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A Macroeconomic Analysis of Household Labor Supply Responses to Large Fiscal Transfers*

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Abstract

The fiscal transfers deployed during the COVID-19 pandemic were unprecedented in scale and strongly progressive. Using CPS/ASEC data, we document that the decline in employment during the pandemic was larger for low-income households and tightly linked to the intensity of transfer receipt, a pattern absent during the Global Financial Crisis. We develop and estimate a two-sector, heterogeneous-household general equilibrium model in which low-income households are borrowing-constrained in normal times but can save out of sufficiently large transfers. Because preferences permit wealth effects on labor supply, transfers both reduce labor supply and raise consumption, and a dollar of transfers is split roughly evenly between the two margins. We find that the effects of transfers are state-dependent: because the borrowing constraint binds more tightly in a deeper recession, the same transfer relaxes a tighter constraint and delivers an employment and consumption response about 40 to 50 percent larger during the pandemic than when the same transfer is introduced in the steady state. In the model, transfers were welfare-improving for recipients, with gains diminishing as transfers increase.

JEL Classifications: E24, E62, J22.

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1 Introduction

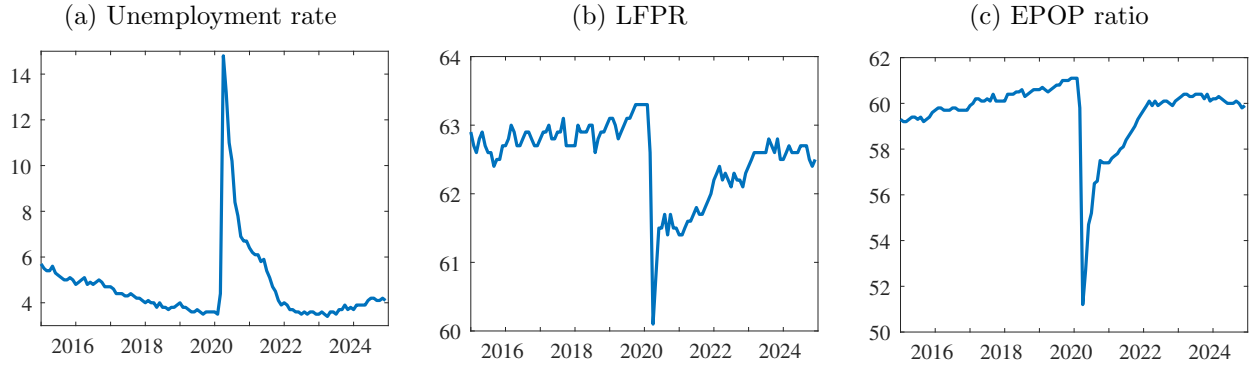
When the COVID-19 pandemic hit in early 2020, the unemployment rate spiked abruptly—from 4 percent to nearly 15 percent—before retracing much of that increase within months and falling below 7 percent by the fall of the same year (see Figure 1a). By conventional measures, the recession was unusually short-lived. Far more persistent, however, was the contraction in labor supply. The labor force participation rate fell by more than 3 percentage points at the onset of the pandemic, an unprecedented decline in postwar data (Figure 1b). Although roughly 40 percent of this initial drop was reversed relatively quickly, participation recovered only gradually thereafter, taking more than two years to return to its pre-pandemic trend. The employment-to-population (EPOP) ratio exhibited similar dynamics (Figure 1c), with a sharp initial decline followed by a protracted recovery.

Fiscal policy responded with an unprecedented expansion of government transfer programs, including economic impact payments in 2020 and 2021, enhanced unemployment insurance benefits, and expanded child tax credits. As we document, these transfers were exceptionally large by historical standards and strongly progressive in their incidence. Another striking feature of the 2021–2023 period was the unusually high level of household savings, which was observed even among lower-income households. These patterns point to possible linkages between government transfers, work incentives, and households’ consumption-saving choices. Our aim is to quantify the macroeconomic effects of these large-scale fiscal transfer programs. Although we primarily concentrate on their implications for labor supply incentives, we also examine how they affected aggregate consumption and output.

Using data from the Current Population Survey Annual Social and Economic Supplement (CPS/ASEC), we first present novel *household-level* evidence on EPOP ratios across the income distribution, alongside detailed measures of transfer receipts relative to household income during the pandemic and recovery. Focusing on households rather than individuals is critical in this context, as transfers are typically received and allocated at the household level and consumption, savings, and labor supply decisions are jointly determined within families. Household-level analysis is therefore closely aligned with the economic channels through which transfer policies affect employment and welfare, as it captures intra-household insurance mechanisms (through income pooling, shared consumption, and labor supply adjustment) that are obscured in individual-level data.¹

¹Focusing on the household is essential because labor supply responses to transfers are not confined to the direct recipient. In a randomized guaranteed-income experiment, Rhodes et al. (2026) find that when one household member receives a transfer, partners and other members reduce their own labor supply by a comparable amount, so that household income excluding the recipient falls substantially.

Figure 1: Aggregate Labor Market Outcomes 2015–2024 (in percent)



Notes: We plot monthly seasonally adjusted data retrieved from FRED.

The COVID-19 episode provides a unique setting for studying the employment and welfare effects of large fiscal transfers: The scale of fiscal transfers during 2020–2021 was unprecedented, far exceeding the magnitude observed during the Global Financial Crisis (GFC), and their incidence was highly progressive across the income distribution. We document two novel empirical findings. First, time-series variation in EPOP ratios across household income groups is tightly linked to the intensity of transfer payments: income groups receiving larger transfers relative to income experienced larger and more persistent declines in employment, followed by a slower recovery.² These relationships are reflected in high rank correlations between transfer intensity and employment outcomes throughout the pandemic and recovery period. Second, income heterogeneity emerges as a much more salient dimension of differential employment dynamics than other forms of individual-level heterogeneity, such as education, age, or race. Interestingly, these patterns are in sharp contrast to those observed during the GFC, when employment dynamics were far less aligned with income-based transfer exposure.

These empirical relationships are not necessarily causal. Two confounding forces are particularly relevant. On the demand side, adverse shocks disproportionately affected low-income households, whose members are more likely to work in sectors that experienced the largest contractions during the pandemic, particularly low-wage, contact-intensive service industries. On the supply side, workers in these same industries faced higher exposure to health risks, leading to elevated illness-related labor supply disruptions. As a result, either force could generate similar employment dynamics across income groups even in the absence of the expansion of government transfers. Disentangling these demand- and supply-side

²The same pattern holds when we consider labor force participation rates by income groups.

mechanisms requires a quantitative model that jointly incorporates both forces and disciplines them using household- and industry-level data on quantities and prices, as explained in greater detail below.

To this end, we develop a general equilibrium model with two production sectors, two types of households, and two types of workers. On the production side, the economy consists of a low-wage and a high-wage sector. The low-wage sector employs only low-skilled workers, while the high-wage sector employs only high-skilled workers. On the household side, the economy features high- and low-income households. The high-income household is made up of a continuum of high- and low-skilled workers, while all members of the low-income household are low-skilled workers.³

We assume that low-income households are less patient than high-income households, so that their borrowing constraint binds and they hold no savings *in the steady state*. However, rather than treating them as permanently hand-to-mouth, we allow these households to accumulate savings when they receive sufficiently large government transfers. This feature allows us to account for nonlinear effects arising from the unprecedented magnitude of the transfers. It is well documented that aggregate household savings rose to exceptionally high levels during the recovery from the pandemic-induced recession (e.g., [Cox et al., 2020](#); [Chetty et al., 2024](#)). Following the methodology of [Aladangady et al. \(2022\)](#), we compute savings by income group and find that low-income households, who typically hold little to no wealth, accumulated a significant amount of assets over this period. Allowing for deviations from the hand-to-mouth assumption is therefore essential for estimating the effects of government transfers on both consumption and labor supply.

To disentangle the effects of the various forces at work during this period, we estimate the model with a wide range of exogenous disturbances: shocks to sectoral total factor productivity, preferences for nonemployment, price markups, the discount factor of high-income households, preferences across the two types of goods, the skill composition of high-income households, and transfers to constrained households. Our estimation relies on industry-level data for productivity, employment, prices, and wages, along with the paths of EPOP ratios for low- and high-income households, which we map directly into the model’s two-sector, two-household, and two-worker structure. The observable variables also include the excess savings of low-income households over 2020–2023.

Our main model results, obtained through a series of counterfactual exercises, are three-fold. First, the 2020–2023 transfers substantially altered employment and consumption dy-

³Workers are split into two distinct groups, and there are no transitions from one group to the other.

namics. Relative to a counterfactual without the transfers, the EPOP ratio for low-income households was 1.9 and 1.4 percentage points lower in 2020 and 2021, respectively. Additionally, these households exhibited higher consumption throughout 2020–2023 and accumulated substantial savings. This last feature matters for the dynamics: because our model allows constrained households to save out of large transfers, they smooth consumption over time. When we instead assume that these households are always hand-to-mouth, they exhibit a larger consumption response in the first two years of the transfer receipt but much lower consumption once transfers cease. In our baseline specification (which allows low-income households to save), we estimate that fiscal transfers reduced the aggregate EPOP ratio by 0.2 to 0.4 percentage point per year over 2020–2023. Although this may seem modest against the large swing of the aggregate EPOP ratio, which fell by roughly 4 percentage points between 2019 and 2020 before recovering about 1.6 percentage points in each of the next two years, it is far from negligible and is comparable to the year-to-year movements in the EPOP ratio observed in normal times. We estimate that, although the transfers supported consumption by recipient households, they did little to lift aggregate consumption relative to the no-transfer counterfactual, because high-income households reduced their consumption as their tax burden increased.⁴ On net, we estimate that aggregate output declined as a result of the transfers. There are two forces at work. On the demand side, the additional spending by recipient households is largely or fully offset by the reduction in consumption by high-income households, so aggregate consumption changes little. On the supply side, the transfers reduce output through the same labor supply channel that drives our other results. As low-income households reduce their labor supply, output in the sector where they are employed falls directly through lower employment. Lower employment also reduces the marginal product of capital in that sector, which lowers investment and the capital stock. Thus, although investment is a component of aggregate demand, its decline here originates in the labor supply response.

Our second model result is that the effects of transfers are state-dependent. Because low-income households are more tightly constrained in a depressed economy, the same transfer relaxes a tighter constraint and therefore delivers a larger response when deployed during the pandemic than when introduced in the steady state. Comparing the two counterfactuals, we find that the pandemic amplifies the consumption and labor supply responses to transfers by roughly 40 to 50 percent at their peak. Most of the literature on transfers studies the con-

⁴In our model, 25 percent of the population resides in constrained households that receive transfers, while the remaining 75 percent is unconstrained and pays lump-sum taxes to finance these transfers.

sumption response, and the literature on state dependence focuses on government spending and output multipliers. Our contribution is to incorporate the labor supply response and demonstrate that it is also state-dependent, operating through wealth effects on labor supply. Because our model is fully structural, the source of the amplification is visible in the path of the shadow value of the borrowing constraint, rather than inferred from a reduced-form nonlinearity.

Third, the fiscal transfers were welfare-improving for the recipients: without transfers, low-income households would have suffered a consumption-equivalent welfare loss of 0.84 percent, while high-income households, who finance the transfers through a lump-sum tax, would have gained only 0.03 percent. We emphasize that in our model, the decline in employment is not a distortion to be weighed against these gains. It is the optimal response of households whose borrowing constraint the transfer payments relaxed, exercising a wealth effect on their labor supply. We also show that the welfare effects of transfers are nonlinear in their size. For example, doubling the observed transfers raises the welfare of low-income households further, but by less per dollar than the observed transfers delivered, because once households are pushed off the borrowing constraint, the marginal utility of consumption falls, and each additional dollar yields a smaller welfare gain.

Relation to the literature. Our paper contributes to several strands of research. First, it relates to work on the macroeconomic effects of fiscal policy under incomplete markets and sectoral heterogeneity during the pandemic. [Guerrieri et al. \(2022\)](#) show that sector-specific supply disruptions can induce aggregate demand shortfalls when goods are poor substitutes and constrained workers lose income.⁵ [Faria-e-Castro \(2021\)](#) models the pandemic as a demand shock to contact-intensive services and finds unemployment insurance effective at stabilizing constrained households’ income. [Bayer et al. \(2023\)](#) study a HANK model with a “quarantine shock” and document larger multipliers for transfers that mitigate income risk. We share the incomplete-markets, two-sector structure, but our focus is the labor supply response to transfers rather than the demand-side transmission of the shock itself.

