This Time It's Different: The Role of Women's Employment in Recessions*

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Abstract

We study the transmission of macroeconomic shocks in a model of the household sector featuring single and married households, joint labor-supply decisions of women and men, and childcare needs that interact with the availability of remote work. Recessions concentrated among women are deeper and more persistent than those concentrated among men, reflecting weaker within-family insurance and a new empirical finding that women re-enter employment more slowly after job loss. Yet recovery from the pandemic recession, which had a disproportionate impact on working women due to school closures and the sectoral distribution of job losses, was surprisingly rapid. We show that in our model, the expansion of remote work and shifting caregiving norms after the pandemic raise female labor supply and men's share of childcare, thereby accounting for the observed recovery. These changes permanently increase female participation and narrow the gender earnings gap, but their effect on future recessions is limited: greater labor force attachment among women weakens the added-worker effect but also accelerates labor market re-entry, leading to offsetting effects on aggregate recession dynamics.

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1 Introduction

Household decisions on labor supply play a central role in the propagation of macroeconomic shocks. In standard macroeconomic models, labor supply arises from the optimizing decisions of single-earner households. While the single-earner assumption may have been an adequate approximation to reality in the mid-twentieth century, when most workers were either single or the sole breadwinner of a family, it is now outdated. In high-income countries, one of the main macroeconomic trends of the past half-century has been a large rise in women's labor force participation accompanied by a narrowing of the gender wage gap. Today, labor supply is driven in large part by the joint decisions of dual-earner households, whose margins of adjustment and incentives are qualitatively different from the single-earner case that macroeconomic models traditionally studied. In particular, dual-earner couples can provide insurance to each other, and among couples with children, labor supply and childcare needs interact. In this paper, we examine how the household sector responds to macroeconomic shocks once the rise in women's labor supply, childcare needs, and joint household decision-making are taken into account.

We base our analysis on a quantitative model of the household sector. The model features women and men, single and married households, households with and without children, and workers who can telecommute and those who cannot. Households decide on consumption, labor supply, and savings, and households with children must decide how to meet childcare needs. The labor market is subject to search frictions: workers may lose jobs and unemployed workers must wait for job offers. Workers who receive job offers decide whether to accept an offer and, if so, whether to work full-time or part-time. Returning to work after an unemployment spell may require paying adjustment costs, such as arranging childcare. The skills of employed workers increase over time due to returns to experience, whereas the skills of workers who are out of employment depreciate. The ability of workers to combine work with childcare responsibilities depends on their occupation: telecommuters can more easily combine the two. The division of labor within the household is, in part, governed by a social norm: some couples hold "traditional" views and prefer that childcare be provided by the mother rather than the father.

We calibrate this model to the pre-pandemic US economy. Among other statistics, the calibrated model matches observed labor market flows, married women's labor supply, the division of childcare in dual-earner couples, estimates of returns to experience and skill loss in unemployment, and the gender wage gap. We also provide novel empirical evidence that women are slower to re-enter the workforce after job loss, and the model matches this pattern as well. Because our model matches these key features of intra-household decision-making and constraints, it is well suited to study how households respond to shocks with asymmetric effects on men's and women's employment. We use the model as a laboratory to understand the impact of different recession shocks on the household sector, where recessions are modeled as a temporary shift in job-loss and job-finding probabilities.

Our first exercise compares the repercussions of recessions that differ in whether employment losses are concentrated among women or men. This comparison is motivated by the gendered nature of recent recessions. Figure 1 displays the difference between the rise in women's and men's unemployment in every recession in the United States since 1948.[1] The figure shows that the Great Recession and the recessions preceding it featured larger employment losses among men than women, whereas the pandemic recession brought much larger losses for women. To bring out the qualitative impact of the gender tilt of recessions, we compare the polar cases of a "he-cession," in which job-loss and job-finding rates change only for men, with a "she-cession," in which only women are affected.[2]

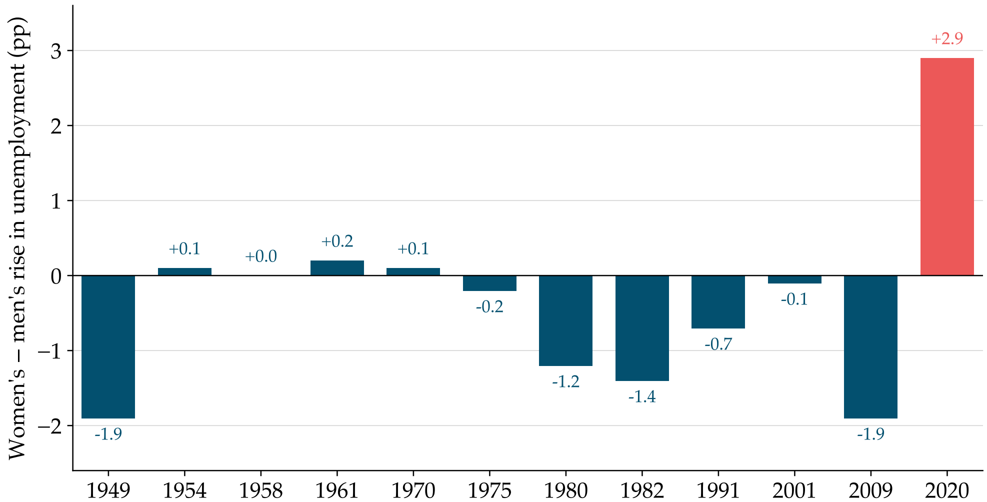
We find that, for the same-sized exogenous labor market shock, the decline in aggregate hours worked is 14% larger in she-cessions than in he-cessions. This difference reflects two channels: reduced within-household insurance in she-cessions and the slower re-entry of women into employment following job loss. This latter force also implies a slower recovery after a she-cession. After a he-cession, labor supply recovers to 99% of its pre-shock level within two quarters. In contrast, recovery from a she-cession takes approximately 50% longer. Despite the larger effect of she-cessions on employment, he-cessions have a larger effect on total household income, due to men's higher baseline earnings and employment. These results highlight how the gender composition of affected sectors can shape both the depth and persistence of aggregate labor market downturns.

The pandemic recession of 2020 had an asymmetric impact on women and men not just because of the distribution of job losses, but also because childcare needs during lockdowns affected parents' and caregivers' ability to work. For a given family, the effect of this change was mediated by the availability of flexible work, most importantly the ability to work from home and thereby combine working with childcare. Our second exercise studies a pandemic recession that, in addition to job losses, features an increase in child-

[1]For pre-Covid-19 recessions, we use the difference in the seasonally adjusted unemployment rate between the first and last months of each recession based on recession dates from the NBER Business Cycle Dating Committee. For the 2020-21 recession, we use the difference between unemployment in February 2020 (the trough in unemployment before lockdown measures were taken) and April 2020 (the peak in unemployment).

[2]The literature had previously also used the term "mancession." We prefer the term he-cession to keep it symmetric with she-cession.

Figure 1: Difference between Rise in Women's and Men's Unemployment, US Recessions from 1948 to 2020



Notes: Data from Bureau of Labor Statistics. Each bar is the rise in the women's unemployment rate minus the rise in the men's unemployment rate from the first to the last month of each recession according to NBER business cycle dates. For the Covid-19 recession, change in unemployment from February to April 2020 is displayed. The underlying series are seasonally adjusted monthly unemployment rates by gender.

care needs. Telecommuting now plays a central role, as telecommuters can combine work with childcare (at a cost), while workers with inflexible jobs do not have that ability. In line with changes in the labor market after the pandemic, we also allow the pandemic recession to lead to a "New Normal" where job offer rates return to the previous level but the prevalence of remote work remains elevated.

We show that, during the pandemic, the increase in childcare needs amplifies the decline in women's employment, as mothers provide a large majority of the additional childcare. Accordingly, the decline in hours worked is particularly large among mothers. Regarding the recovery from the pandemic recession, our he- versus she-cession results might suggest the recovery would be unusually slow. Specifically, the pandemic had a disproportionate impact on women through both the sectoral composition of the labor market shock and the increase in childcare needs, and women are generally slower to return to the labor force after losing employment. Yet, both the data and our calibrated model show a rapid labor market recovery. Through a decomposition exercise, we show that other changes induced by the pandemic—notably, the rapid expansion of remote work and shifts in social norms surrounding caregiving—contributed to the speed of the recovery. Although calibrated exclusively to pre-pandemic data, the model also successfully predicts additional key developments after the pandemic, including a rise in aggregate hours worked driven by working mothers and an increase in men's share of childcare time.

We also characterize long-run changes in the economy that will arise if the shifts brought about by the pandemic persist, as seems likely today. Our model predicts that the economy will transition to a "New Normal" where the female labor force participation rate is 1.3% higher than before the pandemic. Approximately half of this increase is attributable to the expansion of remote work, and the other half to changes in social norms surrounding caregiving. Greater labor force attachment among women also narrows the gender earnings gap by approximately 3.1%.

Our third exercise assesses the longer-run repercussions of the pandemic by comparing recessions that start in the "old normal" (the pre-pandemic labor market) with potential future recessions that start in the New Normal, characterized by more job flexibility and the other long-run changes brought about by the pandemic. For example, the New Normal features lower gender gaps and higher female labor supply, as women work more and accumulate more human capital when flexible jobs are available.

Perhaps surprisingly, we find that future recessions look much like past ones despite substantial changes in labor market behavior. The reason is that the forces reshaping steady-state labor supply have offsetting effects on business-cycle dynamics: greater labor force attachment among women dampens the added-worker effect, while remote work and changing social norms accelerate women's re-entry into employment following job loss. Consequently, large long-run changes in labor market outcomes translate into relatively modest changes in the depth and duration of recessions.

Our work contributes to the literature on the role of women's employment in economic fluctuations. In December 2019, women accounted for the majority of the US labor force for the first time, capping a decades-long convergence between male and female employment. Yet, most business cycle models have long been "unisex," allowing for no gender differences, while many macroeconomic studies of labor supply have been calibrated to data on men's employment only. More recently, studies such as Doepke and Tertilt (2016), Bardóczy (2022), Casella (2022), Fukui, Nakamura, and Steinsson (2023), and Ellieroth and Michaud (2024) argue that the role of women in aggregate fluctuations has changed substantially due to rising female labor force participation. Albanesi (2025) provides evidence that women's employment plays a crucial role in phenomena such as jobless recoveries, the productivity slowdown, and the Great Moderation.[3] Albanesi

[3]Other contributions to the literature on women's employment and household decision-making within macroeconomics include Greenwood, Seshadri, and Yorukoglu (2005), Ortigueira and Siassi (2013), Doepke and Tertilt (2016), Mankart and Oikonomou (2017), Borella, De Nardi, and Yang (2018), Mennuni (2019),

and Şahin (2018) and Coskun and Dalgic (2024) document how the gender breakdown of employment across industries shapes the contrasting cyclicality of male and female employment, which is one aspect of how gender matters for recessions in our model. A key contribution of our analysis relative to the literature is that we explicitly account for childcare needs and for the role of work flexibility in shaping the relationship between childcare and labor supply. These are crucial features given the central role of childcare needs in accounting for differences in women's and men's labor supply, and they have grown more important with the large increase in telework since the pandemic.

One of the central mechanisms in our theory is within-family insurance of job loss and income shocks. In the labor literature, Lundberg (1985) introduced the notion of the "added worker effect," i.e., a worker joining the labor force in response to their spouse's job loss. Additional insurance channels in the family include adjustments on the intensive margin (such as switching from part-time to full-time work) and participation decisions that are responsive to the risk of future income shocks. Studies supporting an important role of within-family insurance include Attanasio, Low, and Sánchez-Marcos (2005), Blundell, Pistaferri, and Saporta-Eksten (2016, 2018), Birinci (2019), García-Pérez and Rendon (2020), Pruitt and Turner (2020), and Guner, Kulikova, and Valladares-Esteban (2025). Meanwhile, Guler, Guvenen, and Violante (2012) and Pilossoph and Wee (2021) analyze the impact of within-family insurance on job search. Ellieroth (2023) uses a joint-search model similar to ours to characterize the quantitative importance of within-household insurance over the business cycle. Unlike existing search models with within-family insurance, our model allows for the accumulation and depreciation of human capital, incorporates single and married households, accounts for childcare needs, and includes different occupations and social norms. All of these features play central roles in our analysis.

Our analysis also contributes to a body of work on the macroeconomic consequences of the Covid-19 recession. Much of this literature combines epidemiological and economic modeling to examine how policy interventions and endogenous behavioral adjustments shape the evolution of the pandemic and its macroeconomic consequences (see,e.g., Eichenbaum, Rebelo, and Trabandt 2021, Berger et al. 2022, Glover et al. 2023, and Brotherhood et al. 2026). Our paper departs from such studies by focusing on the economic consequences of the employment losses and increased childcare needs brought about by the pandemic. In this regard, our approach is more similar to Guerrieri et al. (2022), Gregory, Menzio, and Wiczer (2020), and Danieli and Olmstead-Rumsey (2020), who also

Olsson (2025), and Wang (2019). Macroeconomic studies of the policy implications of joint household decisions include Guner, Kaygusuz, and Ventura (2012), Guner, Kaygusuz, and Ventura (2020), and Wu and Krueger (2021).

examine the macroeconomic transmission of the lockdown shock in models that abstract from epidemiology. These papers focus on different aspects, namely the role of incomplete markets and liquidity constraints, employment stability, and the sectoral distribution of the downturn. Our focus on the differential effects on women and men is a novel contribution.

Our results on the labor market in the post-pandemic era relate to the nascent literature on the consequences of working from home. Many empirical papers focus on the consequences of working from home during the pandemic, but so far only a few integrate working from home into structural macroeconomic models. Barrero, Bloom, and Davis (2026) study the labor productivity and welfare implications of returning to pre-pandemic levels of remote work, arguing that welfare and productivity would be significantly lower and hence the aggregate share of remote work is likely to remain high.[4] Berresheim (2026) analyzes how an increase in the ability to telework affects mothers' occupation choice, labor supply, and careers. Foerster and Ulbricht (2025) focus on how remote work eases the co-location friction between spouses. Lenzi (2025) studies how working from home affects intergenerational mobility through increased parental time with children. Bagga et al. (2025) also emphasize the importance of working from home for the recovery but abstract from gender and childcare. Delventhal, Kwon, and Parkhomenko (2022), Davis, Ghent, and Gregory (2024), Monte, Porcher, and Rossi-Hansberg (2025) and Richard (2025) analyze how increased access to working from home affects city structure and housing markets.[5] In this literature, we are the first to study how working from home will shape the labor market response to future recessions.

In the following section, we document the differences in women's and men's labor market behavior that motivate our study and establish new facts on gender differences in the persistent impact of labor market shocks. Section 3 develops our model and Section 4 describes how we calibrate it to evidence on the US economy. Section 5 contains our quantitative results, and Section 6 concludes.

2 Empirical Regularities on Work and Gender

In this section, we review the empirical evidence that motivates the structural model. We start with evidence on gender differences in labor supply behavior during recessions,

[4]On the other hand, Emanuel, Harrington, and Pallais (2026) and Choudhury et al. (2026) document some negative mental health effects of working from home.

[5]Akan et al. (2025) show that US workers now live significantly farther on average from employers and that distant workers have different sensitivity to firm-level hiring and firing. This may have additional implications for future business cycles.

and then provide new facts on the long-term consequences of job loss by gender, marital status, and the presence of children.

2.1 Gender Differences in Labor Supply Behavior during Recessions

In recent economic downturns preceding the Covid-19 pandemic, such as the Great Recession of 2007—2009, men's employment declined more than women's. Doepke and Tertilt (2016) summarize the evidence on how employment varies over the business cycle for women and men. Table 1 shows that women's aggregate labor supply is less volatile overall than men's, as measured by the percentage standard deviation of the Hodrick-Prescott residual of average labor supply per person. For cyclical volatility, i.e., the component of overall volatility that is correlated with aggregate economic fluctuations, the gap between women and men is even larger. Over the period 1989–2014, men account for more than three quarters of overall cyclical fluctuations in employment, and women for less than one quarter.

One reason women's employment varies less over the cycle is within-family insurance, i.e., some married women increase their labor supply in a recession to compensate for their husband's unemployment or higher unemployment risk.[6] One indication of this channel's importance is that the cyclical volatility of labor supply, illustrated in Table 1, is much lower for married women (to whom the family insurance channel applies) than for single women.

The substantial volatility gap between single women and single men, however, points to additional drivers of gender differences in labor supply beyond within-household insurance. A second channel is the different sectoral composition of female and male employment. In typical recessions, sectors such as manufacturing and construction contract more than education and health care. Men's employment is more concentrated in sectors with higher cyclical exposure, whereas women are more represented in sectors with stable employment over the business cycle. For example, Coskun and Dalgic (2024) show that employment in the "Government" and "Education and Health Services" sectors is counter-cyclical, and that these two sectors account for 40 percent of women's employment but only 20 percent of men's. Conversely, the highly cyclical sectors of "Manufacturing," "Construction," and "Trade, Transportation, Utilities" account for 46 percent of male employment but only 24 percent of female employment.

These two channels are neither exhaustive nor independent. For example, some women may choose to work in a counter-cyclical sector to compensate for their husbands' cyclical

[6] See Ellieroth (2023) for a study documenting the quantitative importance of this mechanism.

Table 1: Volatility of Hours Worked by Gender and Marital Status

	All			Married		Single	
	Total	Women	Men	Women	Men	Women	Men
Total Volatility	1.15	0.87	1.47	0.79	1.16	1.30	2.25
Cyclical Volatility	0.91	0.51	1.23	0.38	0.95	0.70	1.82
Hours Share		42.64	57.36	25.89	39.83	16.75	17.53
Volatility Share		23.68	76.32	10.80	41.51	12.88	34.81

Notes: All data from Current Population Survey, March and Annual Social and Economic Supplements, 1989 to 2014. Total volatility is the percentage standard deviation of the Hodrick-Prescott residual of average labor supply per person in each group. Cyclical volatility is the percentage deviation of the predicted value of a regression of the HP-residual on the HP-residual of GDP per capita. Hours share is share of each component in total hours. Volatility share is share of each group in the cyclical volatility of total hours. See Doepke and Tertilt (2016) for further details.

employment risk. But the bottom line is clear: pre-pandemic downturns affected men's employment more severely than women's.

