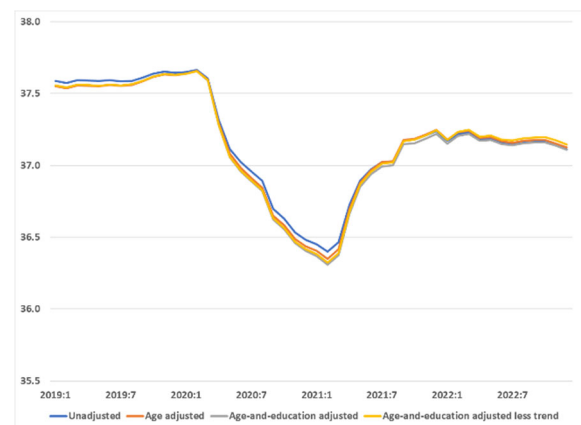
2022 was 62.8 percent, only 0.3 percentage point lower than the February 2020 value. The moving average age-and-education adjusted series tells a somewhat different story, with moving average participation 0.5 percentage point lower in December 2022 than it had been in February 2020. Finally, allowing for pre-existing within-age-and-education group trends tells a story more like the simple age adjustment, with moving average participation about 0.3 percentage point lower in December 2022 than it had been in February 2020.

Figure 3: Unadjusted and Adjusted Labor Force Participation and Average Weekly Hours, 12-Month Moving Averages, January 2019-December 2022

A: Labor Force Participation



B: Average Weekly Hours



Source: Authors' calculations.

Note: Estimates based on CPS data downloaded from IPUMS database (Flood et al. 2022). Adjustment details described in text.

The right-hand panel shows corresponding series for hours of work. On an unadjusted basis, average weekly hours measured as a 12-month moving average fell from 37.7 hours in February 2020 to 37.1 hours in December 2022, a 0.6 hour decline. Although there are differences in average weekly hours across some of the employment subgroups, adjusting for the age or age-by-education composition of employment does not affect the measured overall net

change in average hours. Removing the effects of long-term pre-existing within-group trends in average hours also has little effect on the measured overall net change in average hours.

To be slightly more formal about the relative importance of changes along different margins to the change in the aggregate supply of hours, consider the following identity:

$$(3) \quad TOTHRS_t = POP_t * \frac{LF_t}{POP_t} * \frac{EMP_t}{LF_t} * AVEHRS_t$$

where TOTHRS is aggregate hours worked per week; POP is the population age 16 and older; LF is the number of people age 16 and older in the labor force; EMP is the number of employed people age 16 and older; and AVEHRS is the average weekly hours worked by those who are employed. In this identity, $\frac{LF}{POP}$ is just the labor force participation rate (LFPR) and $\frac{EMP}{LF}$ can be expressed as one minus the unemployment rate (1-UR). Substituting into equation (3), taking the natural log and then differencing gives us:

$$(4a) \quad \Delta \ln(TOTHRS) = \Delta \ln(POP) + \Delta \ln(LFPR) + \Delta \ln(1-UR) + \Delta \ln(AVEHRS)$$

or, equivalently, focusing as we do here on the change in aggregate hours per person age 16 and older:

$$(4b) \quad \Delta \ln(TOTHRS) - \Delta \ln(POP) = \Delta \ln(LFPR) + \Delta \ln(1-UR) + \Delta \ln(AVEHRS)$$

This expression decomposes the change in aggregate weekly hours per adult member of the population into pieces attributable to changes in the labor force participation rate, the employment rate (one minus the unemployment rate) and average weekly hours among the employed. Carrying out the equation (4b) decomposition using 12-month moving averages for the period ending December 2022 compared to the period ending February 2020, the natural logarithm of aggregate hours per person age 16 and older fell by 0.0296, roughly a 2.9 percent decline. Of this decline, 48.7 percent was due to declining labor force participation (which fell 0.9 percentage point or about 1.4 percent) and 49.9 percent to the decline in average weekly hours (which fell 0.6 hour or about 1.5 percent), with a negligible residual attributable to change in the 12-month moving average unemployment rate.⁷

A simple way to put these numbers into perspective is to ask how many missing workers the changes along each of the three margins represents. Holding everything else constant, had labor force participation not declined by the approximately 1.4 percent we observe, allowing the unemployment rate and average hours to change as they actually did, employment would have averaged about 2.3 million higher during calendar year 2022. Based on our separate decomposition of the factors that have contributed to the participation decline, roughly a 1.4 million worker shortfall would remain after allowing for changes in the age-education composition of the population and about a 0.7 million worker shortfall would remain after allowing, in addition, for the continuation of pre-existing within-group participation trends. The approximately 1.5 percent decline in moving-average weekly hours translates into the equivalent

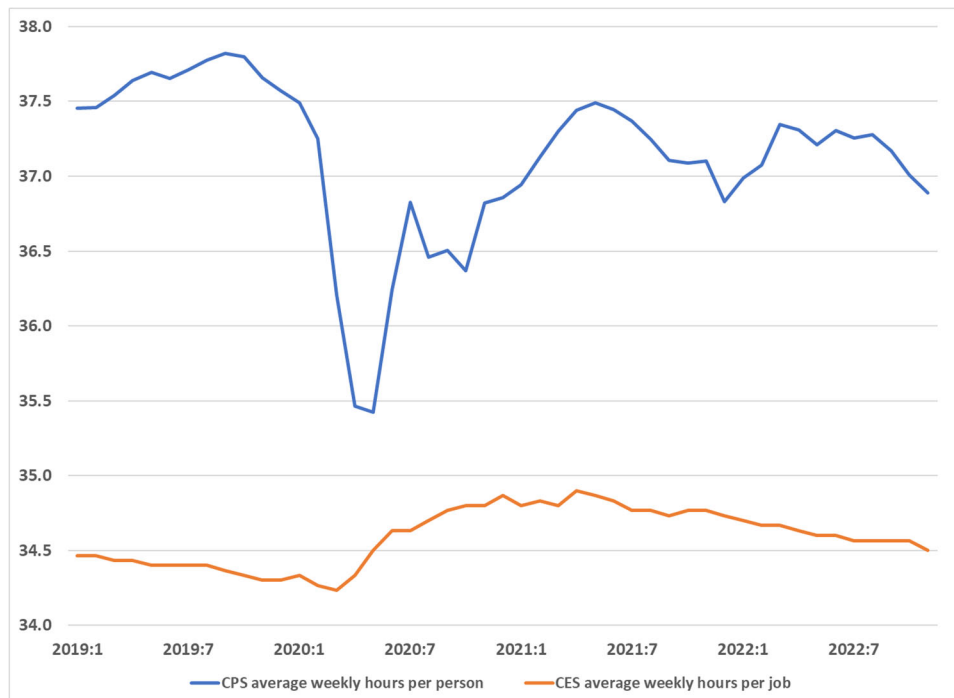
⁷ The overall change and the change attributable to changes in participation would be slightly larger were we to adjust for the new population controls introduced in January 2022. Lee, Park and Shin (2023) report results from a similar analysis that decomposes the change in aggregate hours from 2019 through 2022 into a piece attributable to changes in the employment to population ratio and changes in average weekly hours. They find that changes in average hours have been roughly as important as changes in the employment to population ratio in explaining the post-pandemic aggregate hours shortfall.

of approximately another 2.3 million employment shortfall. In contrast to the participation figures, very little of this is attributable to demographic changes or pre-existing trends. The change in the moving average unemployment rate accounts for less than a 0.1 million employment shortfall.

An Aside on the Measurement of Hours

In these decompositions, after netting out the effects of changes in demographic mix and pre-existing within-group trends, the shortfall in average weekly hours is a more important part of the post-pandemic labor supply shortfall than the corresponding shortfall in labor force participation. As shown in Figure 4, however, someone looking at data from the Current Employment Statistics (CES) survey (the monthly payroll survey) would have a different sense of how hours have changed. For comparability with the average hours estimates presented in Figure 1, the figure shows 3-month moving averages of seasonally adjusted estimates for both CPS and payroll survey hours. In contrast to actual hours of work per employed person as measured in the CPS, which fell sharply at the start of the pandemic and have not fully recovered, average weekly paid hours on private sector jobs as measured in the payroll survey *rose* following the onset of the pandemic, from a 3-month average of 34.3 hours per week in February 2020 to a peak 3-month average of 34.9 hours per week in April 2021 before falling back to a 3-month average of 34.5 hours as of November 2022.

Figure 4: Average Weekly Hours, Current Population Survey and Current Employment Statistics Survey, January 2019–November 2022



Source: Authors' calculations and Bureau of Labor Statistics.

Note: CPS hours data downloaded from IPUMS database (Flood et al. 2022), seasonally adjusted using X-12 seasonal adjustment command in Eviews applying multiplicative X-11 method and auto X-12 seasonal and trend filter. CES hours data seasonally adjusted series as published by Bureau of Labor Statistics. Both series centered 3-month moving averages.