A related strand analyzes the pandemic labor market through search-and-matching models with worker heterogeneity, emphasizing that job losses fell on low-skilled workers and predicting a slow, unequal recovery ([Gregory et al., 2020](#); [Ravenna and Walsh, 2022](#)). We abstract from search frictions for two reasons. First, models without an explicit labor sup-

⁵Related contributions examining how supply disturbances can give rise to aggregate-demand amplification effects include [Bilbiie and Melitz \(2020\)](#), [Baqae and Farhi \(2022\)](#), and [Fornaro and Wolf \(2023\)](#), each emphasizing a distinct transmission mechanism.

ply margin, such as two-state search-and-matching models, cannot capture the labor supply responses that are the focus of our analysis. Empirically, the 2020 unemployment spike reflected temporary layoffs more than sustained search, and participation movements were central to employment dynamics (Cajner et al., 2020; Forsythe et al., 2022; Hall and Kudlyak, 2022). Second, the temporary decoupling of unemployment insurance (UI) eligibility from job search blurred the line between unemployment and nonparticipation. We therefore adopt a neoclassical framework in which labor supply is governed by an intratemporal optimal condition, and any residual wedge is captured by a preference shifter.

The literature on the labor supply effects of pandemic transfers has focused mainly on how the \$600 and \$300 weekly UI supplements affected job search, with Coombs et al. (2022) and Ganong et al. (2024) providing well-identified estimates of increased job-finding probabilities upon benefit expiration. These papers measure benefit generosity at the individual UI-recipient level. Our household-level approach instead captures how *total* transfer generosity relative to household income shapes labor supply, a distinct and arguably more policy-relevant object.

A large micro literature documents household spending out of pandemic transfers. Account-data studies find high MPCs concentrated among low-income, borrowing-constrained households (Baker et al., 2023; Chetty et al., 2024; Karger and Rajan, 2020), while survey-based estimates are much smaller (Parker et al., 2022). Reflecting a modest average response, much of the transfer income went unspent, fueling a historic rise in household savings even among lower-income households. These micro estimates may not be the right object for gauging aggregate effects. Ramey (2025) shows that high micro-level MPCs need not translate into large aggregate effects once general equilibrium effects are accounted for, and that the COVID-19 episode is difficult to interpret because many shocks operated simultaneously. Our framework points to a further reason why the measured spending response can be small. Existing evidence captures only the consumption margin. Through a wealth effect on labor supply, however, households may take part of a transfer as leisure or other non-market activities. A low MPC on goods may therefore reflect a substantial labor supply response rather than an ineffective transfer.

The labor supply margin is not only a logical possibility but a quantitatively important one. A distinct body of evidence shows that transfers reduce labor supply through income/wealth effects, particularly for the large transfers of the kind deployed during the pandemic. Using administrative data on lottery winners, Golosov et al. (2024) estimate that

a dollar of unearned income reduces labor earnings by roughly fifty cents.⁶ This magnitude is close to the cumulative marginal propensity to earn (MPE) implied by our model, in which a dollar of transfer is divided about evenly between higher consumption and reduced earnings, lending external support to the channel that is our focus. For transfers of the magnitude observed in 2020–2023, the labor supply margin is not a second-order refinement but a central channel. A framework that measures only the spending response could understate the total effect of the policy.

Building this labor supply channel into a quantitative model requires departing from common practice in the HANK literature, much of which eliminates the channel by adopting GHH preferences (Greenwood et al., 1988), thereby setting the MPE to zero (e.g., Bayer et al. (2023)).⁷ Auclert et al. (2023) formalize this tension as a trilemma: with frictionless labor supply, a model cannot simultaneously match high MPCs, a small MPE, and a moderate fiscal multiplier. Shutting off the labor supply response is the standard way to achieve the first two, at the cost of the third. A related route delivers a zero MPE not through preferences but by taking workers off their labor supply curve, using sticky wages and demand-determined labor (Erceg et al., 2000; Auclert et al., 2024; Hagedorn et al., 2019). We avoid both devices because they shut down the wealth effect on labor supply that is central to our analysis. We instead retain a nonzero MPE, motivated by two pieces of evidence: the pattern documented in Section 2, in which income groups receiving larger transfers experienced larger and more persistent employment declines, and the findings of the literature on large transfers discussed above. We set the extensive-margin elasticity to standard micro estimates reported by Chetty et al. (2013).

Organization of the paper. The rest of the paper is organized as follows. Section 2 presents the empirical evidence. Section 3 develops the model. The steady-state calibration strategy is discussed in Section 4. Section 5 presents a partial equilibrium version of the model to build intuition. Section 6 describes the details of the estimation of the model. Section 7 then performs a series of counterfactual exercises to assess the macroeconomic effects of fiscal transfers. Section 8 concludes.

⁶Recent randomized evidence points the same way: in a guaranteed-income experiment providing \$1,000 per month to low-income US households, Vivalt et al. (forthcoming) find that transfers reduce recipients' labor supply.

⁷Even in models with separable preferences, such as Kaplan et al. (2018), wealth effects on labor supply are present but play a minor role in the analysis.

2 Labor Market Outcomes by Household Income

This section presents empirical evidence on the relationship between household income and labor market outcomes, focusing on EPOP ratios by household income group. Additional evidence on unemployment and labor force participation rates by income is available upon request. While the existing literature has focused primarily on individual-level outcomes across age, education, race, and industry, our household-level analysis captures how heterogeneity in household income relates to employment dynamics. We analyze the period 2015–2023, treating 2015–2019 as the pre-pandemic baseline.

2.1 Data

We use data from the Current Population Survey March Supplement (Annual Social and Economic Supplement, ASEC). The supplemental surveys are conducted in March every year and ask about various income components for each household and its individual members for the previous calendar year. The ASEC data also include various labor market outcomes in the preceding calendar year, as well as the labor market status of the reporting individuals in the survey month (March). The ASEC sample typically covers about 75,000 households, including some that are not part of the March basic monthly sample.⁸

2.2 Household Income

We define “total household income” as the sum of the following items in the data: (1) farm income, (2) self-employment income, (3) wages and salaries, (4) annuities, (5) child support, (6) disability income, (7) dividend income, (8) retirement distributions, (9) education income, (10) financial assistance income, (11) interest income, (12) other income, (13) public assistance income, (14) pension income, (15) rental income, (16) social security, (17) supplemental security income, (18) survivor income, (19) unemployment compensation, (20) veteran payments, (21) workers’ compensation, (22) energy assistance, (23) food stamps, (24) economic impact payment (EIP), and (25) advance child tax credit.⁹ In the ASEC datasets, there is a variable called total household income (HTOTVAL), which is defined as the sum of items (1) through (21). However, for our purpose, we also include items (22) and (23), even

⁸Note that each year’s survey collects information on the preceding calendar year. The labor market status variable at the time of the survey (March) is an exception and is merged from the basic monthly survey, but again the supplement includes responses from an additional sample that is not part of the basic monthly survey. See page 2-2 of the Technical Documentation available [here](#).

⁹Item (12) corresponds to HOIVAL in the ASEC dictionary.

though those items are listed as non-cash benefits. Item (24), economic impact payment, is reported separately and is not part of HTOTVAL. This component is zero before the 2021 ASEC. For the 2021 dataset, the EIP variable is reported as a sum of Economic Impact Payment 1 (associated with the CARES Act) and Economic Impact Payment 2 (associated with the CRRSA Act). For the 2022 data, it corresponds to Economic Impact Payment 3 (associated with the ARP Act). Item (25), the advance child tax credit, is nonzero only for calendar year 2021.

In the following analysis, we aggregate household members into four groups based on year-specific income quartiles. Table S.1 in the Appendix shows the minimum income level for each quartile of the household income distribution.¹⁰

2.3 Transfers

We define “transfers” as the sum of (13) public assistance income, (19) unemployment compensation, (22) energy assistance, (23) food stamps, (24) economic impact payment, and (25) advance child tax credit.¹¹

In the first column under each quartile of Table 1, we report the average share of transfer income in total household income for each income group between 2015 and 2023. The overall share increased from about 2 percent on average before the pandemic to above 10 percent during the pandemic years (not shown). Not surprisingly, the shares are higher and increased by more in 2020 and 2021 for lower income households relative to the previous years. For example, for the lowest income group, the share of transfers in total household income increased from about 6 percent in 2019 to around 25 percent in 2020 and remained at a similar level in 2021, before returning to pre-pandemic levels in 2022. In contrast, the increase in the highest income quartile was only 2.5 percentage points.

A large share of households within each income group received these transfers. In the second column under each quartile group, we report the share of households that receive any of the six types of transfers listed above. During the 2020–2021 period, almost all households in the three lowest income quartiles received some type of government transfers. In terms of composition, economic impact payments represented the largest share of all benefits over

¹⁰In a small number of instances, items (1) and (2) are reported as negative. This happens because self-employed respondents are asked to report net income (gross receipts minus expenses). When these income entries are negative, we set those values to zero, keeping the share of transfers between 0 and 1.

¹¹Comparing aggregate UI payments between ASEC and NIPA data reveals that UI benefits are under-reported in ASEC. The total EIP amount in the ASEC is fairly similar to the figure reported in NIPA, particularly when combined across 2020 and 2021 (\$844 billion in NIPA versus \$763 billion in ASEC).

Table 1: Share of Transfer Income and Share of Households Receiving Any Transfers (2015-2023)

Calendar Year	First Quartile		Second Quartile		Third Quartile		Fourth Quartile	
	% of Income	% with Transfer	% of Income	% with Transfer	% of Income	% with Transfer	% of Income	% with Transfer
2015	8.3	33.6	1.4	15.1	0.4	7.1	0.2	4.4
2016	8.2	32.6	1.2	13.4	0.4	7.0	0.1	4.2
2017	7.0	29.2	1.1	12.3	0.4	6.2	0.1	3.9
2018	6.6	29.1	0.9	11.9	0.3	6.1	0.1	3.9
2019	5.8	26.3	0.8	10.9	0.3	6.4	0.1	3.9
2020	25.6	97.3	11.0	99.8	6.7	95.3	2.6	69.8
2021	22.6	97.3	9.3	99.4	5.3	87.3	1.8	59.0
2022	7.3	30.1	1.2	13.9	0.4	7.8	0.1	4.0
2023	6.9	28.7	1.0	13.2	0.3	7.7	0.1	4.5

Notes: First column under each quartile: average shares (%) of transfer income in total household income; Second column: share (%) of households receiving any transfer income. Source: CPS/ASEC 2016–2024.

the 2020–2021 period, followed by expanded unemployment compensation (see Table S.3 in the Appendix for a breakdown of the average benefit amount per household).

2.4 Employment by Household Income

We now examine the relationship between employment and household-level income over the same sample period. Note that the household-income measures refer to the entire calendar year. To obtain comparable employment measures, we use the variable `wkswork` in the ASEC dataset, which records the number of weeks each respondent worked in the previous calendar year. We calculate the share of weeks worked for each respondent and interpret the average of these shares as the EPOP ratios for the calendar year. A direct measure of EPOP ratios (the share of employed individuals in the 16+ population) can be obtained by using the labor force status variable for the survey month (March) in the ASEC dataset. However, this measure is problematic, particularly because the March 2020 data point corresponds to the period immediately before the full impact of the pandemic, and by March 2021, the most severe effects of the pandemic had already passed. As a result, the March-to-March comparison does not accurately reflect the employment situation during this period.¹²

¹²An alternative way to obtain average EPOP ratios by income for the entire year is to link the ASEC data to the monthly basic CPS datasets. The drawback of this approach is that it greatly reduces the sample size. In addition, the ASEC respondents who can be linked to the monthly basic CPS datasets do not provide coverage for the entire year.