The recession brought about by the Covid-19 pandemic deviates from these historical trends. As shown in Figure 1, women's unemployment rose by nearly 3 percentage points more than men's by the trough of the 2020 recession. Alon et al. (2022) document a similar reversal or moderation of the cyclical gender gap in labor supply in nearly all of the 26 European countries covered in the European Labor Force Survey (EU-LFS) and in Canada. The deviations are even larger for total hours worked than for employment.

One reason for the disproportionate effect on women lies in the composition of sectors affected by the recession. Alon et al. (2020) show that social distancing measures and lockdowns disproportionately affected sectors in which women are over-represented, such as hospitality. Using O*NET data on occupational characteristics, Mongey, Pilossoph, and Weinberg (2021) show that women are more likely to be able to work from home but are also over-represented in occupations requiring physical proximity. Albanesi et al. (2020) also examine the gender breakdown of employment between high- and low-contact occupations, and find that women account for 74 percent of employment in high-contact occupations. Alon et al. (2022) document similar patterns across European countries and Canada: while male-dominated sectors typically experienced the largest employment declines in past recessions, female-dominated sectors suffered the largest declines during the pandemic.

A second reason for the large impact on women is the increase in childcare needs due to closures of schools and daycare centers. This channel is amplified by the reduced availability of other childcare, such as from relatives, neighbors, nannies, or babysitters, during lockdowns with minimal social contact. Alon et al. (2020) argue that these closures disproportionately affect women, who provide a much larger share of childcare than men: even among married parents who both work full time, mothers provide about 50 percent more childcare than fathers.[7] Similarly, Dingel, Patterson, and Vavra (2020) document that 32 percent of US workers have a child under 14 at home, and that two-thirds of these households do not include an adult who is out of the labor force (e.g., a stay-at-home parent). In 30 percent of households with children, all children are under age 6, underscoring how daycare closures constrain the employment of a large share of the workforce.

Similar childcare patterns exist across developed economies. Doepke and Kindermann (2019) document that women provide the majority of childcare in all industrialized economies, though the gap between women's and men's contributions varies considerably across countries. Alon et al. (2022) show that countries with more severe school closures experienced larger drops in aggregate labor supply during the pandemic, and that these closures can account for up to 25 percent of the cross-country variation in hours worked during the downturn.

The unequal division of childcare and its disproportionate impact on women's employment opportunities are consistent with the observation that much of today's gender earnings gap arises from the "motherhood penalty," whereby women's earnings begin to fall behind men's after childbirth (Cortés and Pan 2023).[8] Empirical evidence suggests that the motherhood penalty arises not only from household specialization in response to gender wage gaps but also from the persistence of social norms surrounding female labor force participation. Data from the most recent round of the World Values Survey show that 22 percent of US respondents either "Agree" or "Strongly Agree" with the claim that "children suffer when mothers work for pay" (see Table A.1). Within couples that hold such traditional views, women are 36.3 percentage points less likely to be employed than their husbands, compared to 17.6 percentage points in other households. In other words, the within-couple employment gap is 18.7 percentage points larger among traditional than among modern couples.[9]

Recent changes in the nature of work, which began to take hold during the pandemic, are weakening the influence of childcare and social norms on gender gaps. Chief among these is the rise of flexible work arrangements and telecommuting. Barrero, Bloom, and

[7] The gap between women's and men's provision of childcare is even larger during regular working hours (8 a.m. to 6 p.m. on weekdays; see Schoonbroodt 2018).

[8] See Kleven, Landais, and Søgaard (2019) and Kleven, Landais, and Leite-Mariante (2025) for recent studies documenting the motherhood penalty using an event-study approach, and Adda, Dustmann, and Stevens (2017) for earlier work using a structural approach.

[9] The gender gap in hours worked between couples with traditional and modern social norms is 18.2 percentage points, slightly smaller than the employment gap between these two groups (see Table A.1).

Davis (2023) show that working from home became ubiquitous during the pandemic and has persisted after its end. By mid-2023, roughly two years after the end of the pandemic recession, nearly 28 percent of all paid workdays were worked from home—about four times the 2019 rate and ten times the mid-1990s rate. Studies such as Adams-Prassl et al. (2020) show that the ability to work from home protects workers from job loss, particularly during the pandemic and its aftermath. Buckman et al. (2025) show that desired work-from-home rates are especially high among women with children.

One reason why work flexibility and telecommuting moderate employment losses is that they ease the conflict parents face between family and career. In addition, they facilitate a more equal division of childcare duties between mothers and fathers. Alon et al. (2020) show that men do 50% more childcare in couples where the husband can telecommute but the wife cannot. This has potentially large implications for labor market outcomes, as Goldin (2014) argues that the lack of flexibility in work arrangements and hours is one of the last major sources of the gender pay gap. Alon et al. (2022) show that work flexibility offers similar benefits across developed economies, and that working mothers benefit in particular. Countries with a larger share of telecommutable jobs experienced smaller declines in aggregate labor supply during the pandemic and a smaller effect on women's employment relative to men's. Moreover, the gender gap in labor supply is concentrated among those who cannot telecommute. Among non-telecommuters, the gap is largest for parents, whereas among those who can work from home the gap is small regardless of children.

2.2 Gender Differences in the Long-Term Consequences of Job Loss

Beyond the mechanisms discussed so far, we also consider the possibility that recessions may have further long-lasting effects on gender equality through scarring and persistent employment declines after job loss. To this end, this section provides new evidence on the persistent consequences of job loss by gender, marital status, and the presence of children. We show that, following a separation, women generally take longer to return to employment and are more likely to leave the labor force than men. These gender gaps in labor market re-entry rates are most pronounced among married couples and those with children, suggesting that childcare needs may also play a central role in the longer-term consequences of job loss.

Table 2 highlights these gender gaps by reporting differences in labor market outcomes 12 months after a job separation, by gender, marital status, and the presence of children. The estimates are derived from data on the civilian population aged 25 to 55 who completed

Table 2: Labor Force Non-Reentry 12 Months after Job Separation by Demographic Group

		NOT-IN-LABOR-FORCE		
GROUP	**E-to-E**	**E-to-NE**	**DiD DATA**	**DiD REG**
sample population	0.030	0.284	–	–
by Gender				
men	0.019	0.197	0.129	0.125
women	0.042	0.350		(0.002)
by Gender, Marital Status, and Kids				
single men, no kids	0.029	0.237	0.042	0.038
single women, no kids	0.034	0.284		(0.003)
single men, small kids	0.024	0.153	0.116	0.108
single women, small kids	0.060	0.305		(0.010)
single men, big kids	0.024	0.198	0.062	0.054
single women, big kids	0.039	0.276		(0.009)
married men, no kids	0.020	0.209	0.128	0.124
married women, no kids	0.042	0.359		(0.003)
married men, small kids	0.011	0.133	0.243	0.239
married women, small kids	0.060	0.425		(0.005)
married men, big kids	0.012	0.134	0.206	0.202
married women, big kids	0.042	0.370		(0.004)

Notes: The table reports the probability a member of each group is out of the labor force 12-month after job loss. Outcomes are derived from the CPS Rotation Group from January 2000 to December 2019. The sample includes prime-age workers age 25 to 55 who completed all eight months in rotation. Small children are households with youngest child under age 5 and big children correspond to households with youngest child aged 5 through 13. Job loss is defined to include all observed job separations. Appendix Table A.2 reports the share not employed. Table A.3 presents robustness estimates which examine only involuntary separations.

all eight months in the CPS rotation sample from January 2000 to December 2019.[10] We identify job-losers as those who transitioned from employment to non-employment (E-NE) in their first four months in the sample. To measure the persistent effects of job loss, we compare the labor supply of job-losers 12 months after their separation to that of individuals in the same demographic group and survey cohort who were continuously employed (E-E) in their first four months in sample.

Table 2 reports differences in labor force participation rates one year after job separation.

[10]The CPS rotation sample has a 4-8-4 structure in which households are interviewed for four consecutive months, rotate out of sample for eight months, and then are interviewed again one-year later for four consecutive months before permanently exiting the sample.

The first column reports, among workers who remained employed (E-to-E) in their first four months in the rotation group, the share out of the labor force 12 months later. The second column reports the same for workers who lost or left a job (E-to-NE). The third column computes the gender gap in labor market non-reentry rates as a simple difference-in-differences of the raw data. Specifically, the computation first takes the difference in employment outcomes between job losers and non-losers within each gender to get the persistent effect of job separation, and then takes a second difference across men and women to get the persistent gender gap in labor market outcomes following job separation. The final column reports a difference-in-differences estimate of the same gender gaps that we discuss below.

The data show large and persistent differences in labor market outcomes 12 months after a job separation. As the first line in Table 2 shows, 28.4% of those who experienced a job separation were not in the labor force 12 months later, compared with only 3% of those who did not experience an initial separation. The persistent effects on labor supply are substantially larger for women than for men.[11] The middle panel ("by Gender") shows that women who experience a job separation are 30.8 percentage points (pp) more likely to be out of the labor force 12 months later, versus only 17.8 pp for men.[12] In other words, women are 13 pp more likely than men to be out of the labor force one year after a job separation. Controlling for time fixed effects, age, race, education, industry, and occupation does not change the results much: the gap falls from 13 pp in the raw data to 12 pp in the regression.

The bottom panel of Table 2 shows that the gender gap in labor market re-entry rates is present within every marital-status and child group, but is most pronounced among married couples and those with children. Within marital groups, the presence of children roughly doubles the effect. The gender gap in labor force participation rates 12 months after a job separation is 4.2 pp for singles without children but 8.9 pp for singles with children. Among married couples, the gender gap is 12.8 pp for those without children compared with 22.4 pp for those with children. Across all sub-groups, the largest gender gap in labor market re-entry rates is among married couples with small children, where women are 24.3 pp less likely to be in the labor force 12 months after a job separation. In summary, the data show a clear pattern in which women in general, and those with children in particular, are substantially more likely to experience long-term declines in

[11] Illing, Schmieder, and Trenkle (2024) also find sizable gender gaps in earning losses after displacement for Germany.

[12] The percentage point gaps can be computed directly from the second panel of Table 2 which reports that the NILF gap is $100 * (0.197 - 0.019) = 17.8$ among men and $100 * (0.35 - 0.042) = 30.8$ among women.

employment and participation following a job separation. These findings are consistent with the notion that childcare needs are a key factor in generating lower labor-force attachment and greater barriers to switching from non-employment to employment.

In addition to direct computations from the raw data, Table 2 provides estimates of the gender gap in labor market re-entry rates using a difference-in-differences (DiD) regression design. The benchmark specification is given by:

$$y_{it} \ = \ \boldsymbol{\beta}_0\mathbf{G}_{it} \ + \ \boldsymbol{\beta}_1\mathrm{F}_i \times \mathbf{G}_{it} \ + \ \boldsymbol{\beta}_2\mathrm{D}_{i,t-1} \times \mathbf{G}_{it} \ + \ \boldsymbol{\beta}_3 \ \mathrm{F}_i \times \mathbf{G}_{it} \times \mathrm{D}_{i,t-1} \ + \ \boldsymbol{\beta}_4\mathbf{X}_{it} \ + \ \epsilon_{it}$$

where y_{it} is a labor market indicator equal to one if individual i is either not employed (right panel) or not in the labor force (left panel). F_i is an indicator for females and $\mathrm{D}_{i,t-1}$ is a treatment indicator equal to one if individual i experienced a job separation one year earlier, in $t-1$. $\mathbf{G}_{it}$ is a standard basis vector whose entries equal one to indicate individual i's membership in one of the mutually exclusive marital-status and child groups. The vector $\mathbf{X}_{it}$ consists of additional controls that may affect labor market dynamics, including fixed effects for year, age, race, education, and initial occupation and industry in $t-1$, before any job loss. In this design, $100 * \boldsymbol{\beta}_3$ captures persistent gender differences in labor supply 12 months after a job separation within each marital-status and child group.

The regression estimates of the gender gap in re-entry rates are reported in the fourth column ("DiD Reg") of each panel. Standard errors appear in parentheses below each estimate. The resulting gender gaps are all statistically significant and of comparable magnitude to the raw-data estimates. The similarity suggests that initial differences in individual and employment characteristics across groups cannot account for most of the gender gaps in labor market outcomes following job separations. Even with these controls, gender differences in participation remain largest among married couples and those with young children.

Overall, the evidence in this section shows large differences across households defined by gender, marital status, and the presence of children in both the labor market impact of recessions and the longer-term repercussions of job loss. The distribution of the labor force across these household types has shifted substantially in recent decades. Moreover, changes brought about by the pandemic recession, such as greater job flexibility and teleworking, will have further repercussions for the impact of recessions and for gender equality in the labor market. To assess the importance of these changes and the overall role of gender and families for the transmission of macroeconomic shocks, we now turn to a quantitative model that can account for the empirical patterns documented so far.

3 A Gendered Model of the Household Sector

Our model focuses on the household sector of an economy with search frictions. Macroeconomic shocks affect households primarily through changes in job-loss and job-finding probabilities. In our analysis, we take the impact of aggregate shocks on these labor-market variables as given and focus on how the household sector responds in terms of labor supply, time allocation, and the accumulation of skills.[13]

3.1 Demographics and State Variables

The economy is populated by a continuum of three types of households: single women, single men, and couples. Every period, a new cohort of singles and couples enters the economy. The household type is permanent, and singles and couples face a constant probability $1-\omega$ of death. Couples stay together and die together, so there are no widows, widowers, or divorcees in the economy.

The state variables of a household include wealth a and the labor market productivity h of each (adult) household member. Additional discrete state variables are kids $k \in \{0, s, b\}$ (no kids, small kid, big kid), job offer of each member $e \in \{E, U\}$ (job offer or no job offer), the occupation of each household member $o \in \{TC, NT\}$ (can telecommute or cannot), and the previous period's labor supply n_{-1} of each member, which governs the possibility that working in the current period requires paying a labor market re-entry cost. Small kids in the model correspond to children under school age (ages 0–5) in the data. We distinguish small and big kids because younger children have greater childcare needs. The unemployed state $e = U$ in the model corresponds to both unemployment and being out of the labor force in the data: it includes both those without an offer and those who receive one but reject it. For couples, a final state variable is the social norm $m \in \{0, 1\}$ where $m = 0$ denotes a "traditional" social norm that values a within-household division of labor in which the mother provides the majority of childcare, whereas a couple with $m = 1$ has the "modern" view that no particular division of childcare is inherently superior.[14] The aggregate state of the economy is denoted by X, which captures the state of the labor market, including job-loss and finding rates by gender, the probability of joining the telework occupation, the rate of change in social norms, and the childcare time requirements of households with children.

[13] It would be conceptually straightforward to extend the model to general equilibrium by modeling firms' job creation and destruction in the usual way and, if desired, adding additional features such as nominal rigidities.

[14] One indication for the relevance of social norms is that men raising children in same-sex couples provide more childcare than men in different-sex couples (Prickett, Martin-Storey, and Crosnoe 2015).

New singles and couples start out with zero assets. Initial human capital is drawn from gender-specific distributions $F^g(h)$ for singles and from a joint distribution $F(h^f, h^m)$ for couples. The initial values of occupation, social norm, the presence and age of children, and last period's employment are drawn from the stationary distribution implied by the current aggregate state.

After the initial period, assets are determined by the household's consumption-savings decision. Labor market productivity evolves stochastically as a function of labor supply: working full-time raises the probability of a productivity gain, while not working may lead to a productivity loss. Employment status and occupation type evolve as a function of shocks: individuals can get laid off, and job offers in a particular occupation arise from a Markov process. People can also decide to reject a job offer or quit a job. Labor supply (conditional on having a job) is either part-time or full-time, chosen by the worker. We include a taste shock over the discrete labor market states so that there is a smooth mapping from state variables to choice probabilities (Bardóczy 2022).[15]

The transition probabilities for employment offers are given by $\pi^g(e'|n, X)$. Employment transition probabilities depend on the aggregate state X, reflecting that jobs are easier to lose and harder to find in a recession. The transition probabilities also depend on the current labor supply n and gender g. The employment state e' at the beginning of the next period denotes whether the worker receives a job offer. If a job offer is received, the worker can still decide whether to accept the offer and, if so, whether to work full-time or part-time. If the individual was not working in the previous period, they must pay a stochastic cost $\kappa^g(n_{-1}, n, k, o)$ to re-enter the labor force, capturing, for example, the need to arrange childcare before returning to work. The transition probabilities for human capital $\pi(h'|h, n)$ are independent of gender and occupation and only depend on current human capital h and labor supply n. People also face constant probabilities of switching occupations and couples may switch social norms, the probabilities for which are given by $\pi(o'|o, X)$ and $\pi(m'|m, X)$, respectively. For singles, the transition probabilities for the arrival and aging of children are given by $\pi^g(k'|k)$ ($g \in \{f, m\}$ indexes gender, female or male), and for couples these probabilities are given by $\Pi(k'|k)$.