Although we cannot fully reconcile the different movements in the CPS and payroll survey hours, we can identify several factors that likely have been at work. First, whereas the CPS is a measure of hours *per person*, the CES is a measure of hours *per job*. Consistent with the level difference between the two series, since some people hold more than one job, average hours per person exceed average hours per job. Changes over time in the prevalence of multiple job holding also may help to explain the differences in the behavior of the two series over time. Data from the CPS indicate that the multiple-job-holding rate fell from 5.2 percent in February 2020 to lows of 4.3 percent in December 2020 and 4.4 percent in January 2021 before eventually

recovering to its pre-pandemic level. All else the same, the initial decline multiple job holding will have led hours per person as measured in the CPS to fall. Because second jobs generally involve fewer hours per week than the average job, a decline in multiple job holding also will cause average hours per job, the concept measured in the payroll survey, to rise. Back-of-the-envelope calculations using CPS data suggest that, holding average hours per week on both primary and secondary jobs constant at their February 2020 levels, the reduction in the multiple job holding rate from February 2020 to its low point would have reduced average weekly hours per person by about 0.1 hour and raised average weekly hours per job by about 0.2 hour. Other evidence suggests that the CPS may understate the multiple-job holding rate (Abraham et al. 2023). Supposing this to be the case and also that the proportional movements in true multiple job holding mirror those in measured multiple job holding, the increase in average weekly hours per job attributable to a lower multiple-job-holding rate could have been larger than 0.2 hour.

A second difference between the CPS and payroll survey measures of hours is that the CPS measures hours *worked*, whereas the payroll survey measures hours *paid*. In the CPS, both people who are employed but not at work and people who usually work full-time (35 or more hours per week) but worked part-time during the survey reference week are asked why this was the case. Possible reasons include own illness, injury or medical problems (which we will refer to as a health-related reason) or being on vacation. To the extent that people who are absent or working reduced hours for these reasons are paid for the time they miss, hours paid would not be affected but hours worked would fall, creating a wedge between the payroll survey and CPS hours series. Since the start of the pandemic, the share of people absent from work or working a part-time rather than a full-time schedule either for health-related reasons or because they were

on vacation (mainly the former) has risen.⁸ Our back-of-the-envelope calculations suggest that, accounting for this growth, the size of the wedge between CPS and payroll survey average hours could have grown by as much as 0.2 hour between February 2020 and December 2022. Because some affected individuals may not have access to paid sick or vacation leave, this could overstate the true effect. On the other hand, because our calculations do not account for people who take paid sick or vacation leave that does not result in their weekly hours falling below the full-time hours threshold (i.e., people who remain full-time even though their hours have fallen or who were part-time before becoming ill), they could understate the growth in the size of the wedge.

Finally, the CPS and payroll survey differ with respect to the target populations for their hours data. Whereas the CPS target population encompasses government workers, the self-employed and unpaid family workers, the payroll survey data cover only private sector wage and salary jobs. We do not have any direct evidence that these differences help to explain the divergence between CPS and payroll survey hours over the post-pandemic period, but they are another reason the two surveys might tell a different story.

During the Great Recession, the first recession for which the payroll survey provides all-employee hours, the movements in household survey and payroll survey hours were broadly similar. During the pandemic and its aftermath, however, this was not the case. Conceptually, we are interested in the hours that individuals are supplying to the labor market and thus in average hours per person, not in average hours per job, and in the hours that people actually work as opposed to the hours for which they are paid. The CPS hours data thus are more suitable for our purposes than the payroll survey hours data.

⁸ Among the reasons people give for missing time at work, hours missed for health-related reasons and vacation seem most likely to be covered by paid leave and thus to contribute to the wedge between payroll survey and CPS hours.

Whose Labor Supply Has Fallen?

The estimates we have presented thus far suggest that there have been notable changes in aggregate labor supply during the post-pandemic period relative to the changes that should have been expected based on shifts in population demographics or the combination of shifts in population demographics and pre-existing trends. This naturally raises the question of which groups in the population are responsible for these changes. Table 1 summarizes the results of an accounting exercise that decomposes the overall change in the 12-month moving average participation rate between February 2020 and December 2022 into the components shown in equation (1) and (1a). The mutually exclusive groups used for these calculations are defined using detailed age groups and, for those age 25 and older, completed education. The decomposition shown in the table's first panel accounts only for changes in age and education mix; the decomposition in the second panel additionally incorporates the projected effects of a continuation of within-group trends. In each case, we are interested primarily in the row in the table that shows the decline in participation in excess of what we would have anticipated based on these factors. Estimates for the whole population are reported in the table's first column; the remaining columns show results by gender and by race and ethnicity.⁹ The table also shows the contribution of different broad age by education groups to the overall decline in participation relative to expectations and, for reference, how the labor force participation rate has changed for each of these same groups, again measured relative to expectations.

⁹ White non-Hispanic includes people who identify as White only and Black non-Hispanic includes people who identify as Black only. Because of small sample sizes, figures are not reported for non-Hispanic individuals who identify as Asian; Hawaiian or Pacific Islander; American Indian, Aleut or Eskimo; or more than one race. People in these excluded groups represent less than 10 percent of the population.

Table 1: Decomposition of Percentage Point Change in 12-Month Moving Average Labor Force Participation Rate, Without and With Trend Adjustments, February 2020-December 2022

	Contribution to Overall Change in LFPR					
	Overall	Men	Women	White Non- Hispanic	Black Non- Hispanic	Hispanic
Total change	-0.90	-1.20	-0.71	-1.29	-0.18	-0.68
Decomposition without accounting for within-group trends						
Within-age-education group participation changes	-0.53	-0.70	-0.48	-0.87	0.13	-0.25
16-24, all	-0.04	0.00	-0.07	-0.04	-0.13	0.02
25-54, less than college	-0.25	-0.34	-0.23	-0.33	0.05	-0.37
25-54, college plus	0.04	-0.05	0.12	-0.01	0.02	0.12
55-64, less than college	-0.05	-0.10	-0.03	-0.10	0.01	0.03
55-64, college plus	0.01	0.01	0.01	-0.01	0.14	-0.02
65 plus, less than college	-0.14	-0.13	-0.18	-0.20	-0.02	-0.06
65 plus, college plus	-0.11	-0.10	-0.10	-0.19	0.06	0.04
Age-education share changes	-0.37	-0.49	-0.24	-0.42	-0.34	-0.45
Interactions	0.00	0.00	0.01	0.00	0.03	0.03
Decomposition accounting for within-group trends						
Within-age-education group participation changes less trend effects	-0.26	-0.32	-0.30	-0.68	0.52	-0.05
16-24, all	0.21	0.30	0.13	0.18	-0.02	0.31
25-54, less than college	-0.05	-0.12	0.00	-0.12	0.30	-0.27
25-54, college plus	0.07	0.00	0.09	-0.01	0.10	0.10
55-64, less than college	-0.09	-0.12	-0.06	-0.14	0.06	-0.07
55-64, college plus	-0.02	-0.03	-0.04	-0.05	0.12	-0.04
65 plus, less than college	-0.21	-0.19	-0.25	-0.27	-0.07	-0.11
65 plus, college plus	-0.17	-0.16	-0.17	-0.26	0.03	0.03
Age-education share changes plus trend effects	-0.65	-0.87	-0.42	-0.62	-0.73	-0.66
Interactions	0.00	0.00	0.01	0.00	0.03	0.03
Change in participation rate since February 2020 (average across detailed component groups)						
16-24, all	-0.25	-1.05	-0.49	-0.33	-0.80	0.11
25-54, less than college	-0.85	-1.06	-0.83	-1.33	0.13	-0.81
25-54, college plus	0.23	-0.25	0.57	-0.07	0.14	0.99
55-64, less than college	-0.33	-0.49	-0.31	-0.39	-0.24	-0.35
55-64, college plus	0.19	0.17	0.15	-0.10	3.89	-1.03
65 plus, less than college	-1.00	-1.05	-1.12	-1.19	-0.13	-0.71
65 plus, college plus	-1.72	-1.54	-1.69	-2.23	1.80	2.46
Change in participation rate since February 2020 relative to pre-existing trend (average across detailed component groups)						
16-24, all	1.44	1.99	0.90	1.48	-0.09	1.56
25-54, less than college	-0.17	-0.39	0.01	-0.51	0.82	-0.58
25-54, college plus	0.35	0.01	0.42	-0.06	0.60	0.86
55-64, less than college	-0.65	-0.79	-0.59	-0.72	-0.17	-1.02
55-64, college plus	-0.45	-0.60	-0.75	-0.80	3.35	-1.68
65 plus, less than college	-1.47	-1.51	-1.55	-1.65	-0.53	-1.26
65 plus, college plus	-2.58	-2.39	-2.76	-3.07	0.97	1.72

SOURCE: Authors' analysis of Current Population Survey data.

NOTE: Pre-existing within-group trends estimated over 2000-2019 period. Detailed age groups are 16-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74 and 75 plus. Detailed education categories for those age 25 and older are less than high school, high school, some college and bachelors degree or higher (labeled as college plus). Race/ethnicity categories are mutually exclusive. Race/ethnicity breakouts exclude non-Hispanic individuals who identify as Asian; American Indian, Aleut or Eskimo; Hawaiian or Pacific Islander; or more than one race. These groups represent less than 10 percent of the population age 16 plus.

The top row in Table 1 shows that the overall 12-month moving-average participation rate declined by 0.9 percentage point between February 2020 and December 2022, but also that there have been some notable differences across groups. Men's participation rate declined 0.5 percentage point more than women's. Participation also declined noticeably more for White non-Hispanics than for either Black non-Hispanics (a 1.1 percentage point difference) or Hispanics (a 0.6 percentage point difference).