Table 2: Employment-to-Population Ratios (%) by Income (2015–2023)

Calendar Year	First Quartile		Second Quartile		Third Quartile		Fourth Quartile	
	Average	March	Average	March	Average	March	Average	March
2015	30.3	33.7	55.6	56.9	67.8	68.9	73.6	74.7
2016	30.3	33.4	56.7	58.3	68.4	69.6	73.5	74.7
2017	30.8	34.2	57.0	58.4	68.0	69.6	73.7	74.7
2018	31.8	34.9	57.2	58.9	68.8	70.0	73.8	74.8
2019	33.4	34.6	57.2	56.8	68.8	68.4	73.4	72.9
2020	27.4	31.3	52.5	55.3	64.4	67.1	71.3	73.3
2021	29.5	34.2	56.0	58.8	67.5	69.5	73.2	74.7
2022	30.0	33.8	57.0	58.5	68.3	69.9	74.3	75.6
2023	31.5	34.7	57.0	58.3	68.4	69.5	74.0	75.0

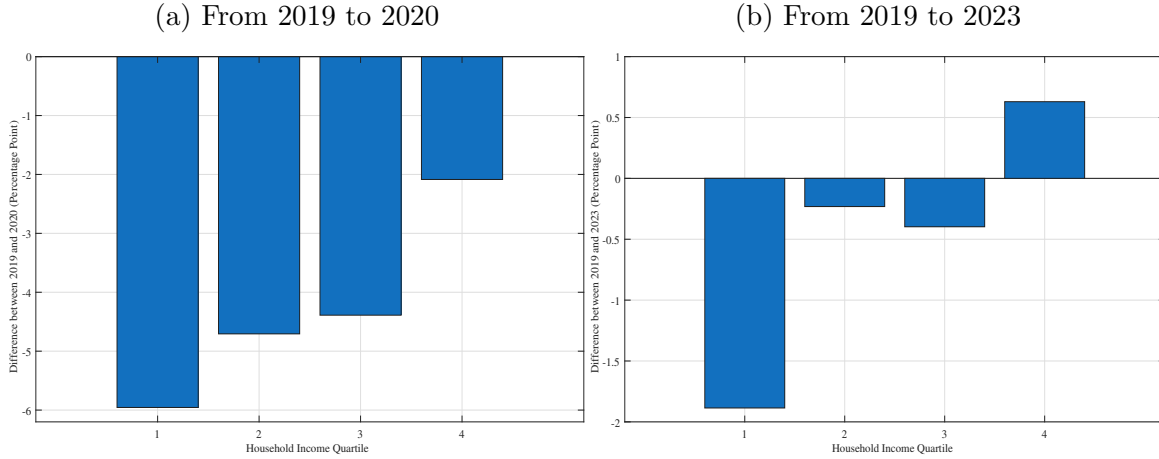
Notes: March values are based on the labor market status variable as of March within the ASEC data. Annual average values are based on the number of weeks employed in each calendar year, reported in the ASEC data in the following year. Source: CPS/ASEC 2016–2024.

For comparison purposes, Table 2 presents both measures, one based on the number of weeks in the preceding year and the other based on the status in the survey month. The two measures are generally close, although the average measures are slightly lower than the corresponding measures as of March.¹³ As mentioned above, the annual average values for 2020 show a much larger drop in employment from 2019 to 2020 than the corresponding values as of March.

One can clearly see a strong positive cross-sectional correlation between EPOP ratios and household incomes. In particular, the average EPOP ratio of household members in the lowest income quartile is about 30 percent over 2015–2023, while those in the highest income quartile have EPOP ratios close to 75 percent. More importantly, their changes between 2019 and 2020 are perfectly rank-correlated with the 2019 level. As shown in Figure 2a, the decline in 2020 relative to 2019 is the largest (6.0 percentage points) for the lowest income group. The size of the decline decreases as the income level increases: 4.7 percentage points (second quartile), 4.4 percentage points (third quartile), and 2.1 percentage points (fourth quartile). Furthermore, a similar pattern holds for recovery. When the levels of 2023 are compared with the levels of 2019 (Figure 2b), the EPOP ratio of the lowest income group remains well below its 2019 level. The EPOP ratios of the middle two groups are 0.2 percentage point and 0.4 percentage point below the level of 2019, respectively, while that

¹³This gap does not reflect seasonality, because the March EPOP ratio is not particularly high relative to its annual average. Instead, it likely reflects the fact that the annual measure is based on the number of weeks worked (`wkswork`).

Figure 2: Changes in Employment-to-Population Ratios



of the highest income group is 0.6 percentage point higher.

Other dimensions of heterogeneity. How does this heterogeneity by household income compare to other dimensions of heterogeneity? Table 3 presents the EPOP ratios by education, age, and race in 2019 and their changes in recent years. As in the case of household income, EPOP ratios are increasing in education and the differences in EPOP ratios across different education groups are large. However, the responses to the pandemic are not necessarily larger for the less educated group. The largest decline between 2019 and 2020 occurred among high school graduates (4.9 percentage points), followed by those with some college education (4.5 percentage points). Although the group with a college degree or more has the smallest decline in the EPOP ratio, the difference from the other groups is not as pronounced. In general, the employment response to the pandemic is relatively similar across the four education groups. The comparison between 2019 and 2023 does not exhibit an apparent ranking pattern. The cross-sectional differences in EPOP ratios by age and race are also substantial, but the rank correlations are again much less clear-cut. Unsurprisingly, the 55+ group has the lowest EPOP ratio, but its initial response to the pandemic is also the smallest. The initial response and recovery are broadly similar for the 16–24 and 25–54 groups.

Comparison with the GFC episode. Another useful comparison is with the GFC, when transfer programs were also enacted. However, a comparison of transfers as a share of income by income quartile, along with a comparison of the share of households receiving transfers between the two episodes, shows that the programs implemented during the COVID-19

Table 3: Changes in Employment-to-Population Ratios by Education, Age, and Race

	Education				Age			Race		
	<HS	HS	SC	C+	16–24	25–54	55+	White	Black	Asian
<i>Levels in 2019</i>	43.7	55.8	63.1	72.2	51.2	80.0	39.2	61.0	58.7	62.3
$\Delta(2020\text{--}2019)$	-4.1	-4.9	-4.5	-3.3	-5.3	-4.3	-2.7	-3.7	-5.1	-4.9
$\Delta(2023\text{--}2019)$	0.8	-1.3	-2.1	-0.7	0.6	0.8	-1.6	-0.7	1.0	0.8

Notes: Changes expressed in percentage points. HS = High School graduate; SC = Some College; C+ = College degree or higher. Education breakdown based on population 25 years and older. Source: CPS.

Table 4: Employment-to-Population Ratios by Income (2006–2014)

Calendar Year	First Quartile	Second Quartile	Third Quartile	Fourth Quartile
2006	33.1	59.6	71.6	74.9
2007	32.7	59.7	71.5	75.2
2008	32.1	57.8	69.9	74.7
2009	30.3	53.8	67.6	73.4
2010	28.4	53.4	67.2	72.4
2011	28.7	53.2	66.1	72.9
2012	29.0	53.6	66.8	73.2
2013	29.4	54.0	66.6	74.0
2014	29.8	55.2	67.2	72.8
Δ (2010–2007)	-4.3	-6.3	-4.3	-2.7
Δ (2014–2007)	-2.9	-4.5	-4.3	-2.4

Notes: Annual average values of EPOP ratios, based on the number of weeks employed in each calendar year, reported in the ASEC data in the following year. Source: CPS/ASEC 2007–2015.

pandemic were much larger, broader in scope, and more progressive (see Appendix Table S.2).

The responses of the EPOP ratios also differ, as shown in Table 4. Although the same cross-sectional differences in their levels across income groups remain, the declines in EPOP ratios occurred more gradually overall during the GFC, as did the recoveries. More importantly, there is no clear rank correlation between income levels and the magnitudes of contractions and subsequent recoveries. If we take 2007 as the peak year before the recession and 2010 as the trough year, the decline in the EPOP ratio is largest for households in the second quartile, while the EPOP ratios of households in the first and third quartiles fell by the same amount. Regarding the pace of recovery, we do not observe a clear correlation pattern between household incomes and changes in EPOP ratios.

In sum, the analysis of this section shows that employment dynamics during the pandemic

years were closely tied to household income and to the intensity of transfer receipt. This income gradient is far more pronounced than the corresponding differences by education, age, or race, and it is absent in the GFC episode. These relationships are not necessarily causal, and disentangling the role of government transfers requires the quantitative model developed in the remainder of the paper.

3 Model

This section presents the model. The economy consists of two production sectors, two types of households, two types of workers, and a government. We use a subscript $s \in \{1, 2\}$ to represent the production sector. The household type is represented by a subscript $j \in \{l, h\}$. These two types correspond to **low-income** (constrained) and **high-income** (unconstrained) households. Workers are of two types, distinguished by the sector in which they can work (type-1 and type-2 workers). The low-income household consists of only type-1 workers, and the high-income household consists of both types of workers. Intuitively, we associate sector 1 with the low-wage service sector and sector 2 with the rest of the economy. Let H_l (H_h) be the total mass of members of the type- l (type- h) households. We normalize the population of the economy to 1 ($H_l + H_h = 1$). Within the type- h household, the exogenous share ϕ are type-2 workers, and $1 - \phi$ are type-1 workers. This exogenous share captures the share of “skilled” workers in the economy available to work in the high-wage sector (sector 2).

3.1 Two Production Sectors

In each of the two sectors $s \in \{1, 2\}$, a continuum of firms produces differentiated varieties of goods, indexed by $i \in [0, 1]$. Each firm i within each sector s produces its output according to a constant-returns-to-scale technology:

$$Y_{st}(i) = A_{st} K_{st}(i)^{\alpha_s} N_{st}(i)^{1-\alpha_s},$$

where Y denotes output, A denotes TFP, K represents the capital stock, and N represents labor input. The subscripts s and t indicate the sector (1 or 2) and time, respectively. The two sectors generally have different capital shares α_s .

Each sector pays a sector-specific wage W_{st} to its workers, while the rental rate of capital R_t is equalized across sectors under the assumption of perfect capital mobility. Each firm

maximizes its profits:

$$\Pi_{st}(i) = P_{st}(i)Y_{st}(i) - W_{st}N_{st}(i) - R_tK_{st}(i), \text{ subject to } Y_{st}(i) = Y_{st} \left(\frac{P_{st}(i)}{P_{st}} \right)^{-\theta_s}, \quad (1)$$

where output Y_{st} is defined by the CES aggregator: $Y_{st} = \left[\int_0^1 Y_{st}(i)^{\frac{\theta_s-1}{\theta_s}} di \right]^{\frac{\theta_s}{\theta_s-1}}$. The optimality conditions can be summarized as:

$$\lambda_{st} = \frac{R_t}{\alpha_s \frac{Y_{st}}{K_{st}}} = \frac{W_{st}}{(1 - \alpha_s) \frac{Y_{st}}{N_{st}}} \text{ and } P_{st} = \frac{\theta_s}{\theta_s - 1} \lambda_{st},$$

where λ_{st} denotes the marginal cost of production.

3.2 Households

We assume that preferences for both household types follow the [King et al. \(1988\)](#) specification:

$$U_{jt}(\cdot) = \ln C_{jt} + \Psi_j \frac{L_{jt}^{1-\frac{1}{\nu}}}{1-\frac{1}{\nu}},$$

where C_{jt} and L_{jt} represent, respectively, total consumption and leisure of the type- j household.¹⁴ The parameter ν represents the extensive-margin elasticity of nonparticipation. Note that both consumption and leisure are pooled within the household. The type- l household is subject to a borrowing constraint. In addition, the type- l household can save only through government bonds, whereas the type- h household can hold both physical capital and government bonds.

3.2.1 Demand Functions and Price Indexes

As noted above, the economy consists of two sectors indexed by s ($s = 1$ and 2), and within each sector there is a continuum of differentiated goods indexed by i that are aggregated according to a CES function with the associated elasticity of substitution θ_s . We also assume that the two sectors' output is aggregated according to another CES function with an elasticity of substitution between the two sectors, ϵ and a sector 2 weight parameter, ω . As

¹⁴The model's *leisure* should be interpreted broadly as non-market time, which may include home production and other non-market activities that became particularly valuable during the pandemic.

a result, the type- j household's demand for good i in sector s is given by:

$$Y_{jst}(i) = Y_{jst} \left(\frac{P_{st}(i)}{P_{st}} \right)^{-\theta_s}.$$

The price index for each sector s and the total expenditures in that sector are, respectively, given by:

$$P_{st} = \left[\int_0^1 P_{st}(i)^{1-\theta_s} di \right]^{\frac{1}{1-\theta_s}} \text{ and } P_{st}Y_{jst} = \int_0^1 P_{st}Y_{jst}(i) di.$$

The allocation of expenditures between the two broad categories of goods is determined by:

$$Y_{j1t} = Y_{1t} \left(\frac{P_{1t}}{(1-\omega)P_t} \right)^{-\epsilon} \text{ and } Y_{j2t} = Y_{2t} \left(\frac{P_{2t}}{\omega P_t} \right)^{-\epsilon},$$

where P_t is the aggregate price index as in:

$$P_t = \left[(1-\omega)^\epsilon P_{1t}^{1-\epsilon} + \omega^\epsilon P_{2t}^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}}.$$

Aggregate demand from each type of household is $P_t Y_{jt} = P_{1t} Y_{j1t} + P_{2t} Y_{j2t}$ for $j = h, l$. Aggregate demand is therefore $P_t Y_t = P_t Y_{ht} + P_t Y_{lt}$. Throughout the paper, we normalize the aggregate price index P_t to 1 for all t , as we abstract from nominal considerations.