3.2 The Decision Problem for Singles

We use v to denote the value functions of singles, while V denotes the value functions of couples. Similarly, $\tilde{v}$ and $\tilde{V}$ denote the value functions at the beginning of the period

[15]This section presents the household value functions without the taste shocks for ease of notation. The version including taste shocks is presented in Appendix B.2. The scale of the taste shock is controlled by the parameter σ.

before job offers are accepted or rejected. The value function for a single person of gender g with a job offer who decides to work is given by:

$$v_E^g(n_{-1}, a, h, k, o, X) = \max_{a', c, l, n, t, t_w} \Big\{ u_S^g(c, l) - \alpha_w^g (t_w)^\phi - \kappa^g(n_{-1}, n, k, o) \\ + \omega\beta\,\mathbb{E}\big[\tilde{v}_{e'}^g(n, a', h', k', o', X')\big] \Big\}.$$

Here β is the time discount factor, c denotes consumption, l denotes leisure, $n \in \{0.5, 1\}$ is labor supply conditional on working (part time or full time), and t is childcare time outside of work. Telecommuters can also provide childcare time t_w while working.[16] Yet, we assume there are limits to this multitasking: $\phi > 1$ captures an increasing and convex utility cost of multitasking.[17] Further, α_w^g is a gender-specific disutility of providing childcare while working. Re-entry costs are given by:

$$\kappa^g(n_{-1}, n, k, o) = \begin{cases} \kappa_L^g(n_{-1}, n, k, o), & \text{with probability } p, \\ \kappa_H^g(n_{-1}, n, k, o) & \text{with probability } 1-p, \end{cases} \tag{1}$$

that is, re-entry costs can be either high or low. The period utility function is given by:

$$u_s^g(c, l) = \log(c) + \alpha_{l,s}^g \log(l),$$

where $s \in \{S, M\}$ is marital status. We allow leisure preferences to depend on gender and marital status to facilitate matching labor supply to the data. The social norm m does not apply to singles because it only affects the time allocation of couples. The constraints for employed singles are:

$$\begin{aligned} c + a' &= w^g h n^{\theta_S^g} + (1+r)a, \\ t + t_w &= \gamma(k, X), \\ t_w &\leq \mathbb{I}(o = TC)n, \\ l + n + t &= T, \\ a' &\geq 0. \end{aligned}$$

[16] The compatibility of telecommuting with childcare has also been found to be relevant in other contexts. For example, Davis et al. (2026) document that fertility rates are higher among adults who can work from home.

[17] For example, watching children for a bit while working may be easy, but ultimately children may require more demanding attention, such as help with homework, making it increasingly stressful to do both simultaneously.

The first constraint is the budget constraint. Wages w^g depend on gender. The parameter $\theta_s^g > 0$ allows for increasing or decreasing returns in labor supply, where $s \in \{S, M\}$ indexes marital status. For example, part-time workers (who supply half as much labor as full-time workers) may be less than half as productive because of commuting time, or more than half as productive because full-time workers get tired, and these effects are allowed to differ by gender and marital status. The second constraint is the childcare-time constraint, which says that total childcare time has to be equal to the childcare need $\gamma(k, X)$, where $\gamma(s, X) > \gamma(b, X) > \gamma(0, X) = 0$. The third constraint states that multi-tasking childcare time cannot exceed the number of working hours n. The fourth constraint is the time constraint, where T is the time endowment. The final constraint is the borrowing constraint.

The value function and constraints for non-working singles are:

$$
\begin{aligned}
v_U^g(a, h, k, o, X) &= \max_{a', c, l, t} \left\{ u_S^g(c, l) + \omega\beta\mathbb{E}\left[\tilde{v}_{e'}^g(0, a', h', k', o', X')\right] \right\}, \\
c + a' &= z w^g h + (1 + r)a, \\
t &= \gamma(k, X), \\
l + t &= T, \\
a' &\geq 0.
\end{aligned}
$$

Here z denotes the unemployment replacement rate relative to potential wages $w^g h$. Notice that, even when unemployed, occupation o is still defined, because it determines the distribution of job offers across occupations next period. That is, the latent teleworking status determines the probability of a teleworking offer in the next period.

The value function at the beginning of the period for a single with a job offer is:

$$
\tilde{v}_E^g(n_{-1}, a, h, k, o, X) = \max \left\{ v_E^g(n_{-1}, a, h, k, o, X), v_U^g(a, h, k, o, X) \right\}.
$$

Without a job offer, there is no employment choice to be made, so we have:

$$
\tilde{v}_U^g(a, h, k, o, X) = v_U^g(a, h, k, o, X).
$$

3.3 The Decision Problem for Couples

We now turn to married households. The overall structure of the decision problem is the same as for singles. The spouses act cooperatively with bargaining weights λ for the wife and $1-\lambda$ for the husband. The couples' decision problem is also shaped by the social norm. If $m=0$ (i.e., the traditional social norm applies), the household suffers a utility loss of ψ per unit of father's childcare time that exceeds maternal childcare time; if instead the mother provides more childcare time, they receive a utility benefit. The value function for two working spouses is given by:

$$
\begin{aligned}
&V_{EE}(n^f_{-1}, n^m_{-1}, a, h^f, h^m, k, o^f, o^m, m, X) = \\
&\max_{\substack{a', c^f, c^m, l^f, l^m,\\ n^f, n^m, t^f, t^m, t^f_w, t^m_w}} \Big\{ \lambda \left(u^f_M(c^f, l^f) - \alpha^f_w (t^f_w)^\phi \right) + (1-\lambda) \left(u^m_M(c^m, l^m) - \alpha^m_w (t^m_w)^\phi \right) \\
&\qquad - (1-m)\psi \left(t^m + t^m_w - t^f - t^f_w \right) \\
&\qquad - \kappa^f(n^f_{-1}, n^f, k, o^f) - \kappa^m(n^m_{-1}, n^m, k, o^m) \\
&\qquad + \omega\beta\, \mathbb{E}\left[\tilde{V}_{(e^f)', (e^m)'} \left(n^f, n^m, a', (h^f)', (h^m)', k', (o^f)', (o^m)', m', X' \right) \right] \Big\}.
\end{aligned}
$$

Married individuals face the same probability p as singles of drawing the low re-entry cost $\kappa_L(n_{-1}, n, k, o)$ (equation 1). The budget and time constraints are:

$$
\begin{aligned}
c^f + c^m + a' = w^f h^f (n^f)^{\theta^f_M} + w^m h^m (n^m)^{\theta^m_M} + (1+r)a&, \\
\left(\left(t^f + t^f_w \right)^\nu + \left(t^m + t^m_w \right)^\nu \right)^{\frac{1}{\nu}} = \gamma(k, X)&, \\
t^f_w \le \mathbb{I}(o^f = TC) n^f&, \\
t^m_w \le \mathbb{I}(o^m = TC) n^m&, \\
l^f + n^f + t^f = T&, \\
l^m + n^m + t^m = T&, \\
a' \ge 0&.
\end{aligned}
$$

We impose a constant elasticity of substitution production function for childcare, with a curvature parameter ν, and require that childcare production must be equal to the childcare constraint $\gamma(k, X)$.

In cases where one or both spouses are unemployed, an unemployed spouse receives unemployment benefits rather than earnings, in the same manner as unemployed singles. The value functions are otherwise analogous to V_{EE}.

At the beginning of the period, if both spouses have a job offer, then the value function is:

$$
\tilde{V}_{EE}(n^f_{-1}, n^m_{-1}, a, h^f, h^m, k, o^f, o^m, m, X) =
$$

$$\max \Big\{ V_{EE}(n^f_{-1}, n^m_{-1}, a, h^f, h^m, k, o^f, o^m, m, X),$$
$$V_{EU}(n^f_{-1}, a, h^f, h^m, k, o^f, o^m, m, X),$$
$$V_{UE}(n^m_{-1}, a, h^f, h^m, k, o^f, o^m, m, X),$$
$$V_{UU}(a, h^f, h^m, k, o^f, o^m, m, X) \Big\}.$$

The initial value functions for the other permutations of job offers are analogous.

3.4 The Stochastic Process for Labor Productivity

Human capital h evolves stochastically to capture the returns to experience and skill depreciation in unemployment. There is a finite grid $h \in H = \{h_1, h_2, \ldots, h_I\}$ of possible human capital levels, where the ratio of subsequent points is constant, i.e., $\log(h_{i+1}) - \log(h_i)$ is constant in i. There are returns to experience, i.e., full-time workers upgrade to the next human capital level with probability η:

$$\pi(h_{i+1}|h_i, 1) = \eta, \quad \pi(h_i|h_i, 1) = 1 - \eta.$$

Part-time workers are half as likely as full-time workers to accumulate human capital:

$$\pi(h_{i+1}|h_i, 0.5) = \frac{1}{2}\eta, \quad \pi(h_i|h_i, 0.5) = 1 - \frac{1}{2}\eta.$$

Individuals who do not work face possible skill depreciation with probability δ:

$$\pi(h_{i-1}|h_i, 0) = \delta, \quad \pi(h_i|h_i, 0) = 1 - \delta.$$

3.5 The Stochastic Process for Kids

The kid state evolves stochastically, with transitions that differ between singles and couples and, among singles, between men and women. Each period, a household with no kids may have a small kid, small kids may age into big kids, and a household with big kids may return to having no kids as adult children leave the house. For singles, the gender-specific transition matrix is

$$\boldsymbol{\pi}^g(k' \mid k) = \begin{bmatrix} 1 - \pi^g(s \mid 0) & \pi^g(s \mid 0) & 0 \\ 0 & 1 - \pi^g(b \mid s) & \pi^g(b \mid s) \\ \pi^g(0 \mid b) & 0 & 1 - \pi^g(0 \mid b) \end{bmatrix}.$$

Similarly, for couples, the transition matrix is

$$\mathbf{\Pi}(k' \mid k) = \begin{bmatrix} 1 - \Pi(s \mid 0) & \Pi(s \mid 0) & 0 \\ 0 & 1 - \Pi(b \mid s) & \Pi(b \mid s) \\ \Pi(0 \mid b) & 0 & 1 - \Pi(0 \mid b) \end{bmatrix}.$$

3.6 The Aggregate State

The aggregate state X captures job-finding and job-loss rates, the share of job offers in the teleworking occupation, the transition probabilities for couples' social norms, and, in our pandemic experiment, childcare time constraints. There are two non-recession states: $X = N$ is the normal-times (i.e., pre-pandemic) state and $X = NN$ is the "New Normal" steady state, in which the offer rate of teleworking jobs is higher and the share of traditional couples lower than in the normal state. When $X \in \{N, NN\}$, households expect to stay in these states with probability one.

There are also different recession shocks that are distinguished by the nature of the shock and the starting point. A standard recession starting from normal times is denoted by $X = R_N$, and a standard recession starting from the New Normal is denoted by aggregate state $X = R_{NN}$. A standard recession is characterized by gender-specific declines in job-finding probabilities and a rise in job-loss probabilities that match the higher incidence of typical recessions on men. During such recessions, all other aggregate characteristics (e.g., social norm and teleworking transitions) are unchanged from their respective steady states. That is, R_{NN} has the same teleworking transition probability as NN. Because the non-recession states are perceived to be absorbing states, recessions arise as unexpected "MIT shocks." Once a recession begins, households expect the recession to continue with probability ρ and return to the respective non-recession state with probability $1 - \rho$.

We also consider additional recession shocks that are designed to isolate the economic channels that we are interested in. Specifically, we consider "he-cession" ($X = H$), "she-cession" ($X = S$), and "pandemic" ($X = P$) shocks. A he-cession is a labor market shock that affects employment transition probabilities only for men, and conversely in a she-cession only women are directly affected. During he- and she-cessions, as in the case of regular recessions, households expect to remain in the shock state with probability ρ and return to the respective non-recession state with probability $1-\rho$. A pandemic shock starts from N and differs from the other recessions in several dimensions: (1) it affects both genders but, unlike a standard recession, hits women's labor market conditions harder than men's; (2) there is a rise in the childcare requirements for parents; (3) the share of teleworking offers jumps once, and teleworking transition probabilities move permanently to their NN values; (4) households expect to transition to the New Normal steady state with probability $1-\rho$, rather than returning to the previous steady state.

3.7 The Stochastic Processes for Occupations and Social Norms

The transition probabilities for occupations and the social norm depend only on the state variable itself and on the aggregate state. Hence, the transition probabilities for occupation are given by $\boldsymbol{\pi}(o'|o, X)$. The transition probabilities for the social norm are denoted $\boldsymbol{\pi}(m'|m, X)$. The transition matrix for $o \in \{TC, NT\}$ is given by:

$$\boldsymbol{\pi}(o'|o, X) = \begin{bmatrix} \rho_{TC}(X) & 1-\rho_{TC}(X) \\ 1-\rho_{NT}(X) & \rho_{NT}(X) \end{bmatrix},$$

and similarly for the social norm $m \in \{0, 1\}$ we have:

$$\boldsymbol{\pi}(m'|m, X) = \begin{bmatrix} \rho_0(X) & 1-\rho_0(X) \\ 1-\rho_1(X) & \rho_1(X) \end{bmatrix}.$$

4 Calibration

We aim to quantify the impact of she-cessions and he-cessions on the aggregate behavior of the household sector, compare how a pandemic recession differs from a she-cession, and discuss the path of future recessions given the trends toward greater remote work and equitable division of childcare. To this end, we first calibrate the normal-times state ($X = N$) of the economy to match key features of the US economy before 2020.

4.1 Externally Calibrated Parameters

The model economy operates at a quarterly frequency. Newly born people in the model correspond to singles and couples at age 25 in the data. A number of model parameters directly correspond to specific empirical observations and can be pinned down individually and others take standard values from the literature. These parameters are summarized in Table 3.

In terms of demographics, the survival probability ω determines life expectancy in the model. Given that we do not model retirement, we interpret the lifespan in the model as corresponding to active working life. As an increasing number of people retire start-

Table 3: Externally Calibrated Parameters

Parameter	**Value**	**Interpretation**
Demographics		
ω	0.99	Expected retirement at age 55
$\bar{s}$	0.4	Share of single households
$\rho_0(N)$	0.96	22% of couples are traditional
$\rho_1(N)$	0.99	Persistence of modern social norms (normalization)
Prices		
r	0.02	Interest rate
w^m	1	Men's hourly wage (normalization)
Labor market		
η	0.03	Returns to labor market experience
δ	0.06	Skill depreciation in unemployment
z	0.3	Unemployment replacement rate
$1-p$	0.4	Probability of drawing high re-entry cost
σ	0.07	Scale of taste shocks
$\rho_{TC}(N)$	0.99	Persistence of TC status (normalization)
ρ	0.83	Recessions expected to last 6 quarters
Household bargaining		
λ	0.3	Women's bargaining weight
Time constraints and childcare		
T	1.5	Time endowment
$\gamma(s,N)$	0.34	Younger kids require 13.7 hours per week
$\gamma(b,N)$	0.11	Older kids require 4.2 hours per week
ν	0.75	CES elasticity of couples' childcare
α_m^w	1	Men's disutility from multitasking (normalization)

Notes: Hours are converted into fractions based on our assumption that one unit of time corresponds to 40 hours per week. Further details on the external calibration can be found in Appendix A.

ing around age 55 in the data, we set ω to match a life expectancy of 55 years.[18] The share of singles is set to match the 40% share of single households in the United States prior to 2020. We make the modern social norm highly persistent (0.99); then, for the persistence of the traditional social norm, we set $\rho_0(N)$ so that the fraction of traditional couples is 22% to match the World Values Survey evidence in Section 2. We match the transition probabilities for children $\boldsymbol{\pi}^g(k'|k)$ and $\boldsymbol{\Pi}(k'|k)$ with evidence on the distribution of different types of households (having younger children, older children, or neither; see Appendix A.6). The interest rate is set to $r = 0.02$, a relatively high value allowing for

[18]Explicitly modeling retirement would primarily affect asset-accumulation decisions in the model. However, given that death is modeled as a shock, people still accumulate a substantial amount of assets and leave accidental bequests.

the fact that households are not compensated for accidental bequests left at their death. Men's wage per efficiency unit w^m is normalized to 1.

Turning to labor market parameters, the returns to experience parameter η is set to match a return to labor market experience of 1.1 percent per quarter, which is computed using the NLSY97 data set (Appendix A.7). The skill-depreciation parameter δ is set to match a quarterly skill depreciation of 2.5 percent, based on evidence from Davis and von Wachter (2011) on the earnings implications of job loss during recessions. The replacement rate z is set to 30% of market wages, slightly lower than the estimate of the US replacement rate in Acemoglu and Shimer (2000) of 40%, to reflect the fact that not all unemployed are eligible for benefits (Doepke and Gaetani 2024). Re-entry costs are set to zero except for non-teleworking married women, whose costs we calibrate internally.[19] The probability of drawing the higher re-entry cost, $1-p$, is 40%.[20] The low re-entry cost is normalized to zero. Finally, once a recession begins, it is expected to continue with probability $\rho = 0.83$ so that the expected duration of a recession is six quarters, in line with the data.

Within married couples, the female bargaining weight is set to 0.3 as estimated by Voena (2015). Each agent's time endowment is normalized to $T = 1.5$. Since we interpret a labor supply of $n = 1$ as a full-time job of 40 hours, this corresponds to a time endowment of 60 hours per week.[21] In the model, we compute labor supply as average hours worked, using zero hours for the fraction that do not work and 0.5 for the fraction that work part-time. The childcare parameters $\gamma(s, N)$ and $\gamma(b, N)$ are calibrated based on information on time spent on childcare in families with younger and older children from the American Time Use Survey. The elasticity of substitution between mothers and fathers in childcare is $\frac{1}{1-\nu} = 4$.[22] Finally, we normalize men's multitasking disutility, α_w^m, to 1, while calibrating the female parameter internally.

In addition to the parameters listed in Table 3, we calibrate the initial distributions of human capital $F^g(h)$ and $F(h^f, h^m)$ to match evidence on the distribution of earnings of singles and couples at age 25 (see Appendix A.7).

[19] Table 6 shows that the model matches re-entry probabilities for married men well despite normalizing their re-entry costs to zero.

[20] A probability of 100% implies fewer flows between employment and unemployment than occur in the data, and counterfactually high duration of unemployment. For interior choices of p it is hard to jointly identify p and the level of the cost κ_H^f. We fix p and calibrate κ_H^f internally.

[21] We interpret our model as allocating fungible time during a typical weekday. Thus, we subtract sleep and personal care time and weekends to arrive at a time endowment of 60 hours per week.

[22] Some papers in the literature assume perfect substitutes by summing husbands' and wives' time (Molnar 2026), while other recent papers find evidence of less substitutability or even complementarity (Moschini 2023; Caucutt et al. 2026).

The calibration yields a stationary distribution in which 51 percent of households have kids, 7 percent of households are single mothers, and 3 percent are single fathers. Among households with children, 45 percent have young kids under the age of six.

4.2 Internally Calibrated Parameters

The remaining parameters are jointly calibrated to match a set of target moments that characterize the US economy before 2020. Most moments are related to the labor market, such as job flows and hours worked, but we also include others such as the Gini coefficient and the marginal propensity to consume. Further details about the data sources and moment computations are in Appendix A.4 and Appendix A.5. Table 4 displays the calibrated parameter values, and Table 5 shows the model fit. Though the parameters are jointly chosen, in most cases there is a fairly direct mapping from a particular parameter to a particular moment.