Given previously-expected demographic changes and pre-existing within-group participation trends, much of the overall change in participation could have been anticipated prior to the pandemic. Adjusting for changes in demographic mix, overall participation would have been roughly 0.5 percentage point lower in 2022 than might have been expected prior to the pandemic; allowing also for the effects of pre-existing trends, it is only about 0.3 percentage point lower.

Again, however, there are some notable differences across groups. Focusing on the estimates that account for pre-existing trends, participation has fallen significantly more than expected for adults age 55-64 and especially for those age 65 plus. Perhaps surprisingly, among those age 65 and older, the decline in participation has been most pronounced for college graduates. This is consistent with the finding of Montes, Smith and Dajon (2022) that excess retirements increased more during the pandemic for those with a college education than for those without a college degree. On their own, unanticipated within-group participation declines among those age 55 and older would have reduced overall participation by about 0.5 percentage point, but that decline has been partially offset by unanticipated within-group participation *increases* (relative to trend) among those age 16-24. Participation among 25-54 year olds has changed very

little overall, but this reflects the offsetting effects of *increased* participation among college graduates and *decreased* participation among those with lower levels of education.

There are also differences by gender and by race and ethnicity. Among college educated adults age 25-54, women's participation has *risen* relative to what would have been projected prior to the pandemic, while participation among college-educated men in the same age range is consistent with a pre-pandemic forecast. Age-, education-and trend-adjusted participation among college-educated adults age 25-54 was roughly constant among White non-Hispanics, but rose for both Black non-Hispanics and Hispanics. Among college educated adults age 65 and older, where the adjusted overall participation rate dropped substantially, increases are observed for Black non-Hispanics and Hispanics. Similarly, the declines in participation among adults age 65 and older without a college education were smaller for Black non-Hispanics and Hispanics than for White non-Hispanics. Consistent with these results, Montes, Smith and Dajon (2022) report that excess retirements increased more during the pandemic for Blacks and Hispanics than for Whites.

For completeness, we also have created similar decompositions of the post-pandemic change in average weekly hours. As can be seen in Table 2, changes in the age-by-education composition of the employed population do not account for any appreciable share of the overall change in average weekly hours since the pandemic's onset—essentially all of the decline reflects within-group hours reductions—nor do pre-existing within-group trends in hours explain much of the observed change. As with labor force participation, men's average weekly hours have fallen noticeably more than women's. Whereas there have been declines in participation relative to trend for some groups but increases for others, however, average weekly hours have fallen for most groups.

Table 2: Decomposition of Change in in 12-Month Moving Average Weekly Hours, Without and With Trend Adjustments, February 2020-December 2022

	Contribution to Overall Change in Average Weekly Hours					
	Overall	Men	Women	White Non- Hispanic	Black Non- Hispanic	Hispanic
Total change	-0.55	-0.80	-0.30	-0.60	-0.43	-0.58
Decomposition without accounting for within-group trends						
Within-age-education group hours changes	-0.55	-0.80	-0.31	-0.58	-0.46	-0.58
16-24, all	-0.02	0.00	-0.05	-0.03	-0.08	0.01
25-54, less than college	-0.24	-0.37	-0.11	-0.22	-0.18	-0.38
25-54, college plus	-0.21	-0.29	-0.11	-0.23	-0.19	-0.17
55-64, less than college	-0.05	-0.06	-0.05	-0.06	-0.03	-0.03
55-64, college plus	-0.02	-0.05	0.02	-0.03	0.04	0.00
65 plus, less than college	0.00	-0.01	0.00	0.00	-0.03	0.01
65 plus, college plus	-0.01	-0.02	0.00	-0.02	0.00	-0.02
Age-education share changes	0.00	0.00	0.00	-0.01	0.01	0.00
Interactions	0.00	-0.01	0.01	-0.01	0.02	-0.01
Decomposition accounting for within-group trends						
Within-age-education group hours changes less trend effects	-0.51	-0.66	-0.40	-0.59	-0.42	-0.39
16-24, all	0.01	0.04	-0.02	0.00	-0.04	0.09
25-54, less than college	-0.22	-0.30	-0.12	-0.22	-0.15	-0.32
25-54, college plus	-0.17	-0.22	-0.16	-0.20	-0.17	-0.14
55-64, less than college	-0.07	-0.06	-0.07	-0.09	-0.04	-0.03
55-64, college plus	-0.02	-0.05	0.00	-0.03	0.03	0.01
65 plus, less than college	-0.02	-0.03	-0.02	-0.02	-0.05	0.01
65 plus, college plus	-0.02	-0.04	-0.01	-0.03	-0.01	-0.02
Age-education share changes plus trend effects	-0.04	-0.14	0.10	0.00	-0.03	-0.18
Interactions	0.00	-0.01	0.01	-0.01	0.02	-0.01
Change in average weekly hours since February 2020 (average across detailed component groups)						
16-24, all	-0.18	0.02	-0.40	-0.24	-0.60	0.07
25-54, less than college	-0.66	-0.94	-0.34	-0.70	-0.42	-0.71
25-54, college plus	-0.75	-1.17	-0.37	-0.78	-0.80	-1.07
55-64, less than college	-0.23	-0.24	-0.24	-0.28	-0.08	0.02
55-64, college plus	-0.28	-0.80	0.26	-0.36	0.96	0.15
65 plus, less than college	0.04	-0.20	0.01	0.04	-0.91	0.51
65 plus, college plus	-0.41	-0.69	0.06	-0.44	-0.17	-2.19
Change in average weekly hours since February 2020 relative to pre-existing trend (average across detailed component groups)						
16-24, all	0.09	0.31	-0.17	-0.02	-0.35	0.60
25-54, less than college	-0.60	-0.75	-0.36	-0.69	-0.33	-0.59
25-54, college plus	-0.63	-0.87	-0.52	-0.68	-0.74	-0.88
55-64, less than college	-0.36	-0.32	-0.40	-0.44	-0.17	-0.02
55-64, college plus	-0.32	-0.84	0.01	-0.42	0.79	0.42
65 plus, less than college	-0.51	-0.71	-0.56	-0.50	-1.49	0.51
65 plus, college plus	-0.79	-1.14	-0.41	-0.83	-0.52	-2.31

SOURCE: Authors' analysis of Current Population Survey data.

NOTE: Pre-existing within-group trends estimated over 2000-2019 period. Detailed age groups are 16-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74 and 75 plus. Detailed education categories for those age 25 and older are less than high school, high school, some college and bachelors degree or higher (labeled as college plus). Race/ethnicity categories are mutually exclusive. Race/ethnicity breakouts exclude non-Hispanic individuals who identify as Asian; American Indian, Aleut or Eskimo; Hawaiian or Pacific Islander; or more than one race. These groups represent less than 10 percent of the population age 16 plus.

III. How Has the Pandemic Affected Participation and Hours?

There are several channels through which the pandemic—and the public policy response to the pandemic—could have contributed to the post-pandemic shortfall in participation and hours that we have documented. One potential explanation sometimes featured in the press is that improvements in household balance sheets due to federal financial assistance during the pandemic may have slowed the return to work. A related explanation is that, by increasing household wealth, the rising stock market and, especially, increases in house prices associated with the pandemic-induced increase in the demand for housing in many locations could have led some people to exit the labor market. Another potential channel is that continuing fear of contracting COVID could be keeping people out of the labor force (Barrero, Bloom and Davis 2022). Finally, long COVID symptoms may have forced some affected individuals to withdraw from the labor force or cut back on the time they spend at work (Bach 2022a, 2022b; Goda and Soltas 2022; Sheiner and Salwati 2022). We consider the evidence pertaining to these various explanations and then summarize the conclusions we draw from the available evidence.

Social Safety Net Expansions during 2020 and 2021

A common explanation for shortfalls in labor supply earlier in the pandemic was that relatively generous social safety net supports were discouraging people from looking for work (see, for example, Morath and Chen 2020; Mitchell, Weber and Cambon 2021). By the beginning of 2022, all of these added supports had come to an end, though, partially as a result, household balance sheets remained healthier through the end of 2022 than might otherwise have been predicted (Barnes et al. 2022). The question is whether the magnitude of the improvement in households' financial situations is sufficient to explain much of a decline in labor supply.

Direct cash support for households during the pandemic came in several forms—more generous and more widely available benefits for unemployed individuals, expansions to the Child Tax Credit that benefitted households with children and economic impact payments received by most households. Federal legislation passed in March 2020 authorized the payment of an extra \$600 per week in benefits to anyone receiving unemployment insurance (UI) benefits between March 27, 2020 and July 31, 2020. Shortly after the expiration of the extra \$600 per week in UI benefits, President Trump signed an executive order allowing disaster relief funds to be used to pay UI recipients an extra \$300 per week. This covered several weeks of benefits. Later legislation provided for an extra \$300 per week, payable to individuals receiving benefits between December 27, 2020 and September 6, 2021. In addition to benefits being made more generous, from March 27, 2020 through September 6, 2021, the potential duration of benefits was lengthened and eligibility for UI benefits was extended to self-employed individuals and others who ordinarily would not have qualified.

During 2021, the Child Tax Credit was expanded from a partially refundable credit of \$2,000 per child to a fully refundable credit of \$3,600 per child under age 6 years and \$3,000 per child age 6-17 years. Under the CTC rules in place in 2020, a household had been required to earn at least \$2,500 to claim the credit. For those with earnings above that amount, the refundable credit was phased in at a rate of 15 cents per dollar of earnings, up to a maximum of \$1,400 per child. Only households with income tax liability of at least \$2,000 per qualifying child could claim the full child credit. Under the 2021 rules, any household with income below the level where eligibility for the credit began to phase out received the full credit.