3.2.2 Unconstrained Household

The type- h household solves the usual dynamic problem without the borrowing constraint, subject to the following budget constraint:

$$C_{ht} + I_t + B_{ht+1} = (H_h - L_{ht})(\phi W_{2t} + (1-\phi)W_{1t}) - T_t + R_t K_{t-1} + (1+r_{t-1})B_{ht} + \Pi_t,$$

where $I_t \equiv K_t - (1-\delta)K_{t-1}$, δ represents the depreciation rate, B_{ht} the government bonds that the type- h household owns, r_t is the interest rate on that asset, T_t are lump-sum taxes that the government collects from the household, and Π_t are profits from all firms in the economy. Recall that the type- h household owns the physical capital used in both sectors. Note also that the household's total consumption and capital investment are allocated across the two sectors as follows: $C_{ht} + I_t = P_{1t}(C_{h1t} + I_{1t}) + P_{2t}(C_{h2t} + I_{2t}) = P_{1t}Y_{h1t} + P_{2t}Y_{h2t} = Y_{ht}$

as stated above. The first-order conditions are straightforward:

$$C_{ht}^{-1} = \Lambda_{ht}, \quad (2)$$

$$\Psi_h L_{ht}^{-\frac{1}{\nu}} = \Lambda_{ht} [\phi W_{2t} + (1 - \phi) W_{1t}], \quad (3)$$

$$\Lambda_{ht} = \beta_{ht} \mathbb{E}_t (1 + r_t) \Lambda_{ht+1}, \quad (4)$$

$$\Lambda_{ht} = \beta_{ht} \mathbb{E}_t \Lambda_{ht+1} (1 - \delta + R_{t+1}), \quad (5)$$

where Λ_{ht} is the Lagrange multiplier associated with the budget constraint above, and β_{ht} is the discount factor of the type- h household. Note also that the right-hand side of the labor supply condition (3) includes a weighted average of wages across both sectors, since the type- h household has members employed in both sectors of the economy.

3.2.3 Constrained Household

The constrained (type- l) household's budget constraint is written as:

$$C_{lt} + B_{lt+1} = (H_l - L_{lt}) W_{1t} + F_t + (1 + r_{t-1}) B_{lt} \text{ and } B_{lt} \geq 0.$$

where B_{lt} denotes the household's bond holdings, L_{lt} represents the number of nonparticipants, and F_t is a lump-sum transfer from the government. Note that $H_l - L_{lt}$ represents the number of employed members, as there is no unemployment in the model. The optimal decisions are characterized by:

$$C_{lt}^{-1} = \Lambda_{lt}, \quad (6)$$

$$\Psi_l L_{lt}^{-\frac{1}{\nu}} = W_{1t} \Lambda_{lt}, \quad (7)$$

$$\Lambda_{lt} = \beta_{lt} \mathbb{E}_t [\Lambda_{lt+1} (1 + r_t) + \Theta_{lt+1}], \quad (8)$$

$$\Theta_{lt} B_{lt} = 0, \quad (9)$$

where Θ_{lt} is the Lagrange multiplier associated with the borrowing constraint, and β_l is its discount factor, which is assumed to be less than β_h . Note also that the constrained household does not own physical capital and thus $C_{lt} = P_{1t} C_{l1t} + P_{2t} C_{l2t} = P_{1t} Y_{l1t} + P_{2t} Y_{l2t} = Y_{lt}$.

3.3 Government

The government collects lump-sum taxes from the type- h household and also makes lump-sum transfers to the type- l household. We also allow the government to issue debt B_t to finance the current-period budget shortfall. The budget constraint is:

$$B_{t+1} = F_t - T_t + (1 + r_{t-1})B_t.$$

One of our experiments entails tracing the effects of an exogenous path of F_t . We assume the following path for taxes:

$$T_{t+q} = (1 + \phi_B)r_{t+q-1}B_{t+q} - \phi_B r_{t+q-1}B + T, \quad (10)$$

where B and T are steady-state values of debt and taxes, respectively. It is required that $q \geq 0$ and $\phi_B \geq 0$. A positive value of q delays tax collection to a future date. A higher value of ϕ_B implies a faster return of the debt level to its steady-state level.¹⁵

3.4 Equilibrium Conditions

The following conditions close the model. The labor market clears for both types of workers:

$$N_{1t} = H_l - L_{lt} + (1 - \phi)(H_h - L_{ht}), \quad (11)$$

$$N_{2t} = \phi(H_h - L_{ht}). \quad (12)$$

The left-hand sides represent labor demand from the two sectors, and the right-hand sides represent labor supply. Capital market clearing requires $K_{1t} + K_{2t} = K_t$ where demand for capital from the two sectors equals the capital stock rented out by the unconstrained household. The clearing of the government bond market requires $B_{ht} + B_{lt} = B_t$. Note that in our exercise below, the type- l household's bond holdings (B_{lt}) are zero in the steady state. But in the transition path, $B_{lt} > 0$ is possible. Summing over the budget constraints of the two types of households yields the following aggregate resource constraint:

$$C_{ht} + C_{lt} + K_t = N_{1t}W_{1t} + N_{2t}W_{2t} + (1 - \delta + R_t)K_{t-1} + \Pi_t,$$

¹⁵We allow the government to issue debt only so that the type- l household can save through it. The allocation is invariant to the parameters ϕ_B and q , which govern only the timing of the lump-sum tax. Because this tax falls entirely on the unconstrained type- h household, the timing of its collection does not affect any household's consumption or labor supply. Ricardian equivalence therefore holds in our model.

which is equivalent to $C_{ht} + C_{lt} + K_t - (1 - \delta)K_{t-1} = Y_t$. And each sector faces the following demand for its product:

$$Y_{1t} = Y_t \left(\frac{P_{1t}}{(1 - \omega)P_t} \right)^{-\epsilon} \quad \text{and} \quad Y_{2t} = Y_t \left(\frac{P_{2t}}{\omega P_t} \right)^{-\epsilon},$$

where $P_{1t}Y_{1t} + P_{2t}Y_{2t} = Y_t$.

4 Calibration

This section describes the procedure for calibrating most of the structural parameters of the model to cross-sectional empirical evidence. Among the structural parameters, three are estimated: ω and ϵ , which appear in the CES aggregator of the two categories of goods, and β_l , the discount factor for the constrained (low-income) household. In addition to these three parameters, we also estimate the parameters that characterize the exogenous processes that drive the model dynamics. The estimation procedure is described in Section 6. Note that while we use 2015 data to set the steady-state targets, the estimation does not impose that the economy is in its steady state in 2015, so that the filtered exogenous process can deviate from their steady-state values.

Tables 5 and 6 summarize parameter values and the first moments, respectively. Appendix D provides full details on the calibration procedure.

4.1 Employment

We assume that 25 percent of the population are members of the low-income household ($H_l = 0.25$) and 75 percent are members of the high-income household ($H_h = 0.75$). We refer to our earlier empirical results (Table 2) showing that members of households in the lowest income quartile had an EPOP ratio of 30.3 percent in 2015, while members of the remaining high-income households had an EPOP ratio of 65.7 percent. We categorize the 2-digit NAICS industries into two broad groups, low-wage and high-wage sectors (sector 1 and sector 2, respectively), determined by their average wages using the Employer Costs for Employee Compensation (ECEC) data compiled by the Bureau of Labor Statistics (BLS).¹⁶

¹⁶Underlying 2-digit industries are (i) construction (23), (ii) manufacturing (31-33), (iii) trade (42, 44-45, 48-49), (iv) information (51), (v) financial activities (52, 53), (vi) professional and business services (54, 55, 56), (vii) education and health services (61, 62), (viii) leisure and hospitality (71-72), and (ix) other services (81). We define the bottom three sectors, (iii), (viii), and (ix), based on their average wages as the low-wage sector. In 2019, the average wage in this low-wage sector was \$17.60, while that in the high-wage sector was

Table 5: Structural Parameters

Parameter	Description	Value
<i>Panel A: Exogenously set</i>		
H_l	Population share for type- l household	0.25
β_h	Discount factor for type- h household	1/1.02
θ_1	Elasticity of substitution within sector 1	2.71
θ_2	Elasticity of substitution within sector 2	2.67
α_1	Capital share sector 1	0.34
α_2	Capital share sector 2	0.39
ν	Elasticity of nonparticipation	0.5
σ	Intertemporal elasticity of substitution	1
δ	Capital depreciation rate	0.1
ϕ_B	Tax policy parameter	1
q	Tax policy parameter	8
<i>Panel B: Endogenously set</i>		
ϕ	Share of high-skill members in type- h household	0.70
Ψ_h	Scale parameter in the utility function of type- h household	0.06
Ψ_l	Scale parameter in the utility function of type- l household	0.36
<i>Panel C: Estimated</i>		
ω	Sector 2 weight of the CES aggregator	0.73
ϵ	Elasticity of substitution between sector 1 and sector 2 goods	4.45
β_l	Discount factor of type- l household	0.97

Notes: Estimated values of ω , ϵ , and β_l are posterior modes. See Table S.4 for more details.

This classification implies employment levels of the low- and high-wage industries at $N_1 = 0.236$ and $N_2 = 0.358$ in 2015, respectively. Recall that the household and industry employment measures are linked by Equations (11) and (12) which provide the mapping between sectoral employment and employment by household type. Because there are two equations and one unknown, we choose ϕ to minimize the distance between the two sides. We apply the same procedure to the data for each year in our sample (2015–2023) and thus obtain different values of ϕ .¹⁷ The time series ϕ_t is treated as one of the exogenous processes driving the model dynamics. We set the steady-state value of ϕ to its 2015 value of 0.70. Lastly, we set the extensive margin elasticity of nonparticipation to 0.5 (see the discussion in Cairó et al., 2022). We also consider alternative values of this parameter in our experiment.

\$28.50.

¹⁷Recall that the parameter ϕ represents the share of members within the type- h household that work in sector 2 (high-wage sector). This parameter captures an exogenous share of skilled workers that are capable of working in the high-wage sector.

Table 6: Targeted First Moments

Moment	Model concept	Steady-State value
Aggregate EPOP ratio	$(N_h + N_l)/(H_h + H_l)$	0.57
EPOP ratio for type- l household	N_l/H_l	0.31
EPOP ratio for type- h household	N_h/H_h	0.66
Employment level in sector 1	N_1	0.22
Employment level in sector 2	N_2	0.35
Wage ratio between sectors 2 and 1	W_2/W_1	1.60
Output ratio between sectors 2 and 1	$(P_2 Y_2)/(P_1 Y_1)$	2.70
Government debt as a share of output	B/Y	1.00
Transfers as a share of income for type- l household	F/C_l	0.08

4.2 Production Sectors

We compute the average capital shares α_s over our sample period using our industry dataset (BLS Major Industry Total Factor Productivity). The data imply $\alpha_1 = 0.34$ and $\alpha_2 = 0.39$, which aligns with the intuition that the low-wage industry has a somewhat lower capital share than the high-wage industry. In 2015, the ratio of average nominal wages between high- and low-wage industries was 1.6 and the ratio of employment levels was 1.5. In our dataset, the output of the high-wage industry relative to that of the low-wage industry is 2.70 in 2015. Using these pieces of information and taking ratios of the optimality conditions for sectors 1 and 2, we calculate the ratio of markups at 0.991, implying that markup levels are roughly the same between the two sectors. This allows us to use empirical evidence on economy-wide price markups. [De Loecker et al. \(2020\)](#) document that the aggregate price markup reached about 1.6 by the mid-2010s. To be internally consistent, we set the markup in sector 2 ($\mathcal{M}_2 \equiv \frac{\theta_2}{\theta_2 - 1}$) at 1.6 and in sector 1 ($\mathcal{M}_1 \equiv \frac{\theta_1}{\theta_1 - 1}$) at $0.991 \times 1.6 = 1.585$. We set the steady-state real interest rate r at 0.02 (so that the rental rate is $R = r + \delta = 0.12$) and the depreciation rate at 0.1 annually. Given the difficulty of obtaining direct evidence on ω and ϵ , we estimate these parameters, yielding $\omega = 0.73$ and $\epsilon = 4.45$.

4.3 Households

We consider a steady state where the borrowing constraint binds for the type- l household, so $B_l = 0$. Table 1 shows that the share of transfer income for low-income households (those within the first quartile) was 8.3 percent in 2015. We set the steady-state transfer level to be consistent with this evidence. We estimate the discount factor of the type- l household, β_l . Although low-income households are constrained in the steady state, they may become

unconstrained if they receive a sufficiently large government transfer, as shown in the next section. Since the value of β_l is informed by the time series of savings and the amount of government transfers, its estimation requires solving the model dynamically. The estimated value of β_l is 0.97. We assume that the steady-state level of government debt is 100 percent of output, namely, $B = 1$.¹⁸ We calibrate the labor supply preference parameters Ψ_h and Ψ_l by using the intratemporal labor supply conditions (3) and (7) together with the targeted steady-state (non)employment levels (L_h and L_l).