The calibrated discount factors for singles and couples match the average MPCs of households in the economy.[23] The calibrated values are somewhat low relative to standard calibrations; macroeconomic models have typically been calibrated to match overall asset accumulation in the economy, but a recent literature documents that such models imply counterfactually low MPCs (e.g., Kaplan and Violante 2014). The model also fits heterogeneity in consumption across households, measured by the Gini coefficient for consumption.

We fix the telecommuting occupation's persistence at 99% and internally calibrate the non-telecommuting persistence to match the 7% pre-2020 telecommuting share (Barrero, Bloom, and Davis 2023), obtaining 99.9%. Telecommuting status is initialized according to the resulting stationary distribution.

The leisure preference parameters $\alpha^g_{l,s}$, conditional on the bargaining power λ and relative female wage w^f, primarily determine the distribution of labor supply across women and men and within couples. The social norm parameter ψ also helps match labor supply, because this parameter specifically affects the labor supply of married mothers. Alon et al. (2020) report that women who could telecommute provided 14% more childcare than women who could not, whereas men who could telecommute provided 50% more childcare, suggesting that women's disutility of multitasking α^f_w is higher than men's. The fact that teleworking men provide 50% more childcare than non-teleworking men informs the convexity parameter ϕ of the multitasking cost.

[23] Kaplan and Violante (2014) and Auclert, Bardóczy, and Rognlie (2023) report a quarterly MPC of about 0.25 for the US economy.

Table 4: Internally Calibrated Parameters

Parameter	Description	Value
Preferences		
β_M	Discount factor, couples	0.96
β_S	Discount factor, singles	0.88
$\alpha_{l,S}^m$	Leisure preference, single men	0.97
$\alpha_{l,M}^m$	Leisure preference, married men	0.41
$\alpha_{l,S}^f$	Leisure preference, single women	0.94
$\alpha_{l,M}^f$	Leisure preference, married women	0.93
α_w^f	Utility cost of multitasking, women	3.28
ϕ	Convex utility cost of multitasking	1.22
$\kappa_{M,0}^f$	Re-entry cost, married women, no kids, NT	0.06
$\kappa_{M,s}^f$	Re-entry cost, married women, small kids, NT	0.15
$\kappa_{M,b}^f$	Re-entry cost, married women, big kids, NT	0.2
Technology		
θ_S^m	Part-time efficiency, single men	1.19
θ_M^m	Part-time efficiency, married men	3.05
θ_S^f	Part-time efficiency, single women	1.26
θ_M^f	Part-time efficiency, married women	0.99
π_{UE}^m	Job offer rate, unemployed men	0.42
π_{EE}^m	Job offer rate, employed men	0.96
π_{UE}^f	Job offer rate, unemployed women	0.51
π_{EE}^f	Job offer rate, employed women	0.99
ρ_{NT}	Persistence of non-telecommuting status	0.999
Social norm and labor market barriers		
w^f	Exogenous female wage gap	0.78
ψ	Social norm penalty	0.75

Notes: Parameters are jointly calibrated to fit the set of moments in Table 5. Parameters with an S subscript refer to singles while M refers to married couples.

Married women's re-entry costs are calibrated to match the difference in re-entry probabilities for married women relative to married men. The calibrated parameters show a pattern of re-entry costs increasing in the age of children.

The returns-to-scale parameters for part-time work θ_s^g help to match the breakdown between part-time and full-time work for different groups. The job offer rates match the job-flows moments in Table 5 which are computed according to the procedure described in Appendix A.8. Job-loss rates are higher for men than women. Employed men face a

Table 5: Model Fit

Moment	Data	Model
Labor supply (hours)		
Labor supply, single men	0.66	0.66
Labor supply, married men	0.9	0.83
Labor supply, single women	0.68	0.71
Labor supply, married women	0.64	0.66
Job flows		
Male E-to-E rate	0.93	0.91
Male U-to-U rate	0.62	0.66
Female E-to-E rate	0.9	0.87
Female U-to-U rate	0.77	0.73
Wage gap		
Gender wage gap (conditional on working)	0.19	0.21
Re-entry moments		
Non-reentry gap (F-M), married, no kids	0.13	0.13
Non-reentry gap (F-M), married, small kids	0.24	0.23
Non-reentry gap (F-M), married, big kids	0.21	0.19
Telecommuting		
Telecommute share	0.07	0.07
Childcare		
Fraction of childcare done by men, full-time couples	0.39	0.41
Childcare ratio (TC/NT): men, small kids, NT wife	1.5	1.42
Childcare ratio (TC/NT): women, any kids, NT husband	1.14	1.06
Social norms		
Ratio of M/F labor supply, traditional vs. modern couples	1.36	1.13
Part time moments		
Share of married mothers working part-time	0.18	0.24
Share of married mothers working full-time	0.52	0.49
Share of males working full-time	0.92	0.87
Share of females working full-time	0.76	0.75
MPCs		
MPC, couples	0.25	0.25
MPC, singles	0.25	0.24
Inequality		
Gini index, consumption	0.35	0.32

Notes: This table compares the model-simulated moments against their empirical counterparts. The re-entry moments are from the "DiD Data" column of Table 2; an explanation of the computation of the other data moments can be found in Appendix A.

quarterly job-loss rate of 4%, while women face a rate of only 1%.[24] Similarly, there is a gender difference in the quarterly job-finding rate for the unemployed: unemployed women will get an offer with a 51% probability, while the probability for men is only 42%. There is some tension between matching the high labor supply of married men and their flow rates. Including both flows and stocks in labor supply as targets results in parameters that fit a combination of the two. Even in normal times, men face higher layoff rates than women and are less likely to receive an offer when they are not working than women, consistent with men's employment being more volatile.

Labor market barriers for women, captured in the relative female wage w^f, are high. This implies that, conditional on working, women's human capital is slightly higher than men's, consistent with women's higher educational attainment in recent years. Finally, the social norm penalty ψ helps match the differences in men's relative labor supply in traditional couples compared to modern couples in the World Values Survey. Because the model's social-norm penalty applies to childcare rather than labor supply, it understates the labor-supply difference between traditional and modern couples.

The targets for labor supply and full- versus part-time status by gender and marital status are key moments for understanding the transmission of gendered recessions. The other important parameters for the labor supply dynamics of she- vs. he-cessions are the re-entry costs; the calibrated values match the evidence in Section 2 about gender differences in the probability of re-entering the workforce after leaving. Specifically, the model matches that women re-enter at lower rates than men, especially when they have children.

In the pandemic experiment, childcare plays a key role. The calibrated model matches gender differences in childcare time for full-time couples as well as how telecommuting affects the division of childcare within married couples. This matters for our long-run projections of how greater telework availability matters for labor supply, human capital accumulation, and the gender earnings gap, as well as the impact of labor market shocks in the New Normal with a higher fraction of workers telecommuting.

Our New Normal experiments also seek to understand how additional progress in social norms around the division of childcare will affect household labor supply. Because the model understates the labor-supply difference between modern and traditional couples, our experiments that reduce the fraction of traditional couples may understate how much the gender gap narrows as social norms evolve.

[24] For more intuitive language, we sometimes use "job-loss rate" for one minus the job offer rate for the employed, and "job-finding rate" for the job offer rate for the unemployed.

4.3 Fit for Non-Targeted Moments

Table 6: Model Fit of Non-Targeted Moments

Moment	**Data**	**Model**
Labor force		
Female-to-male labor force participation ratio	0.84	0.89
Married fathers — unemployed	0.07	0.16
Married fathers — part time	0.04	0.01
Married fathers — full time	0.89	0.82
Childcare		
Childcare division (M/F), both unemployed	0.36	0.46
Couples' joint employment decisions (Husband, Wife)		
Couples: (Unemployed, Unemployed)	0.04	0.01
Couples: (Unemployed, Part time)	0.01	0.01
Couples: (Unemployed, Full time)	0.05	0.14
Couples: (Part time, Unemployed)	0.01	2E-5
Couples: (Part time, Part time)	0.01	4E-4
Couples: (Part time, Full time)	0.02	0.01
Couples: (Full time, Unemployed)	0.25	0.21
Couples: (Full time, Part time)	0.15	0.22
Couples: (Full time, Full time)	0.44	0.39
Non-reentry probabilities (annual)		
Non-reentry probability, married men, no kids	0.19	0.14
Non-reentry probability, married women, no kids	0.32	0.27
Non-reentry probability, married men, small kids	0.12	0.15
Non-reentry probability, married women, small kids	0.36	0.38
Non-reentry probability, married men, big kids	0.12	0.13
Non-reentry probability, married women, big kids	0.33	0.32

Notes: This table compares the model-simulated moments against their empirical counterparts. An explanation of the computation of the data moments can be found in Appendix A.5; the non-reentry probabilities are computed as the difference between the E-to-NE and E-to-E columns for the respective groups in Table 2.

The calibrated model also generates a range of non-targeted moments in normal times that are consistent with the data and are important for the behavior of model aggregates in our recession experiments. These moments and the model fit are reported in Table 6. The model broadly matches the ratio between male and female labor force participation rates, as well as the distributions of married fathers and of couples over employment states (not employed, part time, full time), despite directly targeting only employment shares of married mothers. This suggests that the model performs well in predicting joint decision-making over labor supply within couples.[25] In terms of childcare division, the division among married couples where neither partner works is broadly similar in the model and the data, suggesting the model captures the relevant gender norms around caregiving. Finally, the re-entry probabilities after job loss govern the speed of recovery from recessions. Although we only target the gap between married men and women, the model matches the levels for both groups well, suggesting the model captures the relevant channels affecting re-entry: offer rates, the utility of working vs. not working, and childcare needs.

5 Results

This section uses the model to study how the gender composition of employment shocks shapes aggregate labor market dynamics. We begin by comparing the transmission of shocks in she-cessions and he-cessions and identifying the mechanisms that make recessions affecting women deeper and more persistent. We then turn to the pandemic recession of 2020. We calibrate the model's labor market shocks to match the observed path of employment and examine whether changes in remote work and social norms surrounding caregiving can account for the rapid recovery. Despite being calibrated to pre-pandemic data, the model matches several important non-targeted moments four years after the shock, including an increase in aggregate labor supply driven by women and an increase in fathers' childcare time.

Finally, we examine the long-run implications of these changes. We quantify how remote work and evolving social norms affect aggregate labor supply, the gender composition of employment, and gender inequality, and we decompose the contribution of each channel. We conclude by analyzing business cycles in the New Normal, asking whether permanent changes in household behavior imply that future recessions will differ from past recessions.

Table 7 shows how the variables that vary across aggregate states are set.[26] We set the recession state $X = R$ to match features of the Great Recession of 2007 to 2009. To this end, we measure the employment level changes from peak to trough by gender in the Great Recession. Table A.8 shows men's employment dropped by 5.9 pp and women's dropped by 3 pp from the initial level to the trough of the recession. To match this in the model, we calibrate a gender-specific shock to normal-times offer rates to fit the changes

[25] Because the model's non-employment state combines unemployment and non-participation, we count as out of the labor force those who reject an offer and those who would reject one if they received it.

[26] The choices for the non-recession states are discussed in Section 4 above.

Table 7: Parameterization of Aggregate States

Parameter	Interpretation	Normal	Recession		He-cession		She-cession		Pandemic		NN
		N	R_N	R_{NN}	H_N	H_{NN}	S_N	S_{NN}	P_N	P_N w/o CC	NN
$\pi^m_{EE}(X)$	Offer rate, employed men	0.96	0.92	0.92	0.92	0.92	0.96	0.96	0.86⋆	0.86⋆	0.96
$\pi^m_{UE}(X)$	Offer rate, unemployed men	0.42	0.39	0.39	0.39	0.39	0.42	0.42	0.33⋆	0.33⋆	0.42
$\pi^f_{EE}(X)$	Offer rate, employed women	0.99	0.97	0.97	0.99	0.99	0.96	0.96	0.88⋆	0.88⋆	0.99
$\pi^f_{UE}(X)$	Offer rate, unemployed women	0.51	0.49	0.49	0.51	0.51	0.48	0.48	0.4⋆	0.4⋆	0.51
$\rho_0(X)$	Persistence, traditional norms	0.96	0.96	0.92	0.96	0.92	0.96	0.92	0.96	0.96	0.92
$\rho_{NT}(X)$	Persistence, NT occupations	0.999	0.999	0.996	0.999	0.996	0.999	0.996	0.996	0.996	0.996
$\gamma(s, X)$	Childcare time, younger kids	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.41	0.34	0.34
$\gamma(b, X)$	Childcare time, older kids	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.13	0.11	0.11

Notes: Gray cells indicate a change from the non-recession values. "w/o CC" refers to a pandemic shock that omits changes to childcare.

⋆*We calibrate a sequence of (gender-specific) shocks to offer rates for the pandemic to match the evolution of employment rate deviations from pre-pandemic values. This table reports the offer rates in the first quarter of the pandemic only. See Table A.9 in the Appendix for more details on the path of the calibrated shocks.*

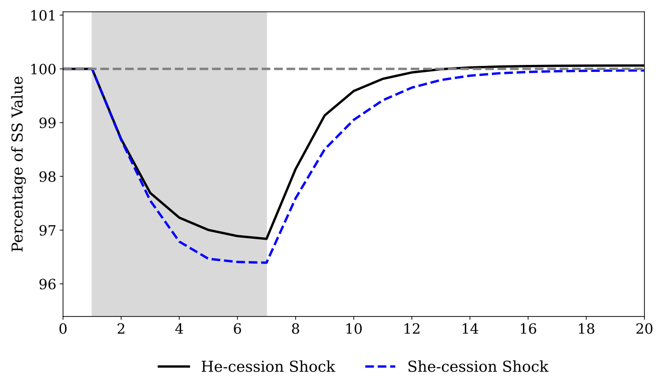
in the employment rate over a recession from the initial steady state to the sixth quarter of the shock, with symmetric shifts in the offer rates from employment and unemployment (declining offer rates from employment correspond to a higher risk of job loss, whereas offer rates from unemployment determine the job-finding probability). This results in a decline in the offer rates for men of 3.2 pp and 2.2 pp for women ("Recession" column in Table 7). In a he-cession, offer rates decline only for men, with the same decline in offer rates as a regular recession ("He-cession" column in Table 7). The she-cession only affects women's offer rates, and for comparability rates decline by the same amount as men's in a he-cession ("She-cession" column in Table 7). For the pandemic state, we directly match the initial change in employment in the actual pandemic recession, and we include additional shocks to childcare needs, teleworking, and social norms (discussed in detail below).

5.1 She-cessions vs. He-cessions

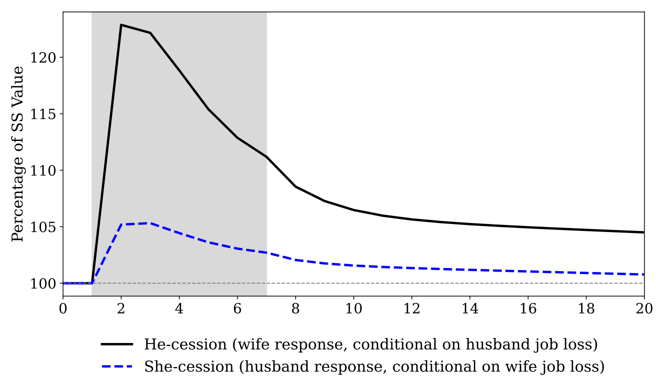
Recessions vary in their relative impact on male and female jobs, with traditional recessions affecting primarily occupations in which many men work (such as construction), while the pandemic recession affected female-dominated occupations in retail and other high-contact areas. To understand how the gender tilt of recessions matters, we compare the polar cases of a stylized he-cession (where only the male job offer rate goes down) with a she-cession (where only the female job offer rate goes down). The magnitude of the decline in offer rates is the same for ease of comparison.

Panels a-c of Figure 2 show how these two types of recessions differ from one another. The first thing to note is that she-cessions are deeper and recovery is slower in terms of

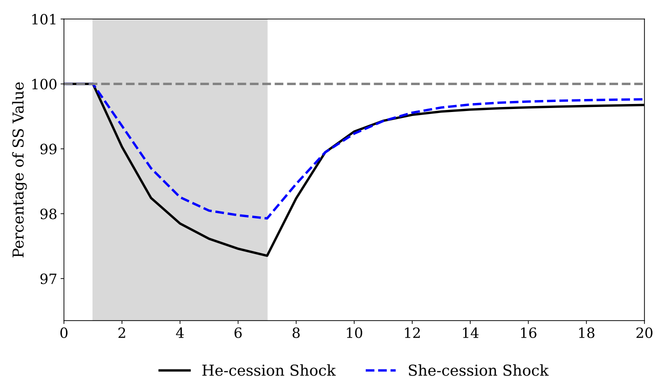
Figure 2: He-cessions vs She-cessions: Aggregate Outcomes



(a) Aggregate Labor Supply



(b) Intra-Family Insurance in Couples (Labor Supply Conditional on Spousal Job Loss)



(c) Aggregate Income

Notes: The panels show (a) aggregate labor supply, (b) the added worker effect (the increase in labor supply from the steady-state level given a spousal job loss in the first shock period), and (c) aggregate income as a percentage of the steady-state values for both a he-cession and she-cession. The shocks last from periods 2 to 7; the corresponding parameters for these shocks can be found in Table 7. See Appendix B.3 for additional robustness definitions of the added worker effect plot in panel (b).

labor market impact (Figure 2a) despite the size of the exogenous shock being the same. Aggregate labor supply drops 14% more in a she-cession compared to a he-cession.