Finally, during 2020 and 2021, the federal government made a series of economic impact payments to households. The first round of payments, included in the March 2020 CARES Act,

consisted of \$1,200 for each adult and an additional \$500 for each qualifying dependent child. The second round of payments, authorized in legislation passed in December 2020, provided \$600 per person. The third round of payments, authorized in the March 2021 American Rescue Plan, provided \$1,400 per person. In every round, benefits were phased out above certain income thresholds, but a majority of households received them. For a family of four with two adults and two children that qualified for the full benefit amounts, these payments totaled \$3,400 during 2020 and an additional \$8,000 in 2021.

Much of the debate about the expansion of the social safety net during the pandemic has centered on the effects of more generous UI payments. Especially during the period when an extra \$600 per week was being paid to benefit recipients, many people received more while unemployed than they had earned while they were working (Ganong, Noel and Vavra 2020). Despite this, studies conducted early in the pandemic generally concluded that the effects on employment were small or nonexistent (see, for example, Petrosky-Nadeau and Valletta 2020, Bartik et al. 2020 and Finamor and Scott 2020). The continuation of added UI benefits through the summer of 2021 had discernible negative effects on job-finding rates that translated into somewhat larger but still modest effects on overall employment (Holzer, Hubbard and Strain 2021; Coombs et al. 2022). Although little direct evidence about the effects of making benefits more widely available and extending their duration is available, those changes also could have affected job search behavior. Except for any persistent effects on household's balance sheets, however, any effects on job-finding rates should have quickly dissipated once the augmented benefits and benefit extensions ended at the beginning of September 2021.

Several studies have examined how expanding the Child Tax Credit (CTC) might have affected employment, hours and earnings. By increasing the credit amount and eliminating the

link between earnings and receipt of the credit, the 2021 changes could have reduced the incentive for members of low-wage households to be employed. Much of the research on the labor supply effects of the CTC expansions has proceeded by applying compensated income and substitution elasticities drawn from the labor supply literature. All of the studies agree that the income effect of a CTC expansion should be small. Corinth et al. (2021) estimate that making the 2021 changes permanent would have an income effect that reduced employment by about 140,000 and the estimates reported in other studies are similar. Where there is disagreement is with respect to the potential substitution effect attributable to program changes. Estimates of the combined effect of a permanent change like that introduced in 2021 range from Duncan and Le Mentestrel's (2019) estimate that employment would be reduced by just 0.15 million, an estimate that assumes no substitution effect, to Corinth et al.'s (2021) estimate that it would lead 1.5 million parents to leave the labor force. Bastian (2022) argues for estimates in between those two extremes. In any case, once again, after the expanded CTC payments introduced during the pandemic stopped at the end of 2021, they would have had a continuing effect only to the extent that household balance sheets made healthier by the temporary expansion of the program during 2021 affected households' labor supply decisions.

Finally, the economic impact payments distributed during 2020 and 2021 could have made it easier for some households to exit the labor force temporarily or return to work more slowly. This might perhaps have been especially true for households whose members were nearing retirement age; the cushion provided by these payments could have made it easier to advance a planned retirement date (Van Dam 2021). The fact that the payments were so universal, however, limits researchers' ability to estimate their effects directly.

To estimate how much the federal dollars that flowed to households during the pandemic might have affected labor supply, we first ask how large an increase in household wealth these payments represented. Then, we appeal to the literature that has estimated the elasticity of labor supply with respect to a pure increase in wealth to translate the increase in household wealth into a labor supply effect.

Estimating how much federal spending on pandemic unemployment benefits contributed to household wealth is tricky. Absent the pandemic, unemployment would not have spiked as it did and, for many households, unemployment benefits only partially replaced lost earnings. As a very generous upper bound estimate, we count as infusions to household balance sheets all of the approximately \$441 billion the federal government spent on Federal Pandemic Unemployment Compensation, which added first \$600 per week and later \$300 per week to recipients' normal UI payments; the approximately \$85 billion spent on Pandemic Emergency Unemployment Compensation, which extended benefit durations; and the approximately \$130 billion spent on Pandemic Unemployment Assistance, which made benefits available to the self-employed and others who ordinarily would not have qualified.¹⁰ When the American Rescue Plan was passed in March of 2021, the Congressional Budget Office estimated that the act's changes to the Child Tax Credit would add about \$85 billion to federal outlays during fiscal years 2021 and 2022 (Congressional Budget Office 2021). Spending on the three rounds of economic impact payments totaled about \$850 billion (Parker et al. 2022).

Pandemic spending directed to households thus totaled roughly \$1.6 trillion. As of the beginning of 2021, according to Census Bureau figures, there were about 250 million people age

¹⁰ These estimates come from https://oui.doleta.gov/unemploy/docs/cares_act_funding_state.html and include spending through October 8, 2022. We have subtracted out spending that flowed to Puerto Rico and the Virgin Islands.

18 and older living in the United States. On a per-adult basis, federal pandemic spending directed to households thus amounted to an average of about \$6,400.

In contrast to the voluminous literature on the effects of wages on labor supply, the literature on the labor supply effects of an increase in wealth is limited. A challenge is that increases in household wealth are seldom exogenous with respect to labor supply decisions. The best evidence we are aware of comes from studies of how lottery winnings affect the winners' subsequent labor supply. If people who receive unexpected money are myopic, the effects of an unexpected financial windfall such as winning a lottery could be larger in the short run than over time; if households are forward looking, however, one would expect the effects to be smaller but more persistent. Consistent with the idea that households are forward looking, Cesarini et al. (2017) find that lottery winners spend their money slowly and that the labor supply effects of a lottery win are relatively stable for at least five years after the win. According to their elasticity estimates, winning a lottery valued at about \$140,000 in 2010 dollars, equivalent to about \$175,000 as of the middle of 2021, reduced winners' labor force participation rate by about 2 percentage points and their weekly hours by about 1.3 hours. Although one might expect these effects to be larger for older adults, they do not vary significantly by age group, at least not through age 65. Winning a lottery also affects a spouse's labor supply but by only about half as much as it affects the winner's. Using the elasticity estimates reported by Cesarini et al. (2017), a wealth increase on the order of \$6,400 would lower labor force participation by less than 0.1 percent and hours by less than 0.1 hour per week even after accounting for effects on spouses' labor supply. Given that much of the money the federal government directed towards households during the pandemic offset losses in earnings rather than representing a net addition to the

household balance sheet, our assessment is that the effects of this spending on labor supply most likely were negligible.

Other Influences on Household Balance Sheets

Although discussions of how strong household balance sheets might be affecting labor supply often emphasize the role of federal payments during the pandemic, these payments have not been the only or even the most important influence on households' financial well-being (Barnes et al. 2022). While a significant number of households suffered serious economic harm due to pandemic shutdowns, others benefitted initially from a rising stock market and rising home prices, the latter arguably a result of changes in the demand for housing induced by the pandemic. Stock prices since have dropped and the housing market also has cooled, but house prices remain significantly elevated. The group of people one might expect to be most affected by a run-up in asset prices are those close to retirement, for whom an increase in household wealth could make earlier retirement possible.

Previous research generally has concluded that short-term fluctuations in the stock market do not significantly affect the timing of retirement (see e.g., Coile and Levine 2011; Goda, Shoven, and Slavov 2012). Research on the effects of short-term house price movements largely has come to a similar conclusion. Bosworth and Burtless (2010), for example, find no evidence in CPS data that trailing three-year house price increases in a respondent's state have a significant effect on the labor force participation of individuals age 55 to 74. Coile and Levine (2011) obtain similar results. Using data from the Health and Retirement Study, Farnham and Sevak (2016) find that year-over-year changes in housing prices do not have a significant effect on retirement rates.

Much of this research has been based on data for periods when the most significant variation in house prices was the large drop experienced in many markets during the Great Recession. The experience with rising house prices during the pandemic could be different. Coile (2022), however, finds no evidence that state-level housing price changes during the pandemic were associated with increased labor market exits among 55-74 year olds. In contrast, a recent paper by Favilukis and Li (2023) using American Community Survey (ACS) household data and Freddie Mac housing returns data, finds that metropolitan area house price increases from 2016 through the middle of 2021 were associated with significantly lower labor force participation among older homeowners. The association for older homeowners is contrasted with that of older renters, for whom house price increases were associated with higher participation; middle aged adults, whose participation did not vary with house prices; and younger adults, for whom house price increases were associated with higher participation. Taken at face value, these results imply a negligible effect of the run-up in house prices on overall participation, but in the author's view can explain much if not all of the decline in participation among adults age 65 and older.

It is unclear, however, exactly what to make of these findings. The authors' participation rate models include a variety of individual and metropolitan area controls in addition to their main house price change variable, but other factors still could explain the associations they find between house price increases and participation. For example, purchases by retirees of homes in smaller cities during the pandemic could have pushed up house prices in those areas while mechanically lowering the participation rate for older adults. Further, Favilukis and Li are interested mainly in the role of rising house prices during the pandemic as a driver of lower participation among older homeowners, but their baseline model measures house price changes over a longer period. Further, they do not obtain statistically significant results for house price

increases that occurred after the start of 2020 while also controlling for pre-pandemic house price run-ups. Even setting these issues aside, there is a question about how any changes in older homeowners' participation behavior in areas where house prices were rising should be interpreted. Rather than house price changes driving declines in participation among older homeowners, it could be that something else—fear of COVID, long COVID or simply the loss of a job—pushed older homeowners out of work and, for those that had benefitted from rising house prices, the fact that they had more home equity then made it possible for them not to return. Regardless, given that more educated adults also are more likely to be homeowners, these findings are qualitatively consistent with the fact that, as documented earlier, the unanticipated declines in participation among college graduates age 65 and older have been larger than those for less-educated older adults.