5 A Partial Equilibrium Analysis

Before estimating the full model, we use a partial equilibrium (PE) version of the constrained household's problem to illustrate the forces in the full model: how transfers move employment; how a transfer is split between consumption, forgone earnings, and saving; and why only large transfers relax a borrowing constraint that binds in normal times. Throughout this section, we hold the wage W_1 and the interest rate r at their steady-state values. Household behavior is characterized by Equations (6)–(9) and we set parameter values to those discussed in the previous section. For ease of exposition, we express transfers as a share of labor income, $\tau_t \equiv \frac{F_t}{(H_l - L_l)W_1}$, with a steady-state value of $\tau = 0.09$.¹⁹

5.1 The Labor Supply Channel

Combining the first-order conditions (6) and (7) gives the intratemporal condition $\Psi_l L_{lt}^{-1/\nu} = W_1/C_{lt}$. Linearizing this condition around the steady state yields:

$$\Delta L_{lt} = \frac{\nu L_l}{C_l} \Delta C_{lt}. \quad (13)$$

Any change in consumption is matched by a proportional change in nonemployment, scaled by ν , so transfers affect employment only through their wealth effect on consumption: when a transfer raises C_{lt} , it raises L_{lt} and lowers employment ($H_l - L_{lt}$) in proportion to ν .

Expressing the type- l household's budget constraint in deviations from steady state yields:

$$\Delta C_{lt} + W_1 \Delta L_{lt} + \Delta S_{lt} = \Delta F_t, \quad (14)$$

¹⁸This value has no consequence on the allocation of the economy as discussed in footnote 15.

¹⁹The first column of Table 1 reports the share of transfers in *total* income (i.e., including transfers); here τ is defined relative to labor income only.

where $S_{lt} \equiv B_{lt+1} - (1+r)B_{lt}$ and $\Delta F_t \equiv F_t - F = (\tau_t - \tau)(H_l - L_l)W_1$. Note that ΔF_t is the transfer in excess of its steady-state level. Dividing Equation (14) by ΔF_t defines the marginal propensities to consume (MPC), to earn (MPE), and to save (MPS):

$$\underbrace{\frac{\Delta C_{lt}}{\Delta F_t}}_{\text{MPC}} + \underbrace{\frac{W_1 \Delta L_{lt}}{\Delta F_t}}_{-\text{MPE}} + \underbrace{\frac{\Delta S_{lt}}{\Delta F_t}}_{\text{MPS}} = 1.$$

These are the household-side sufficient statistics through which transfers affect aggregate demand and labor supply.

Auclert et al. (2023) provide a similar characterization but work with models that mute wealth effects on labor supply. We retain this channel because of the evidence in Section 2 and the literature on large transfers discussed in the Introduction. While wealth effects on employment may be small for ordinary cyclical fluctuations, the pandemic transfers were several times larger, reaching roughly a third of the lowest quartile's labor income at their peak, so even a modest elasticity can deliver the participation response in the data.

The cumulative split is pinned down by preferences. Because net saving sums to zero over the episode (assets begin and end at zero), the present-value sum of Equation (14) gives $\text{MPC}^{\text{cum}} - \text{MPE}^{\text{cum}} = 1$. Using Equation (13), we obtain:

$$\text{MPC}^{\text{cum}} = \frac{1}{1 + \Phi} \text{ and } \text{MPE}^{\text{cum}} = -\frac{\Phi}{1 + \Phi}, \text{ where } \Phi \equiv \frac{\nu W_1 L_l}{C_l}. \quad (15)$$

Since the household is constrained in steady state ($C_l = (H_l - L_l)W_1(1 + \tau)$),

$$\Phi = \frac{\nu}{1 + \tau} \cdot \frac{L_l}{H_l - L_l} = \frac{\nu}{1 + \tau} \cdot \frac{1 - \text{EPOP}_l}{\text{EPOP}_l} = 1.03, \quad (16)$$

so $\text{MPC}^{\text{cum}} = 0.49$ and $\text{MPE}^{\text{cum}} = -0.51$. The roughly even split reflects, in large part, this group's low EPOP ratio: a higher-EPOP group would have a smaller Φ , allocating more of a transfer to consumption, while a lower-EPOP group has larger Φ , reducing earnings more.

The present value of transfers above the steady-state level observed in 2020 and 2021 is roughly 30 percent of the household's annual labor income. Applying Equation (15) to this observed transfer path sends about half to each margin: in present value, consumption rises by about 14.9 percent of annual labor income and earnings fall by about 15.4 percent of annual labor income. Because W_1 is fixed, employment falls in the same proportion as earnings, so relative to the group's steady-state EPOP of about 31 percent, this amounts to a cumulative reduction in the EPOP ratio of roughly 5 percentage points. The estimated

model distributes the total effect dynamically. Note that the cumulative split is the same whether or not the household can save, and the ability to save only affects the timing of the response, which we discuss next.

5.2 The Saving Threshold and the Role of Savings

This section shows how the household that is constrained in the steady state departs from hand-to-mouth behavior when it receives a sufficiently large transfer, highlighting the resulting nonlinearity. We focus on the simplest scenario in which the household receives a large transfer in one period, after which it returns to its steady-state level in the next period.

Because the type- l household is impatient, $g \equiv \beta_l(1+r) < 1$, its borrowing constraint binds with a strictly positive Lagrange multiplier in the steady state. The Euler equation (8) with $B_l = 0$ yields $\Theta_l = \frac{1-g}{\beta_l C_l} > 0$. The household would like to consume more today than its current income permits, but cannot borrow to do so. In this situation, a small transfer simply relaxes the borrowing constraint, and the household continues to behave in a hand-to-mouth manner. Once the transfer is large enough to raise consumption to the point where the Euler equation holds with equality, the constraint becomes slack, and any further transfer is partly saved.

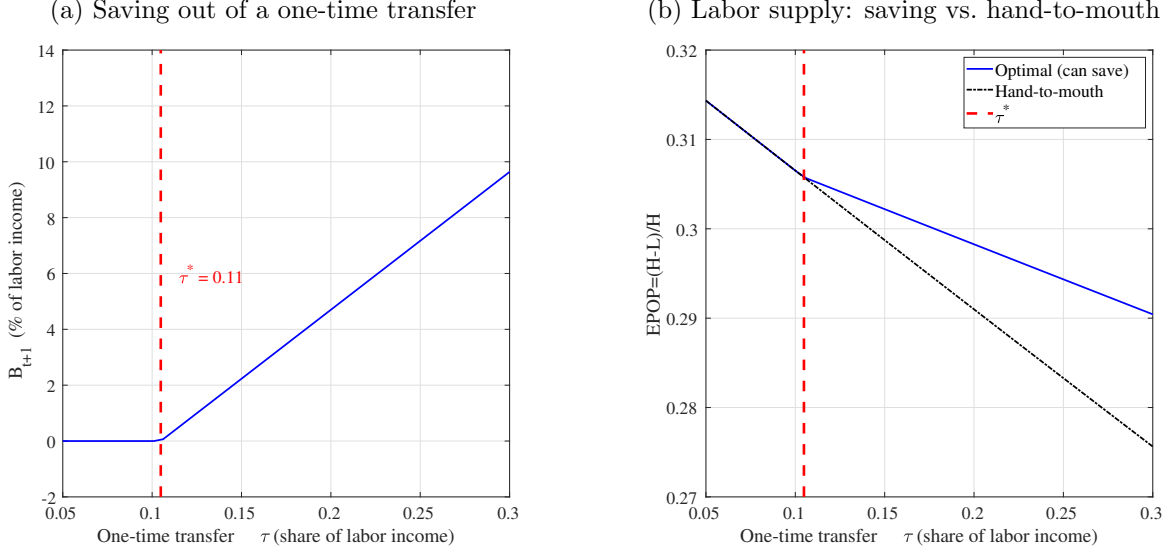
To calculate the threshold transfer level F^* , note first that saving the first dollar of a transfer pays $\frac{g}{C_{l,t+1}}$ next period at a cost $\frac{1}{C_{lt}}$ today. Thus, the constraint binds whenever $\frac{1}{C_{lt}} > \frac{g}{C_{l,t+1}}$. The household consumes the entire transfer until current consumption reaches $\bar{C} \equiv \frac{C_l}{g}$. Hence, the threshold level depends on g and thus on β_l .

The threshold transfer F^* and the associated leisure L_l^* solve $\bar{C} = (H_l - L_l^*)W_1 + F^*$ and $L_l^* = (\Psi_l \frac{\bar{C}}{W_1})^\nu$. Under our baseline calibration,

$$\tau^* = \frac{F^*}{(H_l - L_l)W_1} = 0.11.$$

As $g \rightarrow 1$, the threshold approaches τ (all transfers are saved); the more impatient the household is, the larger the transfer required to trigger saving. Figure 3a confirms the threshold at $\tau^* = 0.11$, and Figure 3b shows how the ability to save reshapes the labor supply response relative to a hand-to-mouth household. Below τ^* , the two coincide, but above τ^* they diverge. The household saves part of the transfer, consuming less and working more than its hand-to-mouth counterpart. Recall that the cumulative effect is identical in the two cases. The difference lies in the timing: part of $\text{MPE}^{\text{cum}} \approx -0.5$ materializes later, as savings are spent, generating a persistent labor supply response that is absent under the

Figure 3: Saving and Labor Supply Effects of a One-Time Transfer



Notes: Panel (a): assets carried into the next year as a share of labor income. Panel (b): within-group EPOP, $\frac{H_L - L_L}{H_L}$, under the optimizing household and a hand-to-mouth household.

hand-to-mouth assumption.

Two caveats apply. First, this is a *one-time-transfer* analysis: it presumes the household treats the transfer as transitory and expects steady state next period. With the persistent, anticipated transfers of the estimated model, the threshold changes: anticipating future transfers raises desired current consumption and can keep the household at the constraint. However, the qualitative mechanism is the same. Second, the analysis holds wages and the interest rate fixed and ignores other shocks. The estimated general equilibrium model in the next section addresses these limitations.

6 Estimation

We estimate three structural parameters (ω , ϵ , and β_l) and the parameters of exogenous processes that drive the model dynamics. We follow a Bayesian approach that allows for an occasionally nonbinding constraint and sample from the posterior with Markov Chain Monte Carlo (MCMC). This section discusses the estimation procedure, the exogenous processes, and the measurement equations linking observed and model-based series.

6.1 Estimation Procedure

As noted above, the borrowing constraint binds for the low-income household in the steady state, but we allow for the possibility that the constraint becomes slack away from the steady state. In our model, this situation might arise as a result of shocks and/or due to government transfers to the low-income household. This feature introduces nonlinearity into the model, and thus we solve the model applying the methodology developed by [Guerrieri and Iacoviello \(2015\)](#) and [Kulish et al. \(2017\)](#) who show that the law of motion of the economy with an occasionally binding constraint can be expressed as a linear system of equations with time-varying coefficients, up to a first-order approximation. [Kulish et al. \(2017\)](#) use the methodology to solve a New Keynesian model with an occasionally binding constraint on the nominal interest rate and then estimate the model by applying the Kalman filter with time-varying coefficients to evaluate the likelihood function. We follow essentially the same procedure to solve and estimate our model, with the difference being that the constraint is occasionally nonbinding (instead of binding).

The approach is to work with two sets of linearized equilibrium laws of motion that characterize the economy's equilibrium around the steady state, one where the borrowing constraint always binds and another where it does not, and to represent the equilibrium as a combination of these two regimes. A key parameter in this setup is the expected duration of the latter regime. Knowing the expected duration, we can describe the equilibrium of the economy as a linear system of equations with time-varying coefficients and estimate such a system with Bayesian techniques by combining the likelihood function, as described in [Hamilton \(1994\)](#), and our priors over the parameters. We set the expected duration of the nonbinding regime to its model-consistent value and sample from the posterior with MCMC.²⁰ Throughout the paper, we evaluate the model at the posterior mode. For further details of the estimation procedure, see Appendix [E](#).

6.2 Exogenous Processes

We introduce exogenous variations for the following variables: (i) Sectoral TFPs (A_1 and A_2), (ii) Discount factor for the high-income household (β_h), (iii) Labor supply preference shifters (Ψ_l and Ψ_h), (iv) Elasticities of substitution between differentiated goods within each sector (θ_{1t} and θ_{2t}), (v) the sector-2 weight parameter of the CES aggregator (ω), (vi) a share of

²⁰We impose two restrictions in estimation: (i) the constraint was binding before 2020, and (ii) the expected duration of the nonbinding constraint at time t equals the model's conditional expectation given shocks realized up to t .