The main reason for deeper she-cessions is that the scope for the within-family insurance is smaller in she-cessions. Figure 2b displays the change in the labor supply of spouses of the gender that is not directly affected by the recession (i.e., women in a he-cession and men in a she-cession) conditional on their spouse losing their job in the first period of the recession. In a he-cession, we observe strong within-family insurance, with many women increasing their labor supply after their husband loses their job. This reaction in labor supply includes both the classic added worker effect (a non-working spouse entering the labor force in reaction to their spouse's job loss) and additional channels such as shifts from part-time to full-time work and a higher attachment to the labor force, i.e., a decline in transitions out of employment. These channels combine to generate a sizable increase in married female labor supply in a he-cession, which dampens the decline in aggregate labor supply. The reverse is not true in a she-cession, because the baseline male labor force participation rate is much higher than the female rate. At the onset of a she-cession, 94.8% of married men are already working, most of them full time, whereas only 82.9% of married women are working at the onset of a he-cession, many of them part time. As a result, there is less scope for men to increase labor supply if their spouse loses their job.

Women's lower probability of re-entering the workforce after job loss also contributes to the depth of the recession. To quantify this channel, Figure B.1 in the appendix plots a counterfactual where women's re-entry costs are set to zero.[27] In that case, she-cessions are only 10.9% deeper than he-cessions, implying that re-entry costs account for around 22% of the difference in the depth of she-cessions compared to he-cessions.

The speed of the labor market recovery after she-cessions is also slower. Labor supply is back to 99% of the steady state level two quarters after the recession shock ends in a he-cession, while it takes three quarters in a she-cession. The main reason is that women take longer to re-enter after a job loss than men. Hence, when a recession is dominated by female job losses, the recession persists longer.

Given the gap in women's and men's average earnings, a larger drop in labor supply during a she-cession does not necessarily translate into a larger drop in income. Indeed, he-cessions are deeper if measured by the percentage drop in aggregate income (Figure 2c). The reason is threefold: men make up a larger share of the labor force, are less likely to work part-time, and earn higher wages. Thus, the income loss if an average man loses

[27] Note that even when women's re-entry costs are zero, there are endogenous gender differences in re-entry probabilities driven by caregiving, leisure preferences, and wages.

a job is higher than when an average woman loses a job. The relative impact of he- and she-cessions on household income will change in the future if the baseline gender gap in labor supply and earnings continues to shrink, as seems likely given that there is now a substantial gender education gap in favor of women among younger cohorts.

Overall, we see that whether a recession shock affects primarily women versus men has a substantial impact on the severity and persistence of the resulting economic downturn. These findings matter not just for comparing different types of economic shocks, but also imply that the nature of recessions changes as the composition of labor supply shifts across gender and household types over time.

5.2 The Pandemic Recession

The recession brought about by the Covid-19 pandemic is a prime example of gendered shock, as women's jobs were much more affected than men's. The pandemic recession was also characterized by additional unique factors such as school and daycare closures and the rise in remote work. We use our model as a laboratory to study how these features shaped the labor market during the pandemic recession and its aftermath.

To model the pandemic labor market shock, we calibrate a sequence of gender-specific offer-rate shocks to match the empirical path of employment rates. The shocks span six quarters and are chosen to match the percentage-point decline in the male and female employment rates relative to their pre-pandemic values; in the data these declines are measured relative to 2020Q1, whereas in the model they are measured relative to employment rates in the normal-times steady state. Table A.9 reports the full six quarter path of the shocks.

The pandemic recession also leads to a 20% increase in childcare obligations (Table 7), implying an increase of 2.7 hours per week for younger children and about one hour for older children. We chose these values to keep childcare needs below the number of hours needed for a part-time job (20 hours per week) to avoid purely mechanical effects of childcare needs on labor supply, especially for single parents, and consistent with the observation that the labor supply effects of childcare needs during the pandemic were more muted than originally expected (Goldin 2022).[28] The childcare shock lasts four quarters, to reflect school reopenings prior to the end of the recession (Fuchs-Schündeln 2022).

[28]Our choices are well below the findings of Adams-Prassl et al. (2020), who show that in a typical work week during the pandemic, US parents working from home spent roughly 22.5 (men) and 30 (women) hours doing childcare and homeschooling, for a total of 52.5 hours.

We also allow for a one-time jump in the share of telecommutable jobs at the beginning of the pandemic recession, which captures the immediate rise in telecommuting at the beginning of the lockdown, increasing the fraction of telecommuting offers to 28.1% (Barrero, Bloom, and Davis 2023). After this one-time shock, the transition probabilities displayed in Table 7 apply, implying a fraction of telecommuters in the New Normal of the same 28.1%.

With regard to social norms, we conjecture that the share of traditional couples will ultimately decline by half, from 22 to 11 percent, in the aftermath of the pandemic. This is motivated by the fact that the pandemic-induced school closures forced many fathers to be a lot more involved with their children together with evidence that temporary changes in the division of labor in the household have lasting effects, not only on the families themselves but also on peers.[29] Appendix Figure B.6 depicts the rise in fathers' childcare time in the model, showing a sudden increases at the onset of the pandemic, followed by a more gradual increase after the pandemic.

Clearly, the future evolution of social norms is difficult to predict. Our calibration here should be regarded less as an empirical estimate and more as an "if-then" scenario: if the pandemic brought about changes in social norms, or if the long run trend toward a more egalitarian division of childcare continues, our simulations answer the question of how the economy will evolve. In the past, gender norms have often evolved rapidly in response to economic changes (e.g., Fernández 2013 and Fogli and Veldkamp 2011). In our simulation, the change in social norms is slower than that implied by the learning model of Fernández (2013) during the rise of female labor force participation in the United States from the 1960s to the 1980s. Below, we also provide a decomposition analysis that examines different outcomes when social norms fail to respond. Hence, while our assumptions on shifting social norms are more speculative than other aspects of our analysis, we believe a shift towards more gender-equal norms is the most likely scenario.

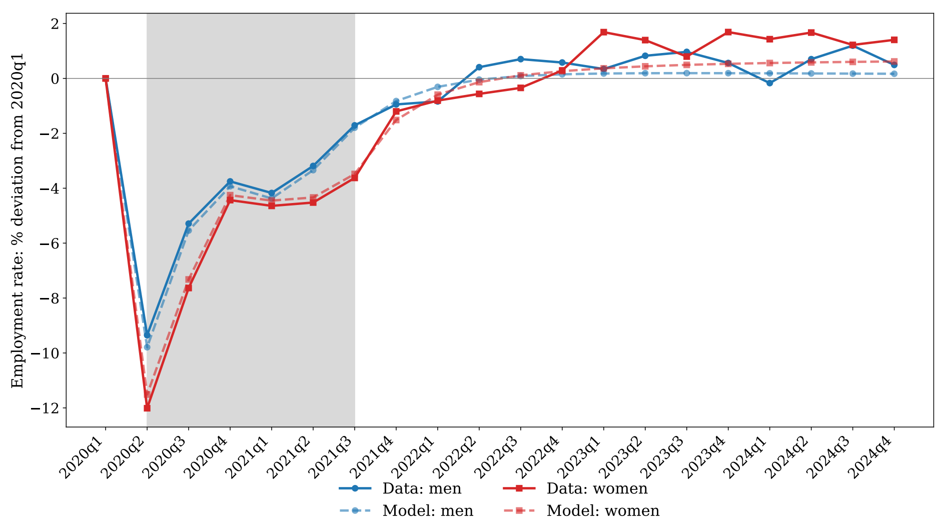
Figure 3 overlays the model and data from 2020 to 2024, where 2020Q2 to 2021Q3 are the calibrated periods. As our earlier work (Alon et al. 2020) anticipated, the calibration suggests that the labor market shock was larger for women: the decline in women's offer

[29] For example, Cowan (2024) finds a post-Covid decline in the gender gap in childcare time, especially for college graduates. Augustine and Prickett (2026) also document a narrowing of the gender gap in childcare and housework time for the US. von Gaudecker et al. (2026) find that the childcare gap fell by more than four hours between late 2019 and mid-2022 in the Netherlands and Ben Yahmed and Malavasi (2025) document an increase in fathers' time with children, especially when only the father can work from home, for Germany. Dahl, Loken, and Mogstad (2014) exploits a paternity leave reform in Norway in 1993 to show how temporary changes can have lasting effects. Further evidence on long-lasting effects of paternity leave forms is summarized in Appendix A.1.

rate is 10.9 pp in the first quarter of the pandemic and only 9 pp for men. Despite only targeting the six quarters of the recession, the model matches the post-pandemic recovery of employment rates closely.

Childcare needs played a role in the dramatic drop in employment. To decompose this, Figure 4 reports the drop in labor supply when only childcare needs change (the yellow line). School and daycare closures, which have recently become more common as a result of disease outbreaks, war, and civil unrest, can reduce household labor supply. These effects are heterogeneous in the population (Figure B.5), with the effects being mildest for teleworking men. The effects on both telecommuting and non-telecommuting women are roughly three times as large as those for non-telecommuting men. Consistent with these predictions, Figure A.1 shows that the difference between male and female labor supply during the pandemic was substantially larger for parents than non-parents.

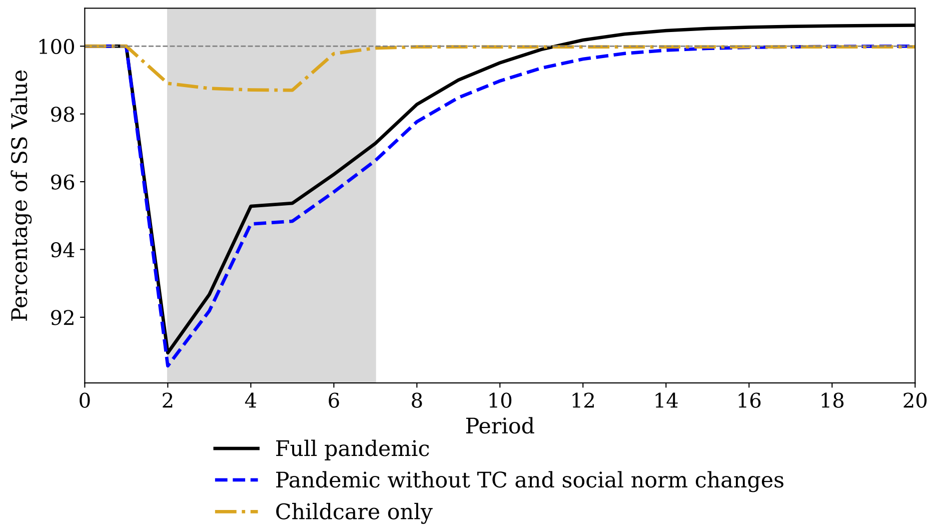
Figure 3: Employment Rates: Model vs Data



Notes: The figure shows the percentage deviations in male and female employment rates in the data between 2020Q1 (base) and 2024Q4, with the model values overlayed (relative to normal-times steady state). For the first six quarters of the pandemic (2020Q2 to 2021Q3). The change in the offer rates are calibrated such that the model matches the empirical percentage-point decline in the employment rate (see Figure B.4 for the targeted percentage-point version). The data uses the monthly CPS series, which is then aggregated to quarterly using an average of the values for the three months in a given quarter. The pandemic labor market shocks apply from periods 2 to 7, whereas the pandemic childcare shocks apply for periods 2 to 5. The corresponding parameters for these shocks can be found in Table A.9.

Figure 4 also demonstrates why, in addition to school reopenings, the pandemic recovery was surprisingly fast (two quarters after the pandemic, labor supply recovers to 99% of its pre-pandemic level). Absent changes in remote work availability and social norms, the recovery would have been much slower, taking an additional two quarters to recover to 99% of the pre-pandemic level. We thus conclude that societal changes brought about

Figure 4: Aggregate Labor Supply: Pandemic Decomposition



Notes: The figure shows the deviation in aggregate labor supply in the baseline pandemic (Table 7) in black, an alternative where remote work and social norms do not change but labor market shocks and childcare are as in Table 7 in blue, and a version where only childcare needs change in yellow.

by the pandemic facilitated a rapid economic recovery.

Table 8: Model vs Data 16 Quarters After Start of Pandemic

Moment	**Data**	**Model**
Fraction of childcare done by men, couples	+10.5%	+17.1%
Married women, hours	+3.0%	+1.5%
F/M employment rate ratio, couples with kids	+2.5%	+2.0%
Aggregate hours	+0.6%	+0.6%

Notes: This table compares the model-simulated moments, averaging periods 17 through 20, inclusive, against their empirical counterparts. The fraction of childcare comes from the 2024 wave of the ATUS data. Hours (both married and aggregate), as well as the employment-rate ratio, comes from averaging January to December 2024 in the CPS monthly data.

Not only did employment recover quickly, but the data suggest that women's labor supply has now shifted to a level that exceeds pre-pandemic labor supply. Table 8 reports several non-targeted features of the data and model four years after the pandemic started. The table shows that the model accurately predicts the observed rise in aggregate hours. The increase in hours is driven by married women, whose hours increased 3% in the data (the model accounts for half of this, predicting a rise of 1.5%).[30] The increase in female

[30]The post-pandemic increase in female labor supply, especially for women with young children, has already received some attention in the literature (Garcia-Jimeno and Hu 2024; Bauer and Steinmetz-Silber 2024).

hours is largely made possible by men shouldering more of the childcare burden. In the data, men are doing a 10% higher share of childcare post-pandemic, consistent with the model predictions.

Our results demonstrate that taking the gendered nature of the pandemic shock is essential for understanding the dynamics of the labor market during the recession and beyond. Moreover, the results also matter for potential future shocks of a similar nature, such as additional pandemics or school closures (which can also happen for other reasons, such as natural disasters or strikes). Lastly, some of the changes brought about by the pandemic are likely to be long-lasting, such as the spread of flexible work. To shed light on this aspect, we next consider how the economy will change if these arrangements continue to persist and the economy transitions to a "New Normal" with higher female labor supply.

5.3 How Will the New Normal Be Different?

Originally induced by the pandemic, work-from-home opportunities appear to have permanently expanded (Barrero, Bloom, and Davis 2023; Hansen et al. 2023). Similarly, some fathers who were forced by the pandemic to spend more time with their children seem to have learned to like it, leading to a permanently more egalitarian division of childcare.[31] We interpret this as a change in social norms. What will be the long run effects of increased teleworking opportunities and changes in social norms? Both of these changes will affect the division of caregiving in the family and accordingly have implications for labor supply of mothers. To assess these forces, we now compute a scenario where we quadruple the fraction of telecommuters and decrease the fraction of traditional couples by half. We call this the New Normal (see Table 7, last column).

Table 9 compares the New Normal (NN) with the old normal (N). In the New Normal, fathers do a lot more childcare. The fraction of childcare done by married fathers increases by 26%. This in turn frees up mothers' time to work, leading to an increase in labor supply both at the extensive and intensive margin. The female participation rate goes up by one percentage point and labor supply of married women goes up by three percent. Table B.2 in the online appendix decomposes these changes between the two underlying forces (more modern couples and more telecommuting) and shows that both are about equally important. The increased labor supply has implications for gender differences in earnings: the gender earnings gap falls by 3.1%. This is largely driven by women switching from part time to full time and to a lesser extent by a decline in the gender

[31] See footnote 29 on this.

wage gap. In the New Normal, women will re-enter more quickly when not working, especially if a husband loses a job. The gap in the re-entry rate between men and women with children falls by a substantial amount. Because of the increased female labor supply, aggregate household income and consumption go up slightly. Aggregate wealth, on the other hand, falls, which is due to a reduced need for households to self-insure.

Table 9: Normal vs New-Normal Steady State Comparison

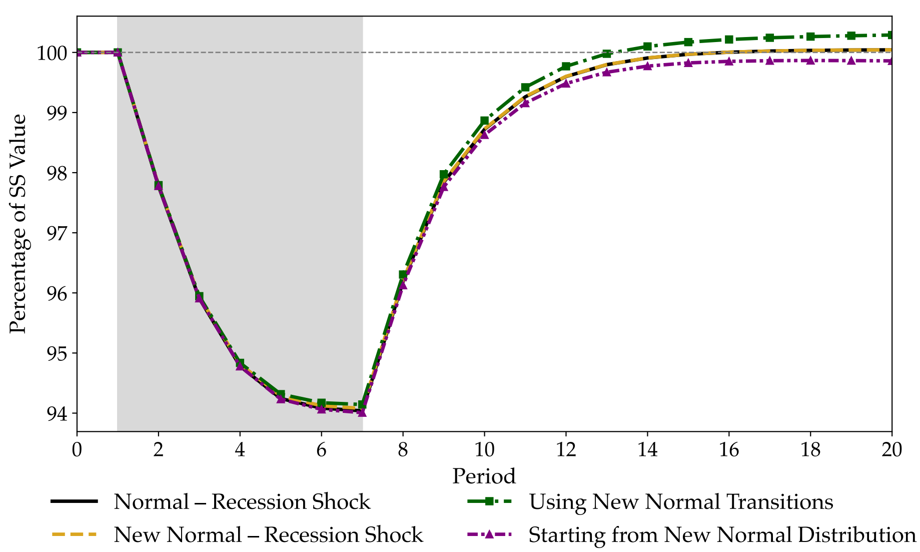
Moment	**N**	**NN**	**Change**
Transitions			
Telecommuting share	0.07	0.28	293.1%
Share of couples with traditional norms	0.22	0.11	-50.0%
Labor supply and participation rates			
Labor supply, aggregate	0.72	0.73	0.7%
Labor supply, married men	0.83	0.82	-1.4%
Labor supply, married women	0.66	0.68	3.0%
Labor force participation rate, men	0.94	0.93	-0.3%
Labor force participation rate, women	0.84	0.85	1.3%
Human capital and wages			
Gender earnings gap (conditional on working)	0.28	0.27	-3.1%
Gender wage gap (conditional on working)	0.21	0.21	-1.2%
Average human capital, men	2.23	2.22	-0.3%
Average human capital, women	2.14	2.15	0.8%
Childcare			
Fraction of childcare done by men, all couples	0.28	0.35	26.0%
Re-entry moments			
Non-reentry gap (F-M), married, no kids	0.13	0.12	-5.2%
Non-reentry gap (F-M), married, small kids	0.23	0.2	-12.8%
Non-reentry gap (F-M), married, big kids	0.19	0.17	-10.7%
Consumption and wealth			
Average MPC	0.24	0.25	0.4%
Aggregate household income	2.55	2.56	0.5%
Aggregate consumption	2.55	2.57	0.5%
Aggregate wealth	0.44	0.43	-1.8%

Notes: The table compares steady-state moments in normal (N) and new-normal (NN) times. The change is the percentage change in the New Normal, relative to the normal times values.