Fear of COVID

Another explanation offered for the continuing shortfalls in labor supply is that fear of contracting COVID or spreading COVID to a family member continues to keep potential workers on the sidelines. We know of two ongoing surveys that have asked questions relevant to understanding how fear of COVID has affected participation—the Survey of Working Arrangements and Attitudes (SWAA) and Census Bureau's Household Pulse Survey (HPS). The SWAA is an online nonprobability survey administered monthly since May 2020 to Americans age 20 to 64 with significant work attachment in the previous year (Barrero, Bloom and Davis 2022).¹¹ The survey has asked about respondents' plans for social distancing since July 2020 and

¹¹ More specifically, from May 2020 to March 2021, the requirement for inclusion in the SWAA sample was earnings of at least \$20,000 in 2019. From April to September 2021, the earnings threshold was \$10,000 in 2019, and from January to March 2022, it was \$10,000 in 2021.

included direct questions about fear of COVID as a reason for nonparticipation since February 2022. The HPS is an experimental probability-based survey first fielded by the Census Bureau at the end of April 2020. The sample for the HPS is drawn from households on the Census Bureau's Master Address File (MAF) who could be matched to a phone number (available for 88 percent of addresses) and/or email address (available for 80 percent of addresses). Data were collected for adults age 18 and older using an online platform (Fields et al. 2020). A question on reasons for nonparticipation has been included in each of the 47 waves of the HPS from June 2020 through December 2022.

In the academic literature, the view that shortfalls in labor force participation are due to COVID fears has been advanced most forcefully by Barrero, Bloom and Davis (2022), who use data from the SWAA to estimate the effect. They estimate that, as of the first half of 2022, COVID fears reduced the labor force participation rate by 2.0 to 2.6 percentage points. The 2.0 percentage point estimate makes use of self-reports solicited from SWAA sample members not currently working or looking for work about the importance of COVID as a factor in their being out of the labor force. The larger 2.6 percentage point estimate is derived from a regression of a zero-one labor force status dummy variable on variables based the SWAA question that captures the extent to which a person expects to continue social distancing.

Are these estimates plausible? According to data from the CPS, the overall labor force participation rate for adults age 20-64 fell by about 0.6 percentage point between February 2020 and February 2022. If fear of COVID had depressed participation among those age 20-64 by 2.0 to 2.6 percentage points, it would explain roughly three to four times the actual observed overall decline. In other words, one would need to believe that, absent the fear of contracting COVID,

participation among adults age 20-64 would have been 1.4 to 2.0 percentage points *higher* in February 2022 than it had been in February 2020.

One thing to note is that, by design, the SWAA estimates do not apply to the entire population age 20-64, but rather to the survey’s target population of people in that age range with significant prior year labor force attachment. If the people excluded from the SWAA are out of the labor force for reasons other than fear of COVID, our very rough back-of-the-envelope calculations suggest that Barrero, Bloom and Davis’s 2.0 percentage point estimate of the importance of COVID concerns for participation among the 20-64 year olds might be as much as 0.4 percentage point lower for that age group as a whole. Similarly, if the excluded group looks similar to the SWAA population with respect to their social distancing plans but their decisions about labor force participation reflect other considerations, adjusting for their omission could lower Barrero, Bloom and Davis’s second 2.6 percentage point estimate by as much as 0.6 percentage point.¹²

There are other potentially more important reasons to be cautious about taking the SWAA estimates at face value. One concern is whether the participants in the pre-recruited online panels used for the SWAA are representative of the target population. As a check, in their August 2022 survey wave, Barrero, Bloom and Davis administered the question used in the HPS that asks the non-employed the main reason they are not working. In roughly comparable samples fielded at about the same time, the percent of the population who gave COVID fears as their main reason for not working was 2.1 percent in the SWAA as compared to 1.5 percent in the HPS, about 0.6 percentage point lower.¹³ Because of the relatively small SWAA sample size,

¹² Details of the back-of-the-envelope calculations that produce this estimate are provided in online appendix A.

¹³ The difference between the two estimates rises to 0.8 percentage point when the SWAA sample is restricted to respondents who gave an acceptable answer to included “attention check” questions.

this difference is not statistically significant, but it is suggestive of a possible upward bias in the SWAA estimates.

In addition, the wording of the SWAA questions and the ordering of the response options may have affected the estimates. The SWAA question about whether COVID fears have contributed to non-work asks non-participants “Are worries about catching COVID or other infectious diseases a factor in your decision not to seek work at this time?” The three response options are: “Yes, the main reason”; “Yes, a secondary reason”; and “No,” listed until mid-2022 in that order. Perhaps because of what survey methodologists refer to as acquiescence bias—the tendency of survey respondents to agree with a survey statement whether or not it reflects their true opinion—the share of people who said fear of COVID was the main reason they were out of the labor force is considerably larger than the share who choose fear of COVID as their main reason for not working when offered a menu of possible reasons (Barrero, Bloom and Davis 2022).¹⁴ Primacy bias—the tendency of respondents to written survey questions to pick the first answer they see—also could have affected the responses. In later testing, the authors found that the share of nonparticipants answering “Yes, the main reason” when asked whether COVID fears contributed to their being out of the labor force was 9.9 percent when that response option appeared first versus 6.6 percent when it appeared last.

The HPS may be a more reliable source of information than the SWAA even though it too may suffer from representation problems—the survey is based on a probability sample, but its response rate has averaged under 10 percent. Low survey response rates do not necessarily imply bias in survey estimates (Groves and Peytcheva 2008) and some research has found that

¹⁴ The SWAA question is also worded more generally to encompass “worries about catching COVID or other infectious diseases,” but the mention of other infectious diseases seems unlikely to account for the much higher number of “yes” responses.

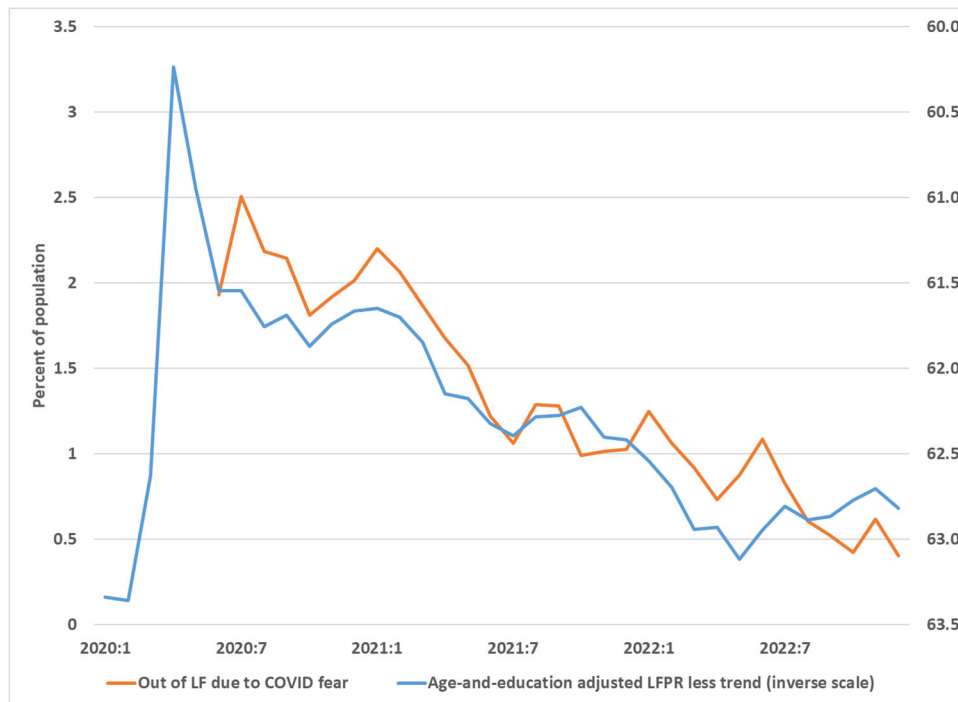
probability samples tend to produce more accurate estimates than nonprobability samples even when the response rates to the former are low (Yeager et al. 2011), but the low HPS response rate nonetheless does suggest caution about interpreting the estimates.

The HPS question about nonparticipation asks adults age 18 and older who were not working during the survey reference week the main reason they were not employed.¹⁵ “I was concerned about getting or spreading the coronavirus” is one of roughly a dozen response options.¹⁶ Figure 5 plots the HPS estimate of the share of the population saying that COVID fears are their main reason for not working and (on an inverse scale) the overall labor force participation rate adjusted for changes in demographic mix and pre-pandemic within-group trends. The HPS estimates are for the survey wave closest in time to each month’s CPS reference week or, in a few cases, are interpolations based on the values for adjacent months. According to the HPS estimates, the share of people 18 and older who said they were not working because of COVID fears peaked at 2.5 percent in July 2020 and had fallen to 0.4 percent by December 2022. The changes in this series and in the labor force participation rate are of similar magnitude and they have moved remarkably closely together over time (the Pearson correlation between them is -0.92). This is consistent both with COVID fears being a part of the explanation for the shortfall in participation during the post-pandemic period and also with their having become much less important over time.