Table 7: Data and Measurement Equations

Data	Model concept
Sectoral TFPs	A_1, A_2
Sectoral output	Y_1, Y_2
Sectoral real wages	W_1, W_2
Sectoral price indexes	P_1, P_2
Household EPOP ratios by income	$(H_l - L_l)/H_l, (H_h - L_h)/H_h$
Share of type- h household members employed in sector 2	ϕ
Share of transfer income received by type- l household	$F/[(H_l - L_l)W_1 + F + (1 + r)B_l]$
“Excess” savings of type- l household	$B'_l/[(H_l - L_l)W_1 + F + (1 + r)B_l]$

type- h household members working in the high-wage sector (ϕ), and (vii) transfer payments to the type- l household (F). We assume each exogenous variable follows an AR(1) process, and that the disturbance to sectoral TFPs (A_1, A_2), labor supply preference shifters (Ψ_l, Ψ_h), and within-sector elasticities (θ_1, θ_2) consists of a sector/household-specific component and a common (aggregate) component, each of which follows an i.i.d. process. Information about our prior and posterior distributions and estimation results is summarized in Appendix E.4.

In addition to the structural shocks that drive the economy, we also introduce measurement errors in observed sectoral prices and TFPs. Consequently, the model dynamics are governed by 13 structural shocks and 4 measurement errors.

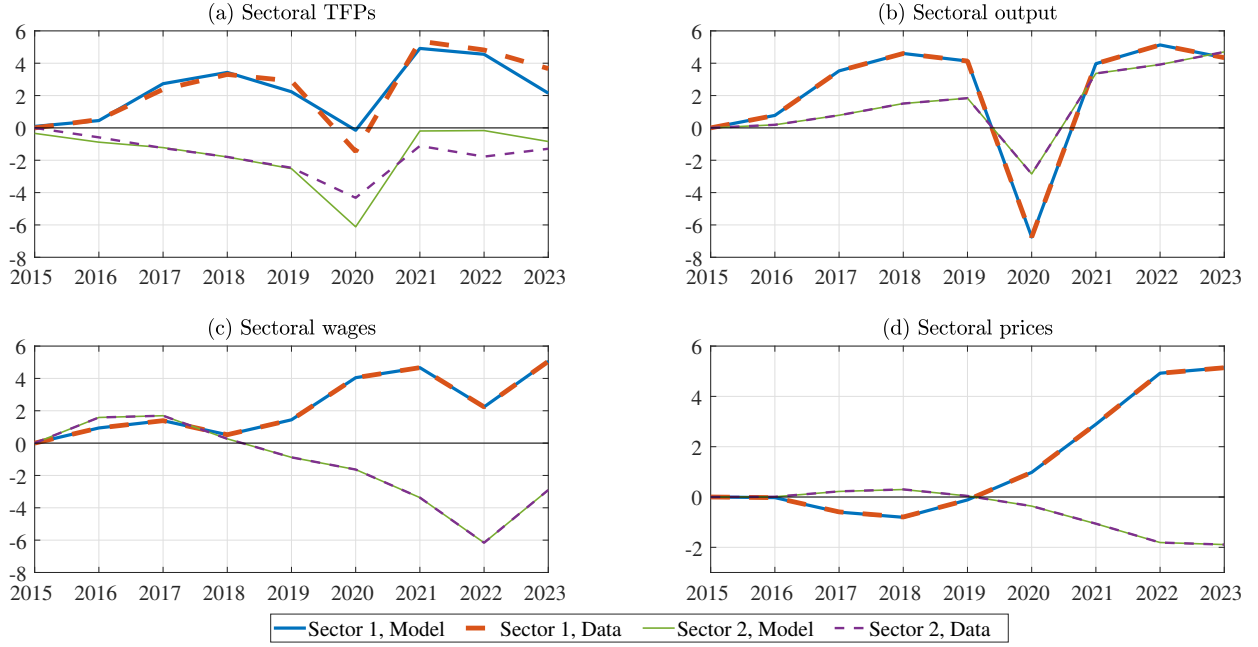
6.3 Data and Measurement Equations

The empirical series and the corresponding model-based variables are presented in Table 7.

Sectoral TFPs, output, and price indexes are all constructed from the BLS Major Industry Total Factor Productivity dataset. Sectoral TFPs are detrended by a deterministic growth component that is common to both sectors. Sectoral output series are detrended by not only the common TFP growth but also population growth and quality changes in labor input. Furthermore, the sectoral price index is expressed as a relative measure with respect to the aggregate price level, aligning with the model’s assumption of a constant aggregate price level. We obtain average wages of the low- and high-wage sectors from the BLS’s ECEC data. We deflate the nominal wage series by the aggregate price index available from the BLS major industry TFP dataset discussed above. Appendix B provides details on the industry-level data.

The evidence on EPOP ratios by income is taken from our results in Table 2. The EPOP ratios are linked to industry employment via ϕ , constructed as described in Section 4.1;

Figure 4: Observables: Industry-Level Data



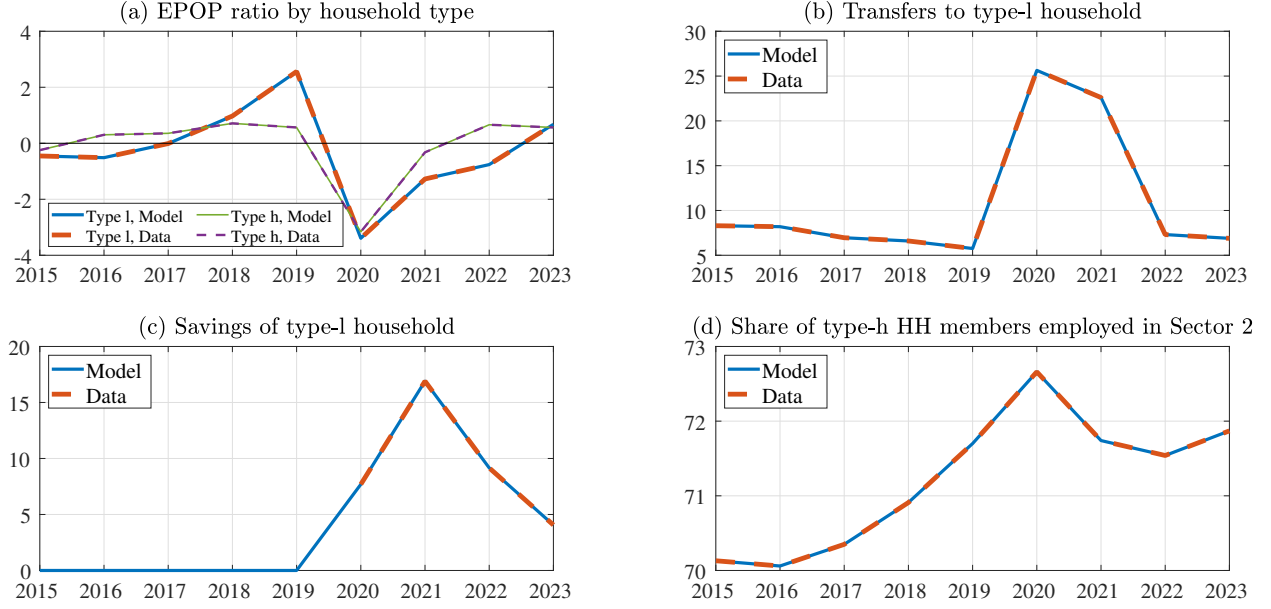
Notes: All values show percent deviations from steady state.

the series for ϕ is treated as observable. The share of transfer income comes from our results in Table 1. To match type- l household savings in the model, we use excess savings by the bottom income quartile as a share of total income. Since we assume the type- l household is constrained during the pre-pandemic period (2015–2019), the appropriate empirical counterpart for its savings during the pandemic is the excess savings measure computed by [Aladangady et al. \(2022\)](#). They estimate US household excess savings as those above what households would have saved if income and spending had grown at pre-pandemic trends. We extend their estimates from 2022:Q2 through 2023:Q4 and express them as a share of the bottom quartile’s disposable income. Appendix C provides details on the excess savings computation.

6.4 Observables and the Fit of the Model

Figures 4 and 5 present the observable series that we use for the estimation of the model. Figure 4 plots sector-level data on TFPs, outputs, wages, and prices along with their model counterparts. Figure 5 does the same for the EPOP ratios for both types of households, transfers and savings for the type- l household, and for the share of type- h household members

Figure 5: Observables: Household-Level Data



Notes: All values in percent. EPOP ratios show absolute deviations from steady state; all other variables shown in levels. In panels (b) and (c), type- l household transfers and savings are expressed as ratios to type- l household income.

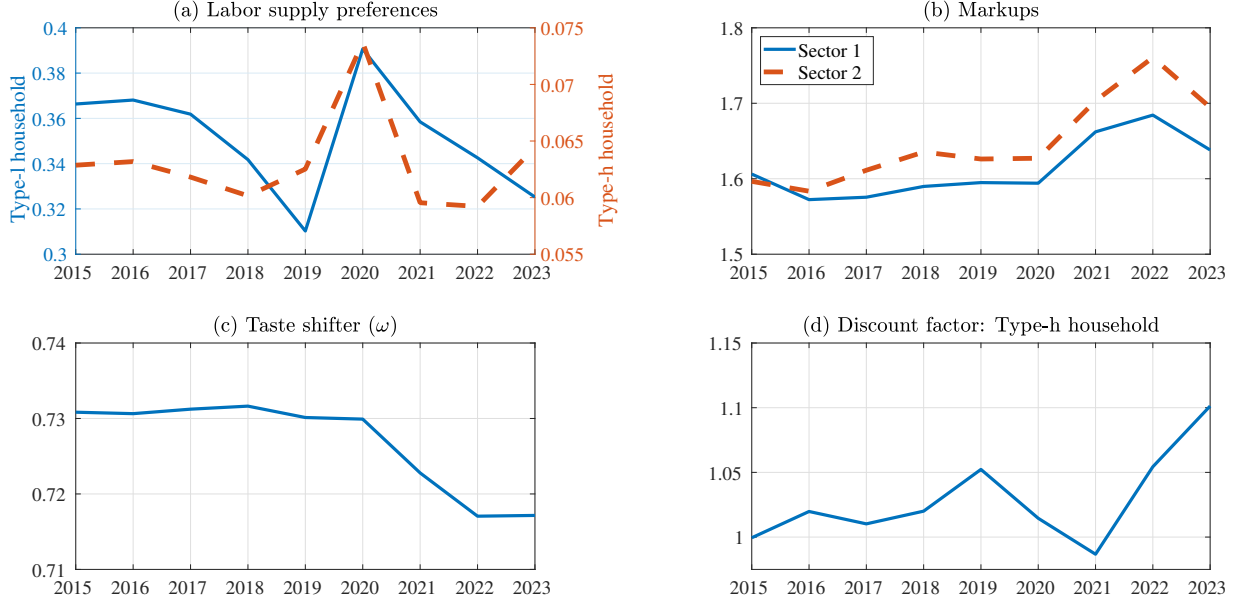
employed in the high-wage sector (sector 2).²¹ By construction, the model closely matches the observed series. The small gaps for TFP reflect measurement error.

The economy saw significant declines in output across both sectors in 2020, although the decrease was considerably more pronounced in the low-wage sector (sector 1). However, between 2019 and 2020, the TFPs of both sectors experienced declines of approximately the same magnitude. Consistent with these observations, the decline in employment at the start of the pandemic is much larger in the low-wage sector than in the high-wage sector. Employment fell by roughly 10 percent in 2020 in the low-wage sector, compared with about 4 percent in the high-wage sector.

There is a significant difference in the behavior of sectoral wages and prices. The wages and prices in the low-wage sector have increased since 2019, while those in the high-wage sector have decreased. These movements in prices and wages, together with those of output and employment, allow the model to distinguish between supply- and demand-side factors. For example, employment in both sectors saw a significant decline; however, wages in the low-wage sector increased, indicating the potential importance of labor supply factors for

²¹As mentioned before, the estimation does not require the model economy to be in a steady state in 2015. Although many parameters are calibrated to match moments observed in 2015 (as discussed in Section 4), the estimated model's 2015 values can still differ from its steady-state values.

Figure 6: Estimated Exogenous Processes



employment in this sector.

6.5 Estimated Exogenous Processes

Figure 6 shows the estimated processes for key exogenous variables in the model: labor supply shifters (Ψ_l and Ψ_h), markups (μ_1 and μ_2), the sector-2 weight parameter ω , and the discount factor for the type- h household β_h . The estimated processes for labor supply shifters in Figure 6(a) show that the preference for not working increased between 2019 and 2020. In 2021 and 2022, this pattern quickly reversed for the type- h household, indicating a recovery in the preference for working. However, the recovery was slower for the type- l household, suggesting a more persistent decline in the willingness to work. This finding is consistent with the fact that low-income households were disproportionately employed in sectors with greater exposure to COVID-19-related disruptions.