Since men do more childcare and women work more in the New Normal, one would expect this to have implications for the business cycle. Recessions are usually dampened by within-family insurance, including the added-worker effect of women entering the labor force when husbands lose jobs (Guner, Kulikova, and Valladares-Esteban 2025). There should be less scope for this effect in the New Normal where women already, at baseline, supply more labor. Thus, one could expect recessions to be deeper.[32] One might also expect recoveries to be slower, since Section 5.1 shows that recoveries from she-cessions are slower.

To assess these arguments, we now compare a regular recession in the (old) normal non-recession state with a recession starting in the New Normal non-recession state. Figure 5 compares the aggregate labor supply decline over time in these two recessions. Surprisingly, the two recessions look essentially identical. Yet this masks important differences. The similar shape is the result of two opposing forces canceling out. On the one hand, a higher female participation rate deepens recessions; on the other hand, the greater availability of telework and a higher fraction of modern couples result in more flexibility in responding to job loss, which dampens recessions. We now illustrate these opposing forces in a decomposition exercise.

Figure 5: Aggregate Labor Supply: Normal vs New-Normal Decompositions



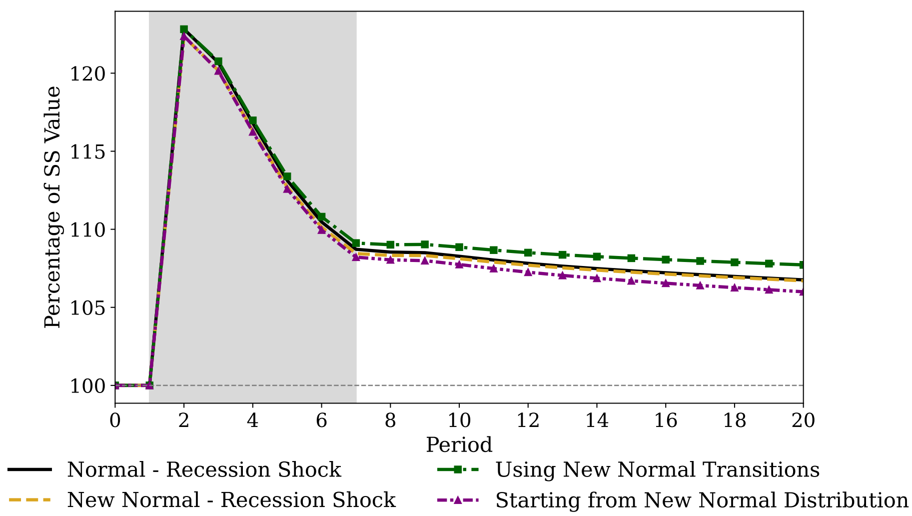
Notes: The figure shows the aggregate labor supply during and following a recession shock; the corresponding parameters for these shocks can be found in Table 7. The figure plots the normal-times and new-normal times recessions, as well as two variations of the normal times where one component of the new-normal is used in each comparison. The changes are: (1) the transition matrices are changed to the new-normal versions; (2) the initial conditions change, i.e., the initial distribution is the new-normal steady state. The percentage deviations are plotted relative to each composition's own starting steady-state value.

The purple line in Figure 5 isolates the effect of the stationary distribution being different in the New Normal, in particular the female participation rate being higher. In the New

[32]For a discussion see for example Section 2.4.1 in Doepke and Tertilt (2016) which shows in a simple model how aggregate labor supply elasticity is U-shaped in female labor supply.

Normal, women are more attached to the labor force (differentially more so than men becoming less attached). When we begin the recession from the New Normal stationary distribution but keep the probabilities of teleworking offers and social norm changes fixed at the old normal, there are fewer women not working at the beginning of the recession who can step in when their husbands lose jobs, and the recession is more severe (Ellieroth and Michaud 2024 analyze this channel in more detail). This can be seen in Figure 6, where the added worker effect starting from the New Normal stationary distribution is smaller than in the old normal.

Figure 6: Women's Added Worker Effect Decomposition - Recession Shock



Notes: This figure decomposes the added worker effect in a recession for women whose husbands lost a job in a recession as percentage deviations from the steady-state values. The figure plots the normal-times and new-normal times recessions, as well as two variations of the normal times where one component of the new-normal is used in each comparison. The changes are: (1) the transition matrices are changed to the new-normal versions; (2) the initial conditions change, i.e., the initial distribution is the new-normal steady state. The percentage deviations are plotted relative to each composition's own starting steady-state value.

However, there is another force working in the opposite direction. More teleworking and more modern couples give families more flexibility to respond to recessions, which dampens the recession. To illustrate this, the green line begins the recession from the old normal stationary distribution but changes the transition rates for telecommuting offers and traditional social norms to match the New Normal. As expected, greater availability of telework and a higher fraction of modern couples makes the recession less severe and speeds up the recovery. One way to interpret this result is that, all else equal, the rise in teleworking and the share of modern couples can amplify the added worker effect: they increase the number of women accepting offers, which makes the recession less severe (see the green line in Figure 6). Taken together, the two forces mean that the shape of recessions in the old and new normal are similar.

6 Conclusion

Our results show that the composition of the labor force in terms of gender and family types as well as the interaction between work and childcare needs play important roles in the transmission of aggregate shocks. Shocks that fall more heavily on women than on men are transmitted differently, owing to differences in within-family insurance and in the persistence of job loss. As a result, she-cessions and he-cessions differ qualitatively: she-cessions are deeper and recover more slowly. Yet the recovery from the largest she-cession, the pandemic recession of 2020, was surprisingly fast. We show that this can be explained in large part by structural changes that enable women to work more, particularly the rise of remote work and changes in social norms around caregiving.

The factors explored in this paper are likely to continue to shape the transmission of macroeconomics shocks in the household sector in the future. The composition of the labor force continues to change, with ongoing changes in women's and men's labor force participation, declining marriage rates among younger cohorts, and population aging. The future labor market will also be shaped by some of the changes brought about by the pandemic, such as the rise of remote work. Technological change will continue to alter both the relative labor market opportunities of women and men and the interaction between childcare needs and labor supply. Tracking and understanding these changes will remain a central challenge for future research on economic fluctuations.

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A Online Data Appendix

A.1 Evidence from Paternity Leave Reforms

Rege and Solli (2013) use a paternity leave reform in Norway in 1993 to estimate the lasting effect of a short-term change in the division of labor in the household. The reform increased the length of subsidized parental leave by a month conditional on fathers taking at least one month. The paper finds a significant negative effect on fathers' earnings (1-3 percent lower for those treated with the reform), which persisted up to the last point of observation when the child is 5 years old. Kotsadam and Finseraas (2011) analyze the impact of the same reform of the division of household labor. They find that couples with children born after the reform have fewer conflicts about household work and that they share household tasks more equally 13 years later. Kotsadam and Finseraas (2013) find that the effect extends to the next generation – when fathers do more, adolescent girls (not boys) do less domestic chores. Thus, gender norms seem to be permanently changed. Dahl, Loken, and Mogstad (2014) document sizable peer effects (in coworkers and brothers) in the uptake of paternity leave in the context of the same Norwegian reform. The estimated effect snowballs over time, leading to a long-run uptake rate that is substantially higher than without the peer effects. They provide some suggestive evidence that the mechanism is likely related to information transmission about the costs and benefits of taking paternity leave.

Patnaik (2019) analyzes a reform in Quebec from 2006 and combines it with time diary data. Fathers exposed to the reform spend more time on housework and childcare activities and mothers spend more time working in the market even four years after the reform. Similar evidence is found in Tamm (2019) for Germany and Farré and González (2019) for Spain.

A.2 Social Norms

Table A.1 summarizes the share of modern and traditional couples in the economy, as well as how employment and labor supply varies across the couple types. The results are derived from the most recently available round of the World Values Survey (WVS), corresponding to Wave 7 which covers the United States in 2017.

Couples are identified based on their response to the question: Q28- *For each of the following statements I read out, can you tell me how much you agree with each. Do you agree strongly, agree, disagree, or disagree strongly? When a mother works for pay, the children suffer.* Traditional couples include those who responded either "Agree" or "Strongly Agree". Modern couples are those who responded either "Disagree" or "Strongly Disagree".

For each couple type, the table reports the employment and labor supply outcomes for both the respondent and their spouse. Employment outcomes are defined as above, and include those that are unemployed and not in the labor force (omitting retired households) as "not employed".

Labor supply is computed consistently with the model outcomes. Full time employees (> 30 hours a week) are assigned labor supply equal to one, while part time employees (< 30 hours a week) are assigned 0.5, and those not employed receive a 0.

Table A.1: Social Norms and Labor Supply within Couples

Couple Type	**Share**	**Employment**		**Labor Supply**	
		Husband	Wife	Husband	Wife
Modern	0.78	0.944	0.768	0.915	0.704
Traditional	0.22	0.947	0.584	0.909	0.516

Notes: Results derived from World Values Survey (WVS) Wave 7 for the USA in 2017. Table entries report the share of modern and traditional couples, as well as how they correlate with employment outcomes. Unemployed and not-in-labor force both included in non-employment, but omit retired households. Labor supply assigns 1 to full time workers and self employed and 0.5 to part time workers.

A.3 Robustness: Gender Gaps in Labor Market Re-entry Rates

Table A.2 performs the same analysis as Table 2 but looking at non-employment rates (NILF and unemployed) 12 months after job separation, rather than just participation. The results again show statistically significant gender gaps in employment re-entry rates which are larger among married couples and those with children. While the qualitative patterns are preserved, the overall magnitudes of the gender gaps in non-employment are smaller, indicating that gender differences in the persistence of labor market declines are more pronounced in participation than in unemployment rates. Appendix Table A.3 presents additional robustness exercises which condition on separations being involuntary (e.g., firing, layoffs) and shows similar persistent gender gaps in labor supply across marital and child groups, albeit of a smaller magnitude.

A.4 Overview of Calibration Data Sources

The calibration targets draw on data from several different sources. Data on childcare hours by gender and marital status come from the American Time Use Survey (ATUS). The telecommuting status of different occupations is derived from the Leave Module of the American Time Use Survey (2017-2018) and is then merged into the Current Population Survey (CPS) to calculate the aggregate occupation shares. All data on employment status, household composition, and the presence of children is likewise taken from the CPS or related Census data sources. Labor market flows are calculated using the CPS matched basic monthly files from 2000–2019. Data on the share of households with traditional or modern social views is derived from the World Values Survey. Finally, auxiliary data used to calculate average child rearing duration comes from the National Survey of Family Growth (NSFG) and data on the returns to (broad) labor market experience is estimated using the National Longitudinal Survey of Youth 1997 (NLSY97).

Table A.2: Labor Supply 12 Months after Job Separation by Demographic Group

	NOT-EMPLOYED			
GROUP	**E-to-E**	**E-to-NE**	**DiD DATA**	**DiD REG**
sample population	0.049	0.393	–	–
by Gender				
men	0.039	0.346	0.061	0.062
women	0.060	0.429		(0.002)
by Gender, Marital Status, and Kids				
single men, no kids	0.059	0.394	0.008	0.006
single women, no kids	0.055	0.398		(0.004)
single men, small kids	0.059	0.313	0.076	0.071
single women, small kids	0.094	0.424		(0.012)
single men, big kids	0.052	0.366	0.028	0.024
single women, big kids	0.067	0.410		(0.011)
married men, no kids	0.037	0.342	0.066	0.066
married women, no kids	0.057	0.428		(0.004)
married men, small kids	0.027	0.279	0.147	0.150
married women, small kids	0.074	0.474		(0.006)
married men, big kids	0.029	0.286	0.114	0.116
married women, big kids	0.057	0.428		(0.005)

Notes: The table reports participation and employment rates 12-month after job loss. Outcomes are derived from the CPS Rotation Group from January 2000 to December 2019. The sample includes prime-age workers age 25 to 55 who completed all eight months in rotation. Small children are households with youngest child under age 5 and big children correspond to households with youngest child aged 5 through 13. Job loss is defined to include all observed job separations. Appendix Table A.3 presents robustness estimates which examine only involuntary separations.

A.5 Further Details on the Calibration Procedure and Moment Computations

Moments on the gender wage gap, labor supply, and labor market flows are calculated from the Current Population Survey. The primary sample includes all households ages 25 to 55 with non-missing entries for marital status, gender, and employment status. The age limit of 55 is chosen to be consistent with our focus on prime-age workers below an age when early retirement becomes common. Unless otherwise stated, the sample period spans the years 2017 to 2018. Individuals are grouped by gender (male, female), marital status (single, married), type of children (none, younger, older), employment status (not employed, part-time, full-time), and occupation type (telecommuting, non-telecommuting).

Child groups correspond to the age of the parents' youngest child in a household, with younger kids corresponding to ages 0–5 and older kids corresponding to ages 6–16. Employment groups

Table A.3: Labor Supply 12 Months after Involuntary Job Loss by Demographic Group

	NOT-IN-LABOR-FORCE				*NOT-EMPLOYED*			
GROUP	**E-to-E**	**E-to-NE**	**DiD DATA**	**DiD REG**	**E-to-E**	**E-to-NE**	**DiD DATA**	**DiD REG**
sample population	0.030	0.121	–	–	0.049	0.315	–	–
Gender								
men	0.019	0.085	0.066	0.065	0.039	0.299	0.020	0.023
women	0.042	0.175		(0.003)	0.060	0.339		(0.004)
Gender and Kids								
men, no kids	0.024	0.100	0.042	0.042	0.047	0.321	0.001	0.003
women, no kids	0.038	0.157		(0.004)	0.056	0.332		(0.005)
men, with kids	0.013	0.063	0.098	0.097	0.030	0.265	0.047	0.053
women, with kids	0.048	0.196		(0.005)	0.066	0.349		(0.006)
Gender, Marital Status, and Kids								
single men, no kids	0.029	0.115	0.012	0.009	0.059	0.344	-0.014	-0.016
single women, no kids	0.034	0.132		(0.006)	0.055	0.326		(0.007)
single men, with kids	0.024	0.079	0.071	0.067	0.055	0.301	0.039	0.039
single women, with kids	0.045	0.172		(0.009)	0.075	0.360		(0.012)
married men, no kids	0.020	0.080	0.077	0.077	0.037	0.290	0.026	0.031
married women, no kids	0.042	0.179		(0.006)	0.057	0.337		(0.007)
married men, with kids	0.012	0.059	0.111	0.111	0.028	0.258	0.050	0.057
married women, with kids	0.049	0.208		(0.005)	0.064	0.344		(0.007)
Gender, Marital Status, and Detailed Kids								
single men, no kids	0.029	0.115	0.012	0.009	0.059	0.344	-0.014	-0.016
single women, no kids	0.034	0.132		(0.006)	0.055	0.326		(0.007)
single men, small kids	0.024	0.058	0.093	0.087	0.059	0.252	0.063	0.063
single women, small kids	0.060	0.186		(0.015)	0.094	0.350		(0.019)
single men, big kids	0.024	0.098	0.051	0.048	0.052	0.344	0.006	0.007
single women, big kids	0.039	0.164		(0.012)	0.067	0.365		(0.016)
married men, no kids	0.020	0.080	0.077	0.077	0.037	0.290	0.026	0.031
married women, no kids	0.042	0.179		(0.006)	0.057	0.337		(0.007)
married men, small kids	0.011	0.056	0.115	0.114	0.027	0.251	0.055	0.060
married women, small kids	0.060	0.220		(0.008)	0.074	0.353		(0.011)
married men, big kids	0.012	0.062	0.109	0.109	0.029	0.264	0.046	0.054
married women, big kids	0.042	0.201		(0.007)	0.057	0.338		(0.009)

Notes: The table reports participation and employment rates 12-month after job loss. Outcomes are derived from the CPS Rotation Group from January 2000 to December 2019. The sample includes prime-age workers age 25 to 55 who completed all eight months in rotation. Small children are households with youngest child under age 5 and big children correspond to households with youngest child aged 5 through 13. Job loss is conditioned on only involuntary separations, in contrast to Table 2 which considers all separations.

are identified using labor force status and usual hours worked. The non-employed includes those who are either unemployed or not in the labor force, part-time includes all those who are employed and usually work fewer than 35 hours per week, and full-time includes all those who usually work more than 35 hours per week.

The gender wage gap is calculated as the average difference between hourly wage of employed men and women relative to the hourly wage of employed men, where wages are derived from CPS data on total annual income, weeks worked, and usual weekly hours.

Data on childcare requirements by gender, telecommuting status, and age of child are calculated using the American Time Use Survey. Childcare time includes all time diary entries related to (1) caring for and helping household children [030100], (2) activities related to household children's education [030200], and (3) activities related to household children's health [030300]. Time use variables are converted to average weekly levels by collapsing across household types using the ATUS supplied weights. The resulting childcare variables are then re-normalized to be consistent with the time endowment of the model, which sets full-time work equal to unity.

To compute the normal-times labor force participation rates (LFPRs), we take a long-run average of prime-age (25-54) male and female rates for between January 2000 and December 2019, using the corresponding FRED data series – [LRAC25MAUSM156S] is used for male LFPR and [LRAC25FEUSM156S] for female LFPR. We find that the average female LFPR over this period is 75.2%; for men, this is 89.7%.

A.6 Calibrating Child Dynamics

The parameters governing the distribution and aging of children are set to jointly match targets on the life cycle of child-rearing by gender and marital status. The moments governing the arrival rate of younger children, the aging of younger children into older children, and the aging of older children into adults are chosen to jointly match (1) the share of households with children, (2) the ratio of older to younger children, and (3) the average duration of child-rearing. Targets (1) and (2) are calculated from our primary CPS dataset so as to be consistent with our other targets. The average duration of child rearing is calculated by summing the duration of childhood in quarters (16×4) with the median inter-pregnancy interval (measured in quarters) multiplied by the average number of children minus one. The inter-pregnancy interval value is taken from the National Survey of Family Growth.