¹⁵ The question is asked of everyone who is not working rather than only of those who are out of the labor force, but, if someone gives fear of COVID as the reason they are not employed, it is likely this fear would also prevent them from actively seeking work.

¹⁶ The exact list of response options has varied slightly over time, but the option related to fear of getting or spreading the coronavirus has been included on the list in every wave in which the question was asked.

Figure 5: Age-Education-and-Trend-Adjusted Labor Force Participation Rate and Percent of Population out of Labor Force Due to COVID Fears, January 2020 (Participation) and June 2020 (COVID Fears) to December 2022



Source: Authors' calculations using Current Population Survey and Household Pulse Survey data.

Note: Age, education and trend adjustments to the labor force participation rate as described in the text. Participation rate for persons age 16 and older; share not working due to fear of COVID for persons age 18 and older.

While the overall relationship between the percent of people saying they are not working because of COVID fears and the adjusted participation rate is very strong, this breaks down when the data are disaggregated by demographic group. As discussed in the first section of the paper, the age group with the largest unanticipated declines in participation since the start of the pandemic has been adults age 65 and older, but this is also the age group *least* likely to say they are out of the labor force due to COVID fears. We initially found this somewhat counterintuitive, since COVID risks are well known to be more serious for older adults. Even if COVID fears

contributed to their choosing not to work, however, people in this age group may be more likely to choose retirement as the main reason they are out of the labor force, leading us to suspect that the responses regarding fear of COVID are less meaningful for this age group. In the data by race and ethnicity, as documented earlier, after adjusting for age, education and trend effects, overall participation has been below expectations for non-Hispanic Whites, in line with expectations for Hispanics, and above expectations for non-Hispanic Blacks. The share of Hispanics and non-Hispanic Blacks citing fear of COVID as a reason for being out of the labor force, however, has been significantly *higher* than the share of White non-Hispanics. The fear-of-COVID information in the HPS is of course collected only from those who are not working. To the extent that COVID concerns are in fact generally greater among groups where a larger percent of people are out of the labor force because of them, though, it may be that the necessity of working—and the opportunity to do so in a very tight labor market—has pushed people in some groups that on average have more limited resources back into the labor market despite real health concerns.

There are, of course, reasons to be cautious in interpreting these numbers. First, as already noted, given the survey's very low response rate, one might wonder about the representativeness of the HPS sample. Second, the responses to the question about why people are not working may be affected by social desirability bias. Some people may feel it puts them in a better light to say the reason they are not working is fear of COVID rather than, for example, that they did not want to be working at this time, leading the estimated downward pull of COVID fears on labor force participation to be exaggerated. Although this is necessarily a guess—albeit a guess informed by our assessment of available data—if forced to assign a number, we would peg the effect of COVID fears on labor force participation at perhaps 0.2 percentage point by

December 2022. Fear of COVID would then explain something under 40 percent of the participation shortfall if the appropriate counterfactual is one that considers only the effects of demographic changes over the post-pandemic period. If the appropriate counterfactual is one that assumes pre-existing trends continued, COVID fears could explain three-quarters of that counterfactual's smaller shortfall.

Long COVID

While the effects of COVID fears on labor supply may be shrinking, there has been growing discussion of the role that long COVID may be playing. Even after their initial recovery, a significant share of COVID sufferers continue to experience debilitating symptoms that may include difficulty thinking or concentrating (“brain fog”), headaches, sleep problems, and depression or anxiety, among other symptoms. It would not be surprising if some of those suffering from long COVID who otherwise would have been working have chosen to withdraw from the labor force or cut back on their hours.

One general approach is to estimate the effect of long COVID as the product of 1) the estimated number of people experiencing long COVID symptoms, 2) the estimated share of these people who would have been working had they not experienced long COVID and 3) the estimated share of this group who have left work because of their long COVID symptoms. This is a sensible strategy, but unless the long COVID population is defined in the same way for estimating the number of long COVID sufferers as for estimating long COVID's labor supply impact, these estimates could be misleading. More specifically, if the size of the long COVID population is defined in an inclusive fashion but the share of workers with long COVID symptoms who have withdrawn from the labor force or reduced their work hours is estimated

based on a group with especially severe symptoms, the impact of long COVID on the size of the labor force could be greatly overstated.¹⁷

One study of how long COVID has affected labor supply that generated headlines when it was released is Bach (2022b). She concludes that, as of June 2022, long COVID may have reduced labor supply by the equivalent of 2 to 4 million full time workers.¹⁸ To arrive at her estimates, Bach first cites an estimate from the Household Pulse Survey that, as of June 2022, about 16 million Americans age 16-65 were experiencing long COVID symptoms, a number that seems roughly in line with other available estimates. She assumes that, absent long COVID, the labor force participation rate for these people would have been the same as the average for the 16-65 year old age group (about 75 percent). This also seems reasonable. Bach's final step is to apply alternative estimates of the share of workers with long COVID who leave the labor force and the share who reduce their hours, together with a rough estimate of how large the reduction in hours might have been. This where the difficulties arise.

Two of the three sources of evidence on how long COVID affects labor supply Bach cites seem especially questionable as sources of estimates to be applied to the full long COVID population. Her largest estimate of the long COVID effect—that the equivalent of 4 million people are not working because of long COVID—draws on employment and hours impacts reported by respondents to an online non-probability survey for which people with suspected and confirmed COVID were recruited through COVID support groups and social media (Davis et al. 2021). The employment and hours impacts underlying her mid-range estimate—that long COVID has reduced labor supply by the equivalent of 3 million workers—come from an online

¹⁷ Sheiner and Salwati (2022) also make this point.

¹⁸ This study updates an earlier estimate reported in Bach (2022a) that, as of December 2021, long COVID reduced labor supply by the equivalent of 1.6 million full-time equivalent workers.

non-probability survey conducted by the United Kingdom’s Trades Union Congress. The methodology statement for this survey states, “The survey was open between 3 April and 27 May 2021 and was promoted on social media, through affiliated unions and long COVID support groups” (Trades Union Congress 2021). Given the way in which participants were recruited, both surveys seem likely to over-represent people for whom long COVID was an especially severe problem. Bach’s lowest estimate—that COVID reduced labor supply by the equivalent of 2 million full-time workers—is based on data collected in the June 2021 wave of the Understanding America Survey COVID panel (Ham 2022). Although it is difficult to be certain how representative the respondents to the UAS COVID panel are and the sample in any case included only 193 long COVID sufferers, this is the most plausible of Bach’s estimates.¹⁹

Obtaining accurate estimates of long COVID prevalence and its effects on labor supply admittedly is difficult. Goda and Soltas (2022) produce an estimate using an approach that does not rely on directly identifying long COVID sufferers. They infer long COVID’s effects on participation using data on the prevalence of health-related work absences and the relationship of these absences to later labor force withdrawal. This approach assumes, reasonably enough, that the significant increases in health-related absences from work since the start of the pandemic can be attributed to COVID infections. Another key assumption is that, as seems to be supported by the data, health-related absences affect labor force withdrawals and reductions in hours similarly whether they are due to COVID or something else.

¹⁹ While this estimate is more plausible than the others, it is not clear to us how Bach translated the UAS estimates into impacts on employment and hours. Ham (2022) reports that, in the UAS data, 25.9 percent of people with long COVID say their work has been “impacted,” meaning that they either left work or were working fewer hours, but the survey did not ask separately about effects on the extensive versus the intensive margin of labor supply.

In their analysis, Goda and Soltas (2022) begin by identifying CPS respondents who missed an entire week of work for health-related reasons. This share has grown significantly since the onset of the pandemic, is correlated with local area COVID case counts and has grown more for workers in occupations that are more likely to require physical presence on the job. Using the longitudinal structure of the CPS to link these records to other interviews with the same people, Goda and Soltas ask how absences from work affect the probability that a person is working at later points in time. Their baseline estimate is that labor force participation falls by about 7 percentage points following a health-related absence. They also find that, following the health-related absence, those who remain employed reduce their hours and are more likely to shift into part-time jobs.

The estimates of COVID's impact on labor force participation can be translated into an estimates of the overall effect of COVID-related illness on the labor force participation rate and full-time-equivalent hours reductions. The authors accomplish the former by combining the estimated number of excess health-related absences during the COVID period with their estimates of how a health-related absence affects subsequent participation. A limitation of the analysis is that people are observed for no more than 14 months after their health-related absence. Goda and Soltas' baseline estimates assume that the effect on participation in later months continues to decay at the same rate as from months 1 to 14; the more extreme cases that bound their estimates assume either instantaneous complete decay (no effect on participation beginning in month 15) or no further decay (effects on participation that persist at the same level as in month 14). Overall, they estimate, as of June 2022, COVID had reduced the size of the labor force by between 340,000 and 590,000 people.