Figure 6(b) shows the implied evolution of price markups by industry. It indicates that price markups rose around 10 percentage points in sector 1 and 13 percentage points in sector 2 from 2020 to 2022, before declining in 2023. These increases are broadly in line with independent estimates. In particular, [Gerinovics and Metelli \(2023\)](#) compute price markups over the period 2018–2023 using firm-level data, following the method of [De Loecker et al. \(2020\)](#). The authors find that the average markup increased in 2021 and 2022 by a total of 15 percentage points, before returning toward its pre-pandemic level in 2023.

Figure 6(c) shows the implied evolution of the weight parameter (ω) in the CES aggregator. Note that ω represents the weight assigned to goods produced by the high-wage sector (sector 2). Thus, a lower value of ω indicates a higher demand for goods produced by the low-wage sector (sector 1), which is consistent with the higher prices and wages in that sector during the last three years of the sample period, as shown in Figures 4(c) and 4(d).

Figure 6(d) shows the estimated path of the discount factor of the type- h household. It is above its steady-state value of $1/1.02$ in most years, reaching about 1.05 in 2019. It then falls to about 0.99 in 2021 and rises sharply to about 1.10 in 2023. A lower discount factor raises current consumption relative to future consumption, so the decline in 2020–2021 supports the consumption of the type- h household, partly offsetting the effects of higher expected taxes and other shocks.²²

7 Macroeconomic Effects of Transfers

This section presents our main findings in four parts. First, we characterize the economic effects of transfers using impulse response functions (IRFs) and present associated MPCs and MPEs implied by the model over time. In doing so, we highlight the model’s nonlinearity by comparing our baseline results to those obtained under the assumption that the type- l household is hand-to-mouth.

Second, we conduct a counterfactual exercise where we feed the model a series of estimated transfer shocks that enable it to exactly replicate the observed path of transfers to low-income households and evaluate the resulting quantitative effects of these transfers. This counterfactual analysis assumes that, at the time the transfer policy is implemented, the economy is in the steady state. It is important to stress that this “add-one-in” counterfactual does not measure the effectiveness of the policy implemented in an environment where the economy is experiencing potentially large shocks.

Third, we perform a separate “leave-one-out” counterfactual exercise, in which we compute the path of the economy after shutting down only the transfer shocks while leaving all other shocks in place. Because the model is nonlinear, these two experiments produce different outcomes. We highlight the state dependence of the policy by comparing the two sets of outcomes. Finally, we study how government transfers affect the welfare of each household.

²²The estimated discount factor β_{ht} exceeds one in several years but follows a stationary AR(1) process around its steady-state value of $1/1.02$.

7.1 IRFs to a Transfer Shock and Dynamic MPCs and MPEs

Figure 7 plots IRFs to a single transfer shock to the low-income household. The magnitude of the transfer shock is the same as that observed in 2020, and the persistence of the shock is set to its estimated value. Unlike the one-time transfer in Section 5, which lasts only one period, this shock decays gradually.

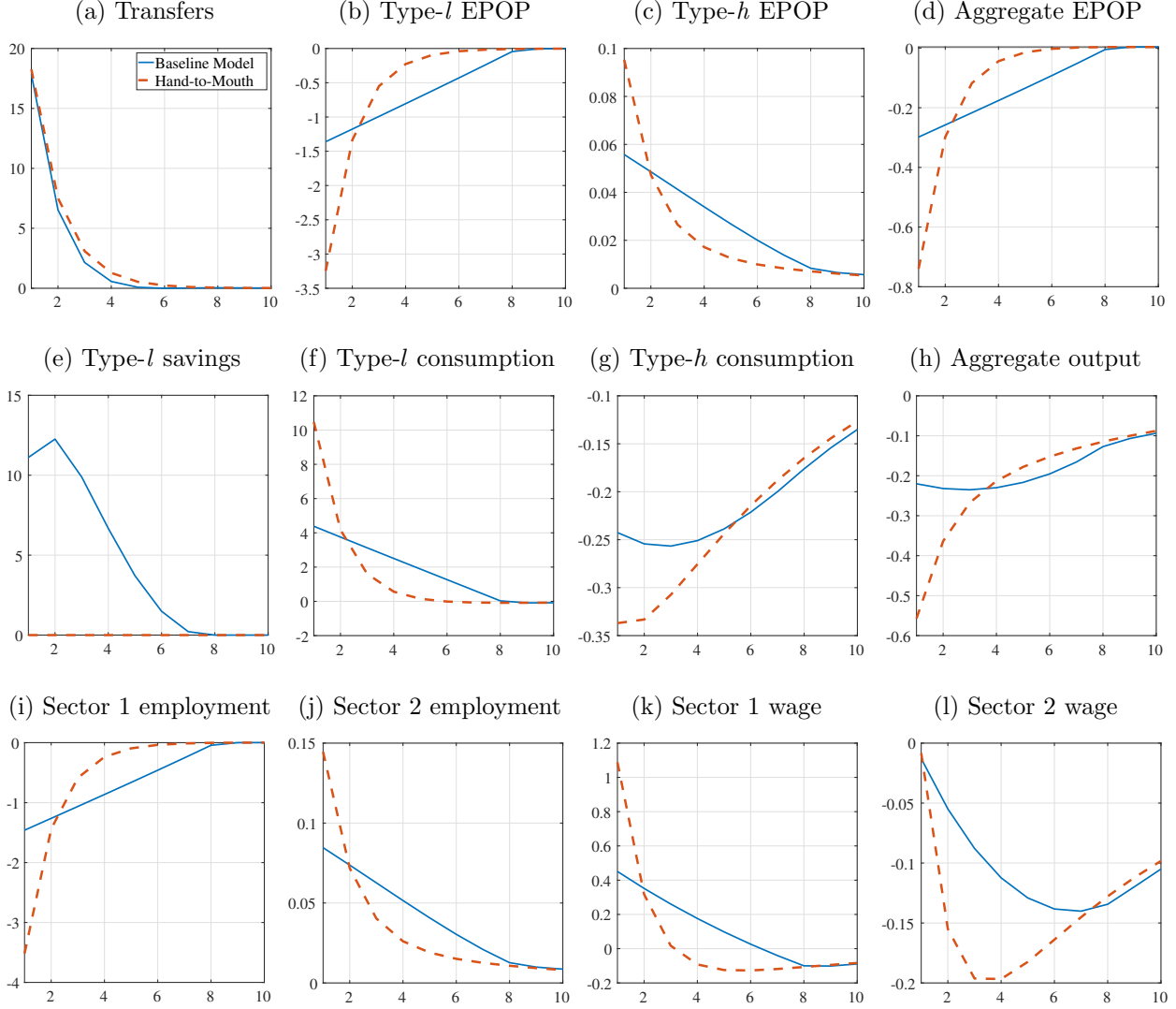
To highlight the model’s nonlinearity stemming from the borrowing constraint faced by the type- l household, we present two sets of results, each corresponding to a different model: (i) in solid blue, our baseline model with the occasionally binding borrowing constraint for the type- l household, which binds in steady state, but might not bind upon a transfer shock; (ii) in dashed red, an alternative model where the type- l household is hand-to-mouth and thus is not allowed to save regardless of the size or type of shock hitting the economy.

In our model, an increase in transfer income for the low-income household leads to an immediate drop in its EPOP ratio and a rise in its consumption (see panels (b) and (f)). Consumption does not increase as much as in the hand-to-mouth case, as our model allows for savings along the transition path (see panel (e)). The smaller increase in consumption corresponds to the smaller decline in the EPOP ratio in our model compared to the hand-to-mouth specification.

The EPOP ratio of the high-income household increases slightly, while its consumption drops due to the anticipation of a higher tax burden to fund transfer payments (see panels (c) and (g)). However, the magnitude of these changes is far less pronounced than that observed for the low-income household. Once more, a hand-to-mouth setup produces effects that are heavily concentrated in the impact period, whereas introducing saving behavior spreads the effects over time and causes the economy to return to its steady state much more gradually.

The overall EPOP ratio declines on net (panel (d)). On impact, it falls by about 0.3 percentage point. In sector 1 (low-wage sector), employment declines primarily due to the reduced labor supply incentive of the low-income household (panel (i)). Note that we allow some members of the high-income household to work in sector 1, which partially offsets the employment decline in that sector. In contrast, employment in sector 2 slightly increases, reflecting a stronger labor supply incentive for the high-income household (panel (j)). Aggregate output falls on net (see panel (h)), as the decline in output in sector 1 dominates. Therefore, the transfer policy results in lower aggregate output in our model, even though it boosts consumption of the low-income household. We will return to this point below. The wage in sector 1 goes up, while the wage in sector 2 drops (panels (k) and (l)).

Figure 7: Impulse-Response Functions to a Transfer Shock



Notes: All values are in percent. Panel (a) shows transfers to the type- l household; panel (e) shows savings of the type- l household; both relative to type- l household income. The remaining panels show percent deviations from steady state, except for the EPOP ratios, which show absolute deviations. The horizontal axis is in years.

MPC vs. MPE. We next compute the MPCs and MPEs implied by the model over time. In Section 5, we studied how a one-period increase in transfers is cumulatively split between consumption and leisure (or work). Here, we compute MPCs and MPEs in a dynamic setting, taking into account the household's expectations about the future evolution of the economy, including subsequent transfers and factor prices.

Table 8 reports annual (for up to 5 years) MPCs (panel A) and MPEs (panel B), in

Table 8: Marginal Propensities to Consume and Earn

	Year 1	Year 2	Year 3	Year 4	Year 5	Cumulative
<i>Panel A: Marginal Propensity to Consume (MPC)</i>						
Baseline	0.137	0.115	0.094	0.074	0.054	0.510
Hand-to-mouth	0.327	0.128	0.048	0.017	0.004	0.502
<i>Panel B: Marginal Propensity to Earn (MPE)</i>						
Baseline	0.114	0.097	0.081	0.066	0.051	0.490
Hand-to-mouth	0.271	0.113	0.049	0.022	0.011	0.498

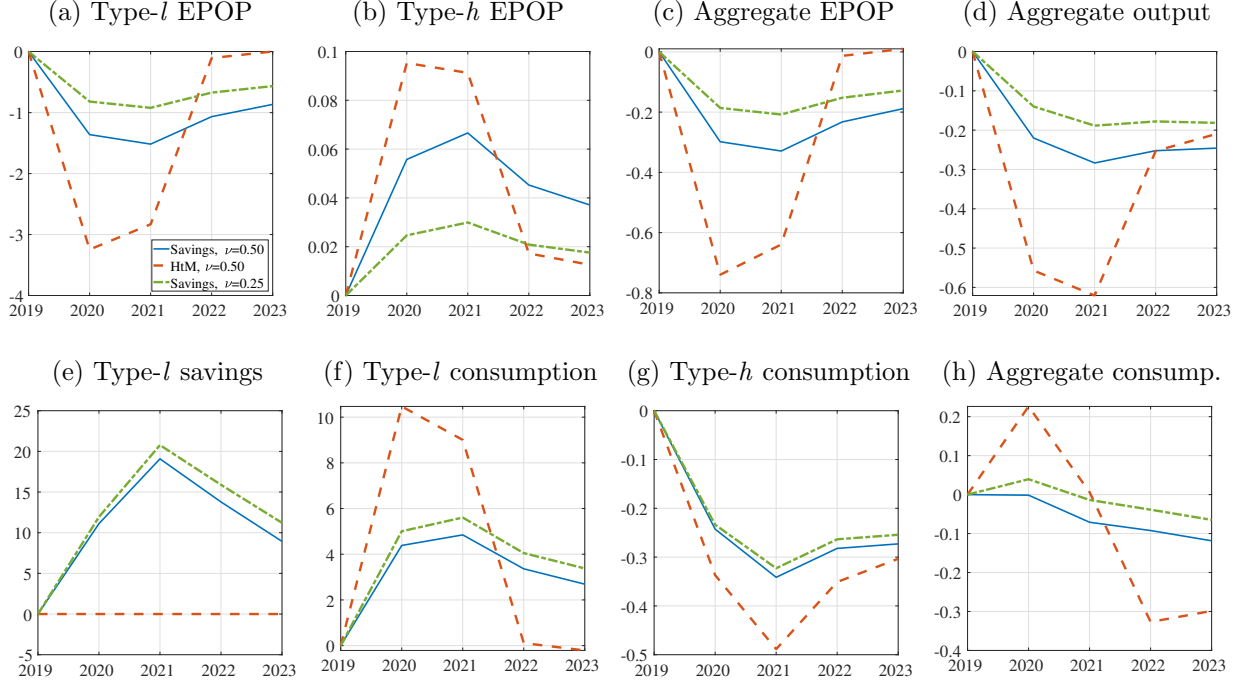
Notes: MPEs are reported in absolute value, that is, as the reduction in earnings per dollar of transfer. Cumulative: present-value sum over all horizons.

response to this single, persistent transfer shock, as plotted in Figure 7(a). The hand-to-mouth household exhibits sharply front-loaded responses: its year-1 MPC is 0.33, more than double the baseline MPC of 0.14, but it declines rapidly to 0.13 in year 2, 0.05 in year 3, and becomes almost negligible in years 4-5. In contrast, the household in the baseline economy spreads its response more evenly: the MPC declines gradually from 0.14 in year 1 to 0.05 in year 5, exhibiting smooth consumption adjustment over time. The earnings response in Panel B mirrors this pattern almost exactly. The hand-to-mouth household reduces earnings sharply in year 1 (MPE = 0.27), with the response decaying rapidly to 0.11 in year 2 and 0.05 in year 3, while the baseline household shows a more gradual decline from 0.11 in year 1 to 0.05 in year 5.