Given the three targets for each group (single men, single women, and couples) in Table A.4, plus the restrictions on the transition matrices in Section 3.5, we have an exactly identified calibration.[33] We can compute the expected child-rearing time over the infinite-horizon using that the expected

[33] It is worth noting that the share of households with children is higher than that of the total population, driven by the age cutoffs for the calibration of 25–55 years old.

Table A.4: Targeted Moments for Child-Rearing Dynamics

Moment	Data	Model
Single women		
Share with children	0.35	0.35
Ratio older-to-younger children	1.67	1.67
Avg. duration of child-rearing (quarters)	88.61	88.61
Single men		
Share with children	0.15	0.15
Ratio older-to-younger children	1.30	1.30
Avg. duration of child-rearing (quarters)	83.23	83.23
Couples		
Share with children	0.69	0.69
Ratio older-to-younger children	1.17	1.17
Avg. duration of child-rearing (quarters)	88.59	88.59

Notes: The table reports the model vs. data moments on child-rearing dynamics. The transition probabilities for each of the three groups are set to match these moments.

time in each kids state is

$$\sum_{t=0}^{\infty}(1-\pi_{exit})^t,$$

where π_{exit} is the probability of transitioning out of that state, either because of the survival probability or because of transitioning to a different kids state.

The expected duration in the small kids state is

$$\frac{1}{(1-\omega)+\pi(b \mid s)} + \frac{\pi(b \mid s)}{(1-\omega)+\pi(0 \mid b)},$$

and the expected time in the big kids state is

$$\frac{1}{(1-\omega)+\pi(0 \mid b)}.$$

Then, weighting by the stationary fraction of households in each state $k \in \{s, b\}$ gets the total expected time conditional on having kids. For example, for single men, the expected duration is

$$\frac{F_s}{F_s+F_b}\left(\frac{1}{(1-\omega)+\pi(b \mid s)} + \frac{\omega \cdot \pi(b \mid s)}{(1-\omega)+\pi(0 \mid b)}\right) + \frac{F_b}{F_s+F_b}\left(\frac{1}{(1-\omega)+\pi(0 \mid b)}\right).$$

where F_k is the stationary fraction of households with kids of age k.

The share with children and ratio of older-to-younger children give us the distribution across kids' ages; the expected duration then provides some additional restrictions on the magnitudes of the transition probabilities. Given these moments, we can numerically solve for the transition probabilities that satisfy the stationary distribution and the expected duration, exactly matching the data values. The resulting parameters are given in Table A.5

Table A.5: Child Transition Probabilities

Parameter	Value	Interpretation
$\pi^m(s \mid 0)$	0.0004	Single men: no kids to small kids
$\pi^m(b \mid s)$	0.0055	Single men: small kids to big kids
$\pi^m(0 \mid b)$	0.0042	Single men: big kids to adults (no kids)
$\pi^f(s \mid 0)$	0.0011	Single women: no kids to small kids
$\pi^f(b \mid s)$	0.0055	Single women: small kids to big kids
$\pi^f(0 \mid b)$	0.0033	Single women: big kids to adults (no kids)
$\Pi(s \mid 0)$	0.0045	Couples: no kids to small kids
$\Pi(b \mid s)$	0.0044	Couples: small kids to big kids
$\Pi(0 \mid b)$	0.0037	Couples: big kids to adults (no kids)

Notes: The table reports the model parameters used to compute the transition matrices for children. The matrices are constructed using these parameters and as described in Section 3.5.

A.7 Calibrating Skill Formation

The human capital grid consists of five grid points with a constant ratio of 1.4 between adjacent points (i.e., moving one step up the ladder increases full-time earnings by 40 percent). The constant ratio of grid points implies that returns to experience and the impact of skill loss are equalized along the grid. We identify the initial position of individuals in the human capital grid using their hourly wage in the CPS. The grid values are initialized so that the boundary between the first and second skill regions equals the average wage of the employed population. The initial distribution of individuals on the grid is chosen to match the (joint) distribution of wages by gender and marital status for those aged 25 to 30.[34] Specifically, we assign to the first grid point the share of people with incomes below the first grid point, to the second grid point we assign the share of all those between the first and second grid points, and so on. Couples are initialized on a two-dimensional grid to capture the assortativeness of marriage markets. Table A.6 summarizes the initial distribution of human capital for single men, single women, and the joint distribution for couples.

The parameters that govern human capital dynamics on the grid are δ and η. Both parameters map analytically into observable data moments. Specifically, the expected wage growth amongst employed individuals will equal ηh_{step}. We therefore set η to match a 1.1 percent average quarterly return to labor market experience that we estimate from longitudinal micro-data in the NLSY97

[34] Couples are included in the sample based on the age of the husband.

Table A.6: Initial Distribution of Human Capital by Gender and Marital Status

Couples					
Husband \ Wife	(1)	(2)	(3)	(4)	(5)
(1)	0.652	0.094	0.003	0.000	0.000
(2)	0.155	0.089	0.002	0.000	0.000
(3)	0.003	0.002	0.000	0.000	0.000
(4)	0.000	0.000	0.000	0.000	0.000
(5)	0.000	0.000	0.000	0.000	0.000
Singles					
Men	0.825	0.170	0.005	0.000	0.000
Women	0.856	0.140	0.004	0.000	0.000

Notes: The table shows the distributions of human capital used to initialize the human capital of new cohorts in the model, calibrated to the CPS data. For couples, initial human capital is initialized over a joint distribution for both husband and wife.

controlling for individual and year fixed effects. Similarly, the expected wage loss from a quarter of unemployment is equal to δh_{step}. We therefore choose δ to match an average quarterly wage loss of 2.5 percent during non-employment, consistent with the annual estimates of lost earnings one year after job displacement in Davis and von Wachter (2011).

A.8 Labor Market Flows in Normal Times and Recessions

Moments related to labor market dynamics are derived from the CPS monthly outgoing rotation groups, between 2000 to 2019. The sample includes prime-age workers, ages 25 to 55, who are not retired or in the military. The non-employed includes both unemployed workers and those not in the labor force.

The model's job offer rates are calibrated to generate realistic labor market flows across employment and non-employment in steady state. The labor market flow targets for normal times are derived from the CPS outgoing rotation group during the sample period 2000 to 2019. Months that fall in NBER dated recessions are omitted from the calculation. In particular, this drops observations spanning the recession from March to November in 2001 and the Great Recession from December 2007 to June 2009. The transition rates are computed at the monthly frequency and then converted to quarterly rates by cubing the result. Table A.7 summarizes the results by reporting the estimated persistence of employment and non-employment by gender in non-recessionary periods used to calibrate the model's job offer rates in normal times.

Recessions are modeled as a temporary reduction in job offer rates which last for the duration of a typical recession. We calibrate the fall in job offer rates to match the typical employment decline during a recession. Specifically, we set the recessionary job offer rates to replicate the decline in employment by gender from the start to the end of the Great Recession, which lasted

Table A.7: Labor Market Flows in Normal Times, 2000-2019

Group	**Employment Persistence**	**Non-Employment Persistence**
Population	0.917	0.716
Men	0.929	0.623
Women	0.904	0.765

Notes: Table entries report the quarterly persistence, estimated from monthly flows, of employment and non-employment for the non-retired civilian sample population of 25 to 55 years old, and by gender. Normal times sample corresponds to non-recessionary months between 2000-2019, as dated by the NBER.

from December 2007 to June 2009.[35] Results are nearly identical if instead we target the fall in employment from peak to trough. Table A.8 summarizes the results by reporting the initial and terminal employment levels during the recession. Consistent with these results, the reduction in job offer rates are calibrated to generate the observed 87.6-81.7 = 5.9 percentage point decline in male employment and 74-71 = 3.0 percentage point decline in female employment between the initial levels and the trough of the recession.

Table A.8: Employment Dynamics during the Great Recession

Group	**Initial**	**Terminal**	**Peak**	**Trough**
Population	0.807	0.767	0.807	0.766
Men	0.876	0.824	0.876	0.817
Women	0.741	0.711	0.741	0.711

Notes: Table entries report monthly employment levels for the start, end, peak, and trough of the Great Recession, between December 2007 and June 2009. Results are reported for the sample population, as well as for men and women separately, and cover the non-retired civilian population, ages 25 to 55.

A.9 Calibrating Pandemic Offer Rate Shocks

We calibrate the offer rates during the pandemic to match the percentage point decline in the employment rate for the first six quarters of the pandemic; that is, we calibrate the employment rate drops for 2020q2 to 2021q3, relative to the employment rate as of 2020q1. Using the CPS monthly series (which is aggregated to quarterly data), we can compute separate rates for men and women, and so calibrate the series of shocks to be gender-specific. Each shock size is applied symmetrically to the job offer rates for both employed and unemployed agents. Table A.9 reports the resulting offer rates, as well as the additional childcare requirements for the first four quarters of the pandemic shock.

[35] This is the main recession in our sample period. The other is the more minor 2001 recession which was very short lived and featured little changes in aggregate employment.

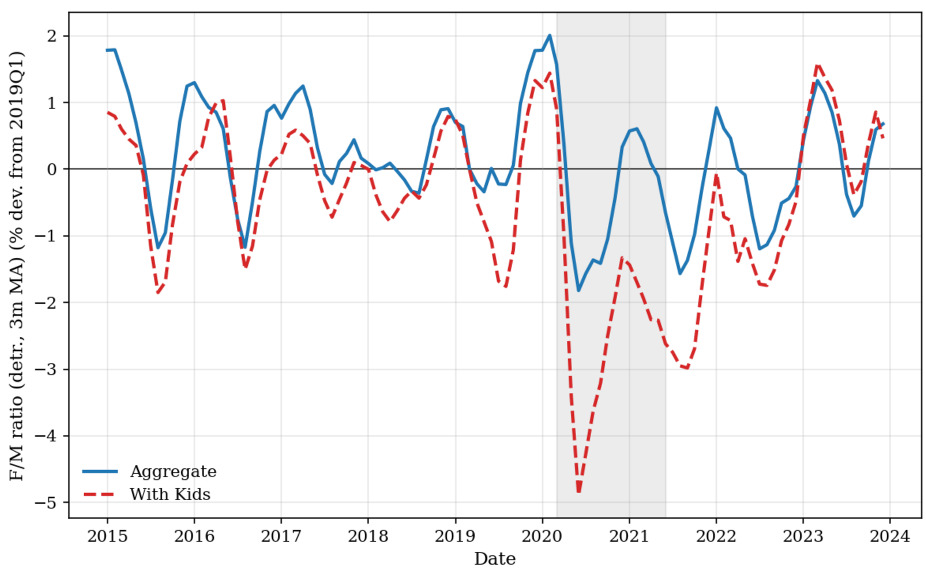
Table A.9: Pandemic Offer Rates and Childcare Requirements

Parameter	Interpretation	Normal	2020q2	2020q3	2020q4	2021q1	2021q2	2021q3
π^m_{EE}	Offer rate, employed men	0.955	0.865	0.954	0.947	0.934	0.942	0.953
π^m_{UE}	Offer rate, unemployed men	0.423	0.333	0.422	0.415	0.402	0.41	0.42
π^f_{EE}	Offer rate, employed women	0.988	0.878	0.979	0.987	0.969	0.96	0.972
π^f_{UE}	Offer rate, unemployed women	0.511	0.401	0.502	0.51	0.492	0.482	0.495
$\gamma(s)$	Childcare time, younger kids	0.342	0.41	0.41	0.41	0.41	0.342	0.342
$\gamma(b)$	Childcare time, older kids	0.106	0.127	0.127	0.127	0.127	0.106	0.106

A.10 Additional Empirical Results

Figure A.1 below shows the ratio of female-to-male employment rates between 2015 and 2024, as computed from the monthly CPS data. The male and female employment rates are independently detrended using an estimated linear trend from January 2015 to December 2019, after which the ratio is computed and a three-month simple moving average is applied. The aggregate employment rates and those conditional on having children are computed (and detrended) separately before any ratios are taken.

Figure A.1: Female/Male Employment Ratio, Detrended



Notes: The figure shows the ratio of female-to-male employment rates using the monthly CPS data and as described in Appendix A.10.

B Online Model Appendix

B.1 Details on Computing the Model

Value and policy functions. The model is solved with value function iteration using the discrete-continuous endogenous grid method (DC-EGM; Iskhakov et al. 2017), given that we use discrete choices over labor supply. The five-point grid for human capital is described in section A.7. The asset grid is discretized and has 100 log-spaced points on the interval 0 to 350 times the maximum income.[36]

The initial guess for the value function is a fixed fraction (10%) of cash-on-hand. In each step, the expected marginal continuation value is computed, the endogenous grid is solved for, and then the upper-envelope step is applied to smooth out any non-monotonicity in the endogenous asset grid. Given these policies and value functions conditional on labor supply choices, the taste shocks are applied (see Appendix B.2 for further details) and the updated expected (marginal) continuation value is computed for the next step of the iteration. We continue until the difference in the marginal values is within the tolerance threshold (1×10^{-9}).

Note that we simultaneously solve the policies for each of the aggregate states. While the normal and new-normal steady states can be solved independently of the values of other aggregate states, given that households expect to stay in these states forever, the value of being in a recession state depends on the steady state values. For both regular recessions R and pandemic recessions P, the probability that the recession will end in every period is set to $1/6$, that is, $\rho_R = \rho_P = 5/6$, and, therefore, the value of the steady states feeds into the shock states through the expected continuation values.[37]

Stationary distribution. Given the optimal policies and transition probabilities, we solve for the stationary distribution. Starting from an arbitrary initial distribution, we iterate the distribution forward one period at a time using the transition rules implied by the savings and labor supply policies and the exogenous transition rules for the various states. Because the asset choices do not necessarily lie directly on a grid, we apply a deterministic method of splitting the mass over the two bracketing gridpoints, with the split of mass depending on the distance to the grid points. As an illustration, consider iterating forward one cell of mass 0.1 with asset policy 0.16, lying between gridpoints 0.1 and 0.2: in this case, a mass of 0.06 would transition to asset gridpoint 0.2 and 0.04 would transition to asset gridpoint 0.1, where we have applied the formula:

$$\Pr(a' = a_i) = \frac{a_{i+1} - a^{pol}}{a_{i+1} - a_i},$$

[36] This multiplier is set such that the asset policy of agents is not extrapolated off of the asset grid.

[37] Note that the expected probability of a shock ending corresponds with the actual shock duration that we consider in Section 5, which is implemented through two "MIT" shocks that bring about the start and end of the recessions.

where i is used to denote the index of the lower bracketing asset gridpoint and a^{pol} denotes the "off-grid" asset policy. We continue the forward iteration on the distribution until the maximum absolute cell-wise change in the distribution is below the tolerance threshold (1×10^{-9}).

Calibration. Starting from an initial guess of model parameters Θ_0, the model parameters are chosen to minimize the loss function:

$$\mathcal{L} = \sum_{k \in \mathcal{M}} w_k \frac{\mid m_k^{model} - m_k^{data} \mid}{\mid m_k^{data} \mid},$$

where $\mathcal{M}$ is the set of moments in Table 5 and w_k is the weight associated with the kth moment in $\mathcal{M}$. The weights used are given in Table B.1 below.

That is, for a given set of model parameters Θ, we solve the value and policy functions, find the stationary distribution, and compute the values of the targeted moments in the model as well as the loss function. We minimize the loss over Θ using the Nelder–Mead simplex algorithm. The search is confined to bounds on each parameter set from prior testing, and terminates at the first of four conditions: (i) the parameter values and the loss both change by less than 1×10^{-3} between iterations; (ii) the weighted loss falls below 0.01 (an average absolute deviation of about one percent); (iii) the loss does not improve over 30 consecutive evaluations; or (iv) the algorithm reaches 500 iterations. We report the parameter vector that attains the lowest loss across all evaluations.

B.2 Taste Shocks

Given that labor supply in the model is a discrete choice, i.e., $n \in \{0, 0.5, 1\}$, we apply "taste shocks" to smooth these choices and allow us to create differentiable expected value functions to use in the discrete-continuous endogenous gridpoint method (DC-EGM) algorithm. More specifically, we add an i.i.d. taste shock ϵ drawn from a Type I Extreme Value (Gumbel) distribution with scale parameter σ, location-normalized so that $\mathbb{E}[\epsilon] = 0$, to the value from each feasible labor supply option. The resulting logit-choice probabilities and log-sum expected values are differentiable in assets, enabling the DC-EGM algorithm to be applied to the continuous consumption-savings problem.

Let us focus on the case for couples (the version for singles is a simplified version where the household is choosing over just their own labor supply, rather than the joint decision). The joint labor supply choice set for a married couple when both spouses have a job offer is $(n^f, n^m) \in \{0, 0.5, 1\}^2$, giving nine possible choices. We first compute the value function conditional on choosing each combination of (n^f, n^m) and accounting for the re-entry costs given previous labor market states (n^f_{-1}, n^m_{-1}), as detailed in Section 3. Let us denote this by $V_{EE}(n^f, n^m \mid n^f_{-1}, n^m_{-1}; \mathcal{S})$, where we use

Table B.1: Moment weights in the calibration objective

Moment	**Weight (%)**
Labor supply (hours)	
Labor supply, single men	6.7
Labor supply, married men	8.0
Labor supply, single women	6.7
Labor supply, married women	8.0
Job flows	
Male E-to-E rate	4.0
Male U-to-U rate	4.0
Female E-to-E rate	4.0
Female U-to-U rate	4.0
Wage gap	
Gender wage gap (conditional on working)	4.0
Re-entry moments	
Non-reentry gap (F-M), married, no kids	3.3
Non-reentry gap (F-M), married, small kids	3.3
Non-reentry gap (F-M), married, big kids	3.3
Telecommuting	
Telecommute share	9.3
Childcare	
Fraction of childcare done by men, full-time couples	4.0
Childcare ratio (TC/NT): men, small kids, NT wife	4.0
Childcare ratio (TC/NT): women, any kids, NT husband	2.7
Social norms	
Ratio of M/F labor supply, traditional vs. modern couples	0.7
Part time moments	
Share of married mothers working part-time	1.3
Share of married mothers working full-time	1.3
Share of males working full-time	1.3
Share of females working full-time	1.3
MPCs	
MPC, couples	7.3
MPC, singles	6.7
Inequality	
Gini index, consumption	0.7

Notes: The table shows the weights applied (as a percentage of total weight) to the targeted moments in Table 5.