As Goda and Soltas explain, there are at least two reasons why these estimates might be too low. First, some workers could have experienced COVID-related absences outside the CPS reference week. Using information on the rate of month-to-month persistence in being absent for health-related reasons to estimate the rate of escape, they estimate that the typical absence lasts a little over three weeks. This implies that missed episodes lead their participation estimates to be understated by about 22 percent, adding about 75,000 to 130,000 people. Second, the estimates include only people who experienced COVID while employed. Assuming that the likelihood of experiencing a serious bout of COVID is the same for non-workers as for workers and that COVID reduces the likelihood of a non-worker entering the labor force by the same percentage as it increases the likelihood of a worker leaving the labor force adds 95,000 to 165,000 people to the estimated COVID effect. Together, these adjustments raise the authors' estimates of the participation effect by 50 percent, implying that between 510,000 and 885,000 people were out of the labor force in June 2022 due to earlier having contracted COVID.²⁰

We have built on the Goda and Soltas (2022) analysis in several ways. First, to assess whether the estimated effect of long COVID has been growing, we extended the time period for the analysis through December 2022. We find somewhat larger long COVID effects as of December 2022 than as of June 2022, though given the nature of these estimates we would be cautious about placing too much weight on the differences. Our baseline estimate for December 2022 is that between 370,000 and 730,000 people were out of work as a result of previous excess health-related work absences, up from an estimate based on our calculations of 350,000 to 610,000 for June 2022.²¹ Inflating the December numbers by 50 percent to account for people

²⁰ Goda and Soltas (2022) report estimates of how making the two adjustments just described affect their baseline estimates; we have used those numbers to approximate the corresponding figures for their high and low estimates.

²¹ Our June 2022 estimates are slightly higher than the original Goda and Soltas estimates. The main reason is that, rather than attempting to estimate the decay rate from the data, which proved to be problematic for subgroup

whose absences from work did not occur during the CPS reference week or who were not working at the time of their health-related episode, our range is 555,000 to 1,095,000 people.

Second, after replicating Goda and Soltas' event study estimates of the effects of absences from work on hours in subsequent months, we then convert those hours effects into a measure of full-time equivalent workers lost. Our baseline estimate is that, as of December 2022, the hours reduction associated with excess post-pandemic absences translates into the equivalent of losing 130,000 to 285,000 full-time workers. By the same reasoning that Goda and Soltas apply to their labor force effect estimates, we adjust for the absences that occurred outside the CPS reference week and for the possibility that individuals who were not working at the time of their COVID episode work fewer hours if they do return to work. This increases the range of the hours effect to 195,000 to 428,000 full time equivalents. The combined effect of hours and participation on labor supply is thus the equivalent of 750,000 to 1,523,000 people. At the high end, this is not too different from the Bach (2022b) lower bound estimate.

Our final extension to the Goda and Soltas (2022) analysis is to build on their results to investigate how the decline in labor supply attributable to long COVID was distributed across people with different demographic characteristics. We do not find any notable differences by sex or by race and ethnicity. We were especially interested in whether there were differences between people under age 65 and people age 65 and older, as we thought differential long COVID effects might explain the differing pattern of labor force changes between older and younger adults. Our objective was to determine whether long COVID might help to explain why

analysis, we assume for our baseline estimates that the effects of health-related absences on participation and hours fade out over the three years following the last observation at 14 months after the absence. Other differences in our calculations are that we used the weight the BLS applies for published CPS estimates (compwt) rather than the so-called final weight (wtfinl); for the control variable in the event study equation capturing the presence of a child in the household, we counted only children under age 18; and we made use of event study coefficients estimated using data through December 2022 rather than June 2022.

participation has fallen more for older adults. Results reported by Goda and Soltas (2022) show (and we confirm) that the effects of a health-related work absence lasting a week or more on subsequent labor force participation are larger for adults age 65 and older than for younger adults. The excess rate of week-long absences for health reasons during the pandemic period also has been larger for older adults. Despite this, reflecting the lower pre-COVID participation rate among those over age 65, the percentage point participation rate effect has been *smaller* for this older group than for adults age 16-64.

Rather than analyzing information on health-related absences and attempting to infer their effect on subsequent labor force participation, Sheiner and Salwati (2022) develop estimates that make use of CPS information on disability status. As was true of the prevalence of health-related absences from work, the share of people who report a disability has risen noticeably since the start of the pandemic, both absolutely and relative to trend. Using the different labor force participation rates they observe for people with and without a disability both before and after the COVID period, Sheiner and Salwati (2022) tease out estimates of the impact that long COVID has had on overall labor force participation among those age 16 to 64.

To produce these estimates, Sheiner and Salwati (2022) assume that, had they not gotten sick, those with long COVID would have had the same participation rate as nondisabled adults of the same age and sex. They also must make an assumption about how the participation rate of people with an existing non-COVID disability evolved during the COVID period. The simplest assumption is that it would have been the same as in 2019, but they also consider an alternative under which they assume a continuation of the rising trend estimated over the 2017-2019 sample period. Based on these assumptions, they estimate that long COVID has reduced the size of the labor force by between 281,000 and 562,000 people, where the larger number assumes that the

participation rates of previously-disabled adults continued on their rising trend. An additional complication is that the growing availability of remote work since the pandemic could have led more of the existing population with disabilities to enter the labor force. If this has occurred and increased the participation of disabled adults age 45-64 by 5 percent, the total estimated labor force shortfall among those age 16-64 attributable to COVID is larger, in the range of 400,000 to 683,000 people. Sheiner and Salwati also produce an estimate of the effect of long COVID on hours worked by those who remain employed, but it is much smaller, roughly 20,000 to 39,000 full time equivalents. This contrasts with the considerably larger effect on hours obtained by Goda and Soltas (2022).

Sheiner and Salwati chose to focus their analysis on adults age 16 to 64, but the labor market decisions of older adults also may have been affected by long COVID and we have replicated their calculations including adults age 65 and older. Our calculations make use of 2022 data for the full calendar year rather than for January-September as in the original Sheiner and Salwati paper. Adding participation shortfalls among those age 65 and older raises the estimated long COVID effects; we estimate a range of 318,000 to 906,000 people out of work due to long COVID, as compared to Sheiner and Salwati's range of 281,000 to 683,000 people.²²

We also have replicated Sheiner and Salwati's hours analysis. Our original intention had been to include people age 65 and older in these calculations, but the results for that group did not make sense and we abandoned the effort. Our estimates are nonetheless somewhat larger than Sheiner and Salwati's estimates, in this case because the hours shortfall in 2022 compared

²² In addition to adding an estimate for adults age 65 and older, we also use a different weight than Sheiner and Salwati (compwt rather than wtfinl), but neither this nor using data for the full 2022 calendar year makes much difference to the estimates. The calculations for our high end estimate implied that, for the 65 plus age group, more people left the labor force due to long COVID than actually had long COVID. We capped this estimate at the number of people with long COVID.

to the pre-pandemic period looks larger when considering data for the full calendar year as opposed to just January-September. Hours are more seasonal than participation and are relatively high during the summer months, which we suspect means that comparing estimates for January-September 2022 to estimates for the full 2019 calendar year leads to an understatement in how much hours have changed. Even so, the full-time equivalent effect of reductions in hours due to long COVID that we estimate remains small compared to the effect of long COVID on participation, just 40,000 to 58,000 full-time equivalent workers.

Based on the available evidence as just described, our best guess is that long COVID may have reduced the number of people in the labor force by perhaps 700,000 people, a participation rate decline of a bit less than 0.3 percentage point. This figure is consistent both with the estimation method proposed by Goda and Soltas (2022) and with that suggested by Sheiner and Salwati (2022).²³ While the two approaches give broadly similar answers to the question of how long COVID has affected participation, they give rather different answers to the question of how it has affected hours. Because estimates of the hours effect based on Sheiner and Salwati's approach seem to us to be more sensitive to noise in the data, we are more comfortable with using the Goda and Soltas approach to estimating this effect.. Our best guess is that reductions in hours attributable to long COVID have reduced overall labor supply by the equivalent of about 300,000 workers.²⁴

²³ More specifically, the 700,000 number is the roughly the average of the midpoints of the ranges from the two studies.

²⁴ This is roughly the midpoint of the range for the hours effect we estimated using the Goda and Soltas approach.

IV. Conclusion

The labor market has changed significantly since the start of the pandemic. Over the 12 months ending December 2022, the labor force participation rate was about 0.9 percentage points below the 12-month average ending in February 2020. This is a shortfall of close to 2.4 million workers. The 0.6 hour reduction in the moving average level of average weekly hours over the same period contributed an additional labor supply shortfall that is the equivalent of about another 2.4 million workers. Our goal in this paper has been to better understand what explains these changes.

Table 3 summarizes our assessment of the changes in participation and average weekly hours since February 2020 and the factors we believe have contributed to those changes. The first panel of the table reports estimates for the decline in the labor force participation rate; the second panel translates those declines into thousands of people; and the third panel presents estimates for the decline in average weekly hours in terms of their equivalent in thousands of people. As we hope is clear from the discussion earlier in the paper of the evidence on which these estimates are based, the numbers in the table are very much in the nature of guesstimates. Though we do not attach great confidence to the exact magnitudes reported, we are more confident in our general conclusions regarding the orders of magnitude of the various effects.

As shown in the table, much of the decline in labor force participation over the past three years should have been anticipated even absent the pandemic. Exactly how much change should have been anticipated depends on what one believes to be the relevant counterfactual. If the labor force participation rate would have evolved after February 2020 based solely on demographic factors—specifically, changes in the age and education composition of the population—

Table 3: Explaining the Post-Pandemic Declines in Labor Force Participation and Full-Time Equivalent Hours

	Counterfactual: Demographic Adjustment Only	Counterfactual: Demographic and Trend Adjustment
Total labor force participation rate decline through 2022	0.90	0.90
Anticipated change based on chosen counterfactual	-0.37	-0.65
Unanticipated change based on chosen counterfactual	0.53	0.26
Selected pandemic-related factors		
Healthier household balance sheets	0.00	0.00
Fear of COVID	0.20	0.20
Long COVID	0.27	0.27
Residual unexplained change	0.06	-0.21
Total labor force decline through 2022 (thousands)	2,390	2,390
Anticipated change based on chosen counterfactual	990	1,710
Unanticipated change based on chosen counterfactual	1,400	670
Selected pandemic-related factors		
Healthier household balance sheets	0	0
Fear of COVID	530	530
Long COVID	700	700
Residual unexplained change	170	-560
Worker-equivalent hours decline through 2022 (thousands)	2,450	2,450
Anticipated change based on chosen counterfactual	0	210
Unanticipated change based on chosen counterfactual	2,450	2,240
Selected pandemic-related factors		
Healthier household balance sheets	0	0
Fear of COVID	0	0
Long COVID	300	300
Residual unexplained change	2,150	1,940

Source: Authors' estimates.

Note: Basis for rough effect size estimates described in text. Person counts rounded to nearest 10 thousand.

participation at the end of December 2022 was still more than 0.5 percentage point or about 1.4 million people below where we would have expected it to be. If the evolution of the participation rate also would have reflected the continuation of pre-existing within-group trends, the unexplained shortfall is somewhat less than 0.3 percentage point or about 0.7 million people. In addition to these anticipatable factors, we believe that both fear of COVID and long COVID have put downward pressure on the participation rate, though in both cases we estimate the

magnitude of the effect to be considerably smaller than some previous analyses have suggested. The demographic factors incorporated in our first counterfactual together with fear of COVID and long COVID explain almost all of the decline in the participation rate over the past three years; those factors plus the pre-existing within-group trends incorporated in the second counterfactual *more than* fully explain it. Put somewhat differently, under the second counterfactual, had the labor market been as strong as it was in December 2022 and the pandemic not occurred, the labor force participation rate would have been about 0.2 percentage point *higher* than it was in February 2020. Although the unemployment rate was comparable in December 2022 to what it had been in February 2020, as discussed earlier in the paper, other indicators including the job vacancy rate provide reason to suspect the December 2022 labor market could be even tighter. This makes it plausible that, absent the pandemic and with the tightness of the labor market as it was in December 2022, demographic- and trend-adjusted participation in December 2022 could have been a bit above its February 2020 level. Alternatively, because earlier data were not revised when new population controls reflecting information from the 2020 Census were introduced in January 2022, it may be that the February 2020 labor force participation rate is slightly understated and the factors we have identified exactly explain what has happened to it since.

We have been less successful in explaining the differences in the changes in labor force participation across demographic groups. The largest reductions in participation relative to expectations have occurred among older adults and especially the most educated older adults. The shortfall in participation among White non-Hispanics has been greater relative to prior expectations than participation among Black non-Hispanics or Hispanics. Neither for fear of COVID nor for long COVID did we find direct evidence that allows us to account for the

differences we observe. Many older adults would have been exiting the labor force shortly regardless and those with means are likely to have had flexibility about exactly when that transition occurred. COVID may have led some to re-evaluate how long they wanted to continue working even if the reason is not fear of COVID *per se* or direct effects related to long COVID. Although we have reservations about how to interpret the results reported by Favilukis and Li (2023), their findings that participation has declined more among older homeowners who have benefitted from rising house prices are consistent with the speculation that this may reflect a rethinking of priorities on the part of some older adults. White non-Hispanics as a group have greater accumulated wealth than Black non-Hispanics or Hispanics and the decision not to work could be more financially feasible for them.

The bottom panel of Table 3 tells a different story about average weekly hours. Neither demographic changes nor pre-existing trends can account for much of the decline in average weekly hours we observe between the year ending February 2020 and the year ending December 2022. In contrast to our conclusion with regard to participation, we do not believe that fear of COVID helps to explain the decline in hours. Long COVID is part of the story, but in our estimation does not account for more than about 10 percent of the hours decline. The decline in hours is thus more of a puzzle.

Average weekly hours as measured in the CPS are considerably more cyclical than the labor force participation rate and it is possible that, given time, hours will recover to pre-pandemic levels. Consistent with a considerable amount of anecdotal evidence, however, it also is possible that the lower level of hours reflects a broad-based re-evaluation regarding the balance people wish to strike between their work and personal lives. The media are full of stories about “quiet quitting” (see, e.g., Telford 2022 and Rosalsky and Selyukh 2022) and professionals

who are opting to step back from demanding working schedules (see, e.g., Krueger 2022). If this is the explanation for the reduction in hours we observe, it could be much longer lasting.

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Online Appendix A

Adjusting the Barrero, Bloom and Davis (BBD) (2022) estimates to produce estimates for the full population rather than the SWAA population

The SWAA sample includes only people age 20-64 with significant prior-year earnings, defined in most waves as earnings in excess of \$10,000. According to published data from the 2022 Annual Economic and Social Supplement (ASEC), of those age 25-64 as of March 2022, 79% had worked in 2021. This number can be refined by using the ASEC microdata to determine the share of people age 20-64 who had more than \$10,000 in earnings in 2021, but as a starting point, suppose that the SWAA sample omits about 21% of the population age 20-64. The question of interest is how the BBD estimates of the effect of COVID fears and social distancing on labor force participation would change if they were adjusted to apply to the full population.

Estimate based on share of population giving fear of COVID as reason for not seeking work

From February-July 2022, approximately 13% of the SWAA sample is out of the labor force (BBD Table 3, p. 44). Given that the SWAA sample covers about 79% of the population, about 10.3% of the population as a whole is out of the labor force and in the group represented by the SWAA sample $[(0.13)*(0.79)]$.

Suppose that all of the non-labor-force-participants in the group excluded from the SWAA sample were out of the labor force for a reason other than fear of COVID. This might be reasonable insofar as this is generally a group without any strong labor force attachment. Among those in the BBD out-of-the-labor force sample, 9.3% said fear of COVID was the main reason they were not seeking work and 12.5% said it was a secondary reason. Counting all of the first group and half of the second group, if the BBD out-of-the-labor force sample represents 10.3% rather than 13% of the population age 20-64, the adjusted estimate of the share of the population out of the labor force due to fear of COVID would be 1.6%, about 0.4 percentage points less than the original BBD estimate using this approach of 2.0%.

Estimate based on relationship between social distancing plans and labor force participation

The BBD estimate based on what people say about their social distancing plans and how that is related to whether they are in the labor force also can be adjusted to take account of the fact that a significant share of the population is not represented in the SWAA sample. In the SWAA data, the distribution of responses to the question of social distancing plans is as shown in the first column of the table below (normalized to sum to 1,000):

Social Distancing Plans	Normalized Number in SWAA with Stated Plan	Normalized Number in SWAA with Stated Plan Who Are Out of the Labor Force	Normalized Number in Full Population with Stated Plan	Normalized Number in Full Population with Stated Plan Who Are Out of the Labor Force
Complete return	420	42	531	110
Substantial return	310	32	392	82
Partial return	145	20	183	43
No return	125	32	158	52

Based on the overall share of the SWAA sample that is out of the labor force (about 13%) and the incremental effect of social distancing plans from the regression of being out of the labor force on whether a person planned a substantial return, a partial return or no return to pre-pandemic activities, the normalized number of people in each category who are out of the labor force is approximately as shown in the table's second column.

Again in normalized numbers, if the SWAA includes only about 79% of the population age 20-64, the full population would include about another 265 people. For our calculations, we need to know how many of these people would be out of the labor force.

The share of people who are out of the labor force in the full population is a weighted average of the share out of the labor force in the SWAA sample plus the share out of the labor force among those excluded from the SWAA sample. We can estimate the share of those omitted from the SWAA sample who are out of the labor force by solving for X in the following expression:

$$(0.13)*(0.79) + X*(0.21) = 0.23$$
$$X = 0.61$$

This means that about 161 of the extra 265 people would be out of the labor force.

Suppose that the extra 265 people are distributed with respect to their social distancing plans in the same way as the SWAA sample. Suppose further that there is no relationship between social distancing plans and labor force participation, so that the 161 people in this group who are out of the labor force are distributed in the same proportions with respect to their social distancing plans. The resulting population and out of the labor force numbers would be approximately as shown in the third and fourth columns of the table.

In the adjusted data, 20.7% those planning a complete return to pre-pandemic activities are out of the labor force. This rises to 20.9% among those planning a substantial return, 23.5% among those planning a partial return and 32.9% among those planning no return. The increment to the share out of the labor force for each of the latter three categories and their shares of the adjusted population can be used to back out a rough estimate of the impact of social distancing plans on labor force participation comparable to the original BBD estimate, but for the full population. Among those planning a substantial return, for example, a 0.2 percentage point larger share are out of the labor force and that group represents 31% of the population, meaning that their contribution to the share of the population out of the labor force is about 0.1 percentage point. Summing across the social distancing plan groups, these calculations suggest that continued plans to social distance reduced participation by 2.0 percentage points (0.1 percentage point among those planning a substantial return, 0.4 percentage point among those planning a partial return and 1.5 percentage points among those planning no return), 0.6 percentage point less than the original BBD estimate of 2.6 percent.