$\mathcal{S}$ to denote the other states for brevity. The probability of choosing $n^f = i$ and $n^m = j$ jointly is given by

$$P(n^f = i, n^m = j \mid n^f_{-1}, n^m_{-1}; \mathcal{S}) = \frac{\exp\big(V_{EE}(n^f = i, n^m = j \mid n^f_{-1}, n^m_{-1}; \mathcal{S})/\sigma\big)}{\sum_{(\tilde{n}^f, \tilde{n}^m) \in \{0, 0.5, 1\}^2} \exp\big(V_{EE}(\tilde{n}^f, \tilde{n}^m \mid n^f_{-1}, n^m_{-1}; \mathcal{S})/\sigma\big)}.$$

Choosing $n^f = 0$ or $n^m = 0$ implies using relevant value functions for unemployed agents, as discussed in Section 3. Since the nine taste shocks are i.i.d., the expected value prior to their realization is given by the log-sum formula

$$\tilde{V}_{EE}(n^f_{-1}, n^m_{-1}; \mathcal{S}) = \sigma \log \left(\sum_{(n^f, n^m) \in \{0, 0.5, 1\}^2} \exp \left(\frac{V_{EE}(n^f, n^m \mid n^f_{-1}, n^m_{-1}; \mathcal{S})}{\sigma} \right) \right),$$

which smooths out kinks in the value function and is differentiable in assets, allowing us to use the derivative of the continuation value to back out the consumption choice in the DC-EGM algorithm. The choice probabilities, $P(n^f, n^m \mid \cdot)$, weight the marginal utility of wealth across the discrete labor supply states, yielding smoother expected marginal value functions for the EGM step; both the log-sum integration and the EGM step are nested within the standard value function iteration loop.[38]

Two features of this setup are worth noting. First, the nine taste shocks are defined over the *joint* choice (n^f, n^m) rather than separately over each spouse's labor supply option; the logit is therefore computed simultaneously over all nine combinations, preserving the interaction between spouses' decisions through the shared budget constraint and childcare production function. Second, the cases in which one or both spouses lack a job offer follow the same structure with a restricted choice set. When only the wife receives an offer ($e^f = E$, $e^m = U$), the husband is constrained to $n^m = 0$ and the log-sum runs over the wife's three options alone. That is,

$$\tilde{V}_{EU}(n^f_{-1}; \mathcal{S}) = \sigma \log \left(\sum_{n^f \in \{0, 0.5, 1\}} \exp \left(\frac{V_{EU}(n^f \mid n^f_{-1}; \mathcal{S})}{\sigma} \right) \right),$$

and the case in which only the husband receives an offer is symmetric. When neither spouse has an offer, $n^f = n^m = 0$ is the unique feasible choice, no taste shock is drawn, and $\tilde{V}_{UU} = V_{UU}$ exactly.

For singles, the same logic applies to a single decision-maker choosing $n^g \in \{0, 0.5, 1\}$. When a single of gender g receives a job offer, each option is perturbed by an i.i.d. Type I EV taste shock

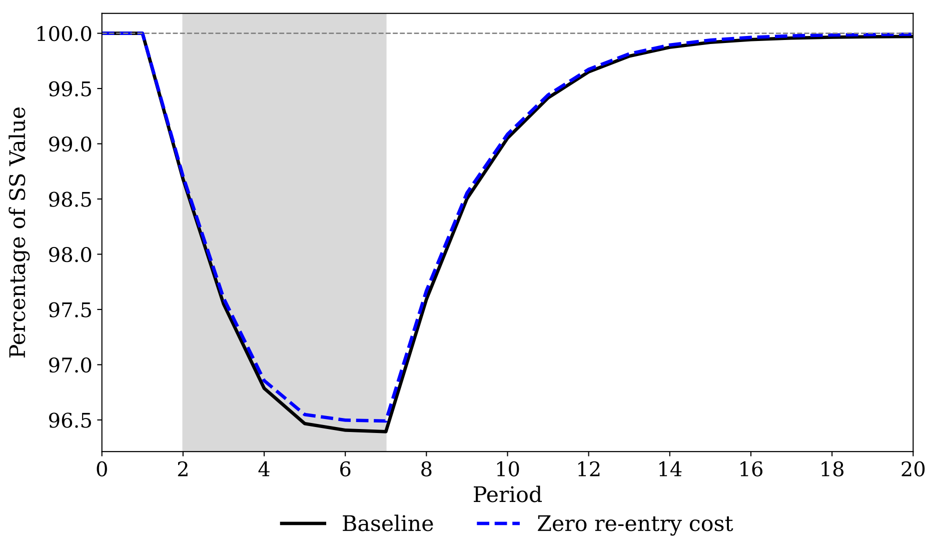
[38] Because the taste shocks do not fully remove non-convexity in the problem, we also apply the upper-envelope step to handle any non-monotonicity in the endogenous grid.

and the log-sum expected value $\tilde{v}_E^g(n_{-1}^g)$ is defined analogously to the couple's version described above; when no offer arrives, $n^g = 0$ is forced and no shock is drawn.

B.3 Additional Model Results

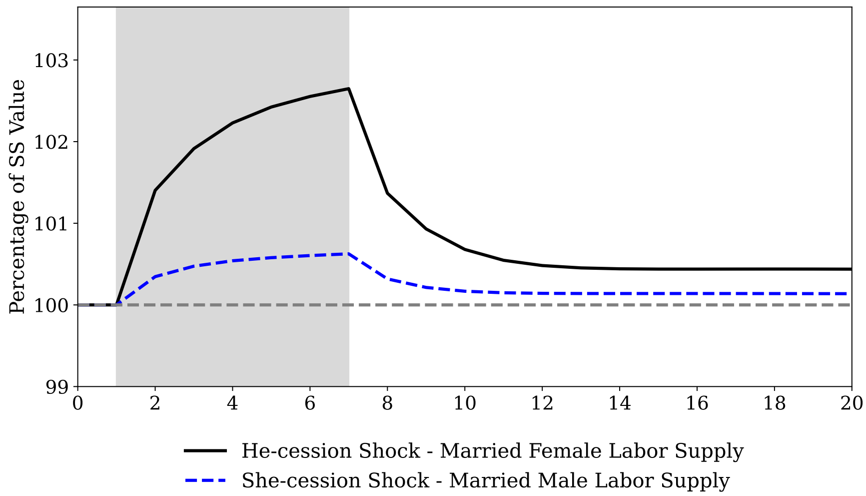
In this section, we present additional model results as referenced in the main body of the paper. Figure B.1 compares the aggregate labor supply in the standard she-cession (as defined in Section 5.1) to the version where all re-entry costs are zero. Figure B.5 plots the change in employment rate during the childcare-only shock, plotting separate lines by gender and TC status. Figure B.2 repeats the added worker effects in Figure 2b without conditioning on spousal job loss; Figure B.3 computes the added worker effect as a difference-in-differences, relative to the control group whose spouse does not lose their job in the first period of the shock. Table B.2 shows the difference between the Normal and New Normal steady states when changing only the TC transitions or only social norm transitions.

Figure B.1: Aggregate Labor Supply in She-cession: Comparison with Zero Re-entry Costs



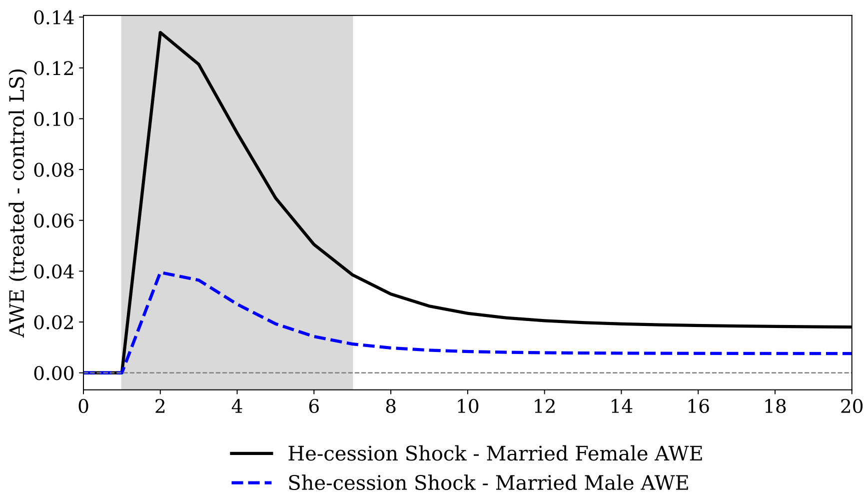
Notes: This figure plots the percentage deviations of the aggregate labor supply from its steady state level. The black line ("baseline") shows the standard she-cession and parameterization as discussed in the text (see Figure 2a for more detail). The blue dashed line ("zero re-entry cost") shows the aggregate labor supply for the same shock but setting all re-entry costs to zero (for the steady state and shock periods).

Figure B.2: Response of Married Male (Female) Labor Supply in a She-cession (He-cession), All Couples



Notes: The figure plots the response of married male labor supply during a she-cession shock, compared to the response of married female labor supply during a he-cession shock. Unlike Figure 2b, this does not condition on spousal job loss.

Figure B.3: He-cession vs She-cession - Added Worker Effect (Conditional on Spousal Job Loss)



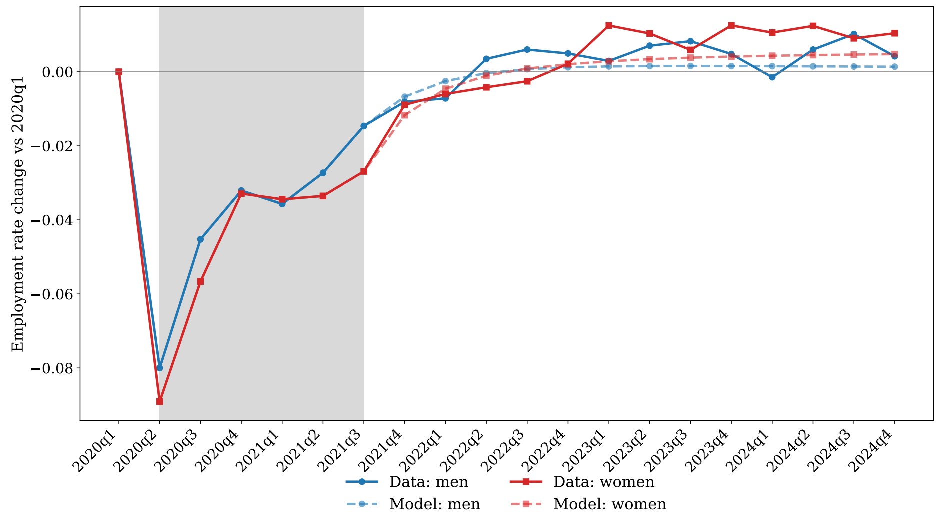
Notes: The figure shows the Added Worker Effect (AWE) in terms of additional labor supply. It computes the increase in labor supply conditional on spousal job loss in the first period of the shock (period 2) relative to the control group whose spouse did not lose a job in the first period of the shock.

Table B.2: Normal vs New-Normal Moments: TC & Norms Decomposition

Moment	**N**	**NN**	**Δ(N→NN)**	**TC**	**TC Δ from N**	**Norm**	**Norm Δ from N**
Transitions							
Telecommuting share	0.07	0.28	293.1%	0.28	293.3%	0.07	-0.1%
Share of couples with traditional norms	0.22	0.11	-50.0%	0.22	0.0%	0.11	-50.0%
Labor supply and participation rates							
Labor supply, aggregate	0.72	0.73	0.7%	0.73	0.5%	0.72	0.2%
Labor supply, married men	0.83	0.82	-1.4%	0.83	-0.7%	0.83	-0.8%
Labor supply, married women	0.66	0.68	3.0%	0.66	1.2%	0.67	1.9%
Labor force participation rate, men	0.94	0.93	-0.3%	0.94	0.1%	0.93	-0.4%
Labor force participation rate, women	0.84	0.85	1.3%	0.85	0.7%	0.85	0.6%
Human capital and wages							
Gender earnings gap (conditional on working)	0.28	0.27	-3.1%	0.28	-1.0%	0.27	-2.2%
Gender wage gap (conditional on working)	0.21	0.21	-1.2%	0.21	-0.1%	0.21	-1.2%
Average human capital, men	2.23	2.22	-0.3%	2.23	-0.0%	2.22	-0.3%
Average human capital, women	2.14	2.15	0.8%	2.14	0.3%	2.15	0.6%
Childcare							
Fraction of childcare done by men, all couples	0.28	0.35	26.0%	0.3	7.4%	0.33	17.5%
Re-entry moments							
Non-reentry gap (F-M), married, no kids	0.13	0.12	-5.2%	0.13	-3.0%	0.13	-2.2%
Non-reentry gap (F-M), married, small kids	0.23	0.2	-12.8%	0.22	-4.8%	0.21	-8.7%
Non-reentry gap (F-M), married, big kids	0.19	0.17	-10.7%	0.18	-6.3%	0.18	-4.5%
Consumption and wealth							
Average MPC	0.24	0.25	0.4%	0.24	0.1%	0.25	0.3%
Aggregate household income	2.55	2.56	0.5%	2.56	0.3%	2.56	0.3%
Aggregate consumption	2.55	2.57	0.5%	2.56	0.3%	2.56	0.3%
Aggregate wealth	0.44	0.43	-1.8%	0.43	-0.6%	0.43	-1.2%

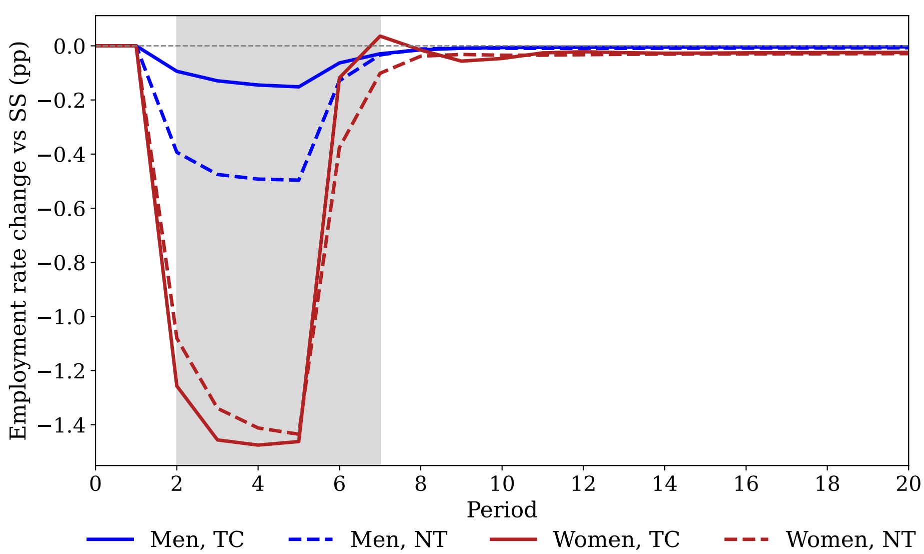
Notes: The table shows the steady-state moments in the normal and new-normal times, with two additional sets of results for which which the normal-times steady state is re-computed using, one at a time, the (1) new-normal TC and (2) new-normal traditional social norm persistence. The corresponding parameters for these states can be found in Table 7.

Figure B.4: Employment Rates: Model vs Data



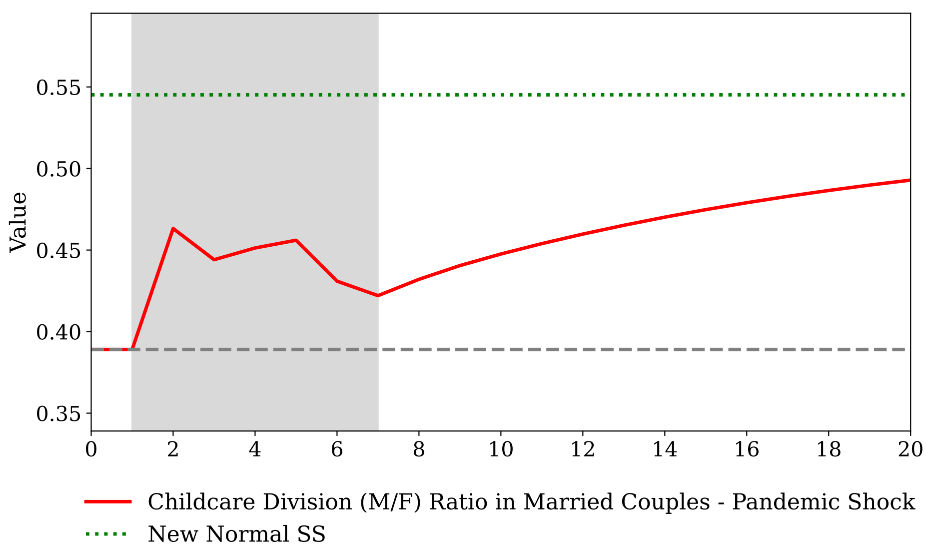
Notes: The figure shows the percentage-point deviations in male and female employment rates in the data between 2020Q1 (base) and 2024Q4, with the model values overlayed. For the first six quarters of the pandemic (2020Q2 to 2021Q3), the change in the offer rates are calibrated such that the model matches the empirical percentage-point decline in the employment rate. The data uses the monthly CPS series, which is then aggregated to quarterly using an average of the values for the three months in a given quarter. The pandemic labor market shocks apply from periods 2 to 7, whereas the pandemic childcare shocks apply for periods 2 to 5. The corresponding parameters for these shocks can be found in Table A.9.

Figure B.5: Employment Rate Changes: School and Daycare Closure Shock Only



Notes: The figure shows the changes in employment rates for different gender-occupation groups for the childcare shock described in Section 5.2 and parameterized in Table A.9.

Figure B.6: Gender Division of Childcare: Pandemic Recession



Notes: The figure shows the changes in the ratio of male to female childcare time in married couples in the model during the pandemic shock describe in Section 5.2 and parameterized in Table A.9.