Despite the stark contrast in the timing of responses, the two specifications yield almost the same cumulative effects: the total effect is split between consumption and leisure at roughly 50:50, just as in the earlier PE analysis.²³ In the previous PE exercise, allowing agents to save (rather than constraining them to be hand-to-mouth) did not alter the cumulative split because the interest rate was fixed and the split was thus fully determined by preferences. In the present exercise, wages and the interest rate adjust, so the cumulative split can differ across the two specifications. In practice, the difference is small (Table 8).

²³In our earlier exercise the split was slightly tilted toward MPE than a 50:50 division. This discrepancy is due to the fact that the previous exercise assumed higher transfers for one period only, whereas the current exercise allows for some persistence. In addition, the endogenous interest rate response can influence the cumulative split.

Figure 8: Macroeconomic Effects of Transfers under Alternative Model Specifications



Notes: All values are in percent. All panels show percent deviations from steady state, except for the EPOP ratios and type- l household savings, which show percentage-point deviations. Type- l household savings are expressed as a ratio of type- l household income. The legend “savings” refers to our baseline model where type- l household is allowed to save; “HtM” refers to an alternative model where type- l household is assumed to be hand-to-mouth and thus not allowed to save.

7.2 Sequence of Transfer Shocks

Figure 8 presents the counterfactual trajectories of the economy obtained by feeding the estimated sequence of transfer shocks for the period 2020–2023 depicted in Figure 5(b) into the model. This exercise isolates the effect of transfers by shutting down all other shocks. Our baseline model (blue solid lines) features an occasionally binding borrowing constraint for the low-income household and sets the elasticity of nonparticipation to $\nu = 0.50$. We compare this baseline specification to two alternatives: one where the low-income household is always hand-to-mouth (red dashed lines) and the other where it is permitted to save but its labor supply is less elastic at $\nu = 0.25$ (green dash-dotted lines).

Under the baseline model, the type- l household accumulates substantial savings (panel (e)), enabling a much smoother and thus persistently higher consumption path (panel (f)). In contrast, the hand-to-mouth household (dashed lines) cannot save transfers, leading to a much larger consumption response in the first two years, but much lower afterwards when transfers are no longer available.

The high-income household raises labor supply and reduces consumption, reflecting the negative wealth effect of anticipated taxes. Although it is not constrained, its responses depend on whether the low-income household can smooth its consumption. When the low-income household can save, movements in factor prices are more gradual and thus the high-income household's adjustment is also smoother and more persistent. When the low-income household is hand-to-mouth, price changes are front-loaded and so are the high-income household's responses. The present value of its tax burden is the same in both cases.

On net, the aggregate EPOP ratio drops by roughly 0.3 percentage point in 2020 in the baseline model and the effect persists for several years, even after excess transfer payments are discontinued in 2022 (panel (c)). Aggregate consumption changes little because the increase in spending by the low-income household receiving transfers is largely or fully offset by the reduction in consumption by the high-income household (panel (h)). Aggregate output drops and the decline is more noticeable (panel (d)). On the demand side, in addition to the slight declines in aggregate consumption, investment also decreases. The latter result stems from the fact that investment in sector 1 declines as a result of lower employment in that sector. On the supply side, reductions in both aggregate employment and the capital stock lead to the drop in aggregate output.

A lower value of ν at 0.25 shifts the responses toward consumption and away from leisure. Equations (15) and (16) indicate that the cumulative division shifts from 50:50 to roughly two-thirds to consumption and one-third to leisure. The green dash-dotted lines are consistent with this shift.

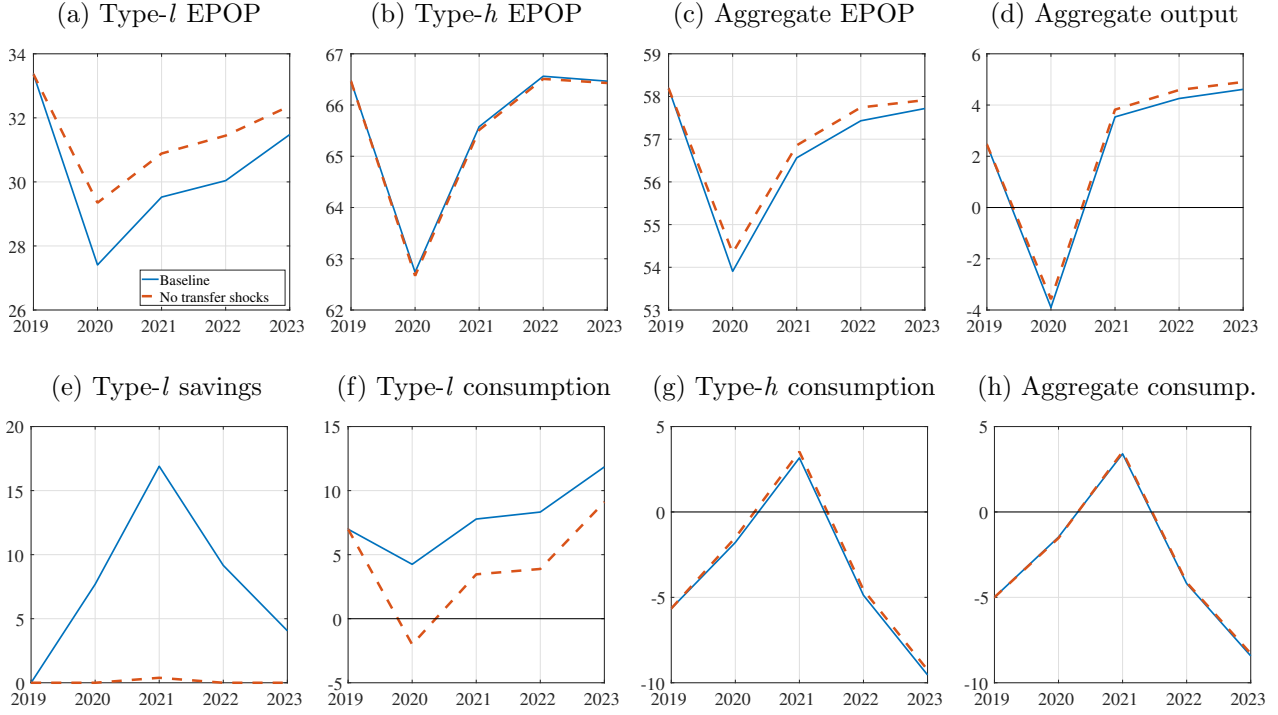
The overall patterns in Figure 8 underscore that both the labor supply margin and the savings channel are quantitatively important for understanding the effects of pandemic-era transfers. The labor supply elasticity primarily governs the consumption-leisure tradeoff and thus the magnitude of employment responses, while the ability to save determines intertemporal smoothing capacity.

7.3 State Dependence of Transfers During the Pandemic

We now quantify the macroeconomic effects of government transfers during the 2020–2023 period through a leave-one-out counterfactual exercise. Specifically, let $X_h^{\mathcal{P}}(\mathcal{S})$ be the variable of interest X for a state $\mathcal{S} \in \{ss, pan\}$ (steady state versus pandemic) in year h under policy $\mathcal{P} \in \{\text{transfer}, \text{no transfer}\}$. The effect of the transfer shocks is measured by:

$$CF_h^X(\mathcal{S}) = X_h^{\text{transfer}}(\mathcal{S}) - X_h^{\text{no transfer}}(\mathcal{S}).$$

Figure 9: Macroeconomic Effects of Transfers

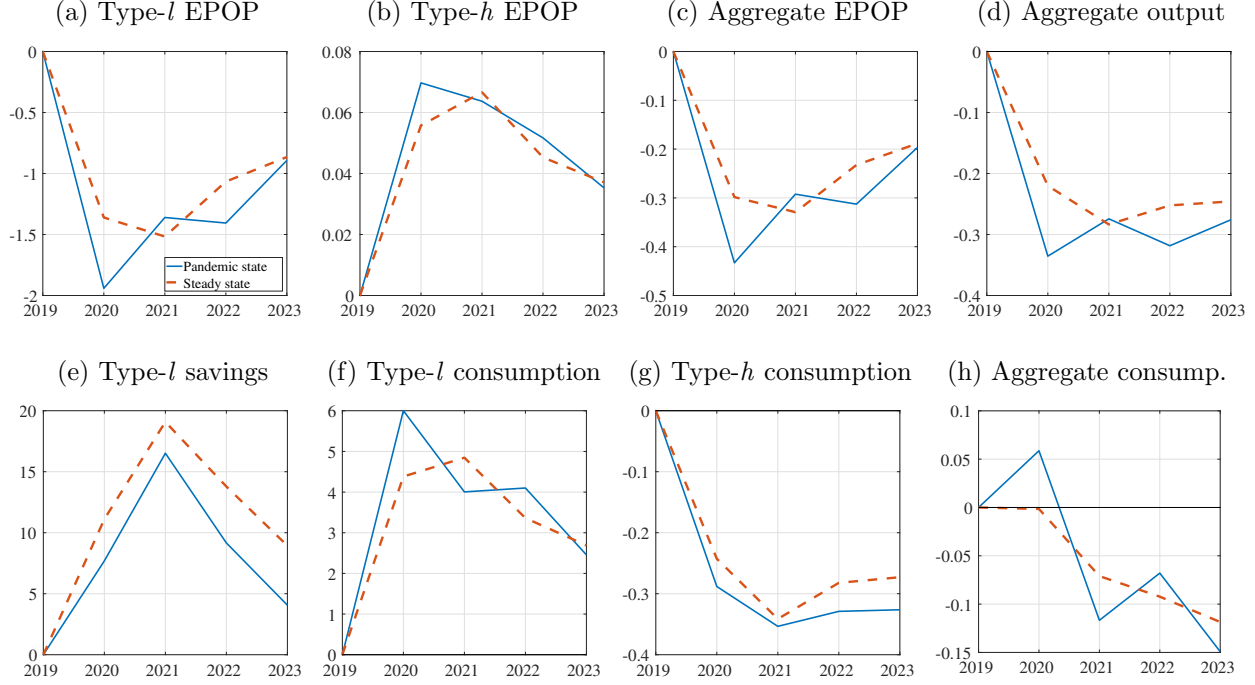


Notes: All values are in percent. All panels show percent deviations from steady state, except for the EPOP ratios and type- l household savings, which show levels. Type- l household savings are expressed as a ratio of type- l household income.

Previously in Figure 8, we presented $CF_h^X(ss)$. Figure 9 presents the counterfactual paths of the economy with and without the transfer shocks, $X_h^{\text{transfer}}(pan)$ and $X_h^{\text{no transfer}}(pan)$, respectively. The indicator ‘pan’ means that all other shocks are active. Figure 10 then compares the two counterfactual paths $CF_h^X(pan)$ and $CF_h^X(ss)$.

Focusing on the size of the transfer effects (as measured by $CF_h^X(pan)$ shown in blue lines in Figure 10), we find that transfer payments substantially raised the consumption of the low-income household over the entire sample, while at the same time significantly lowering its EPOP ratio. In contrast, the employment and consumption responses of the high-income household, driven by the negative wealth effect, are much smaller in magnitude. According to this counterfactual exercise, the aggregate EPOP ratio declined by 0.2–0.4 percentage point per year during the pandemic. Although this magnitude may seem small, it is comparable to typical year-to-year changes in the EPOP ratio seen in non-recession years. It thus represents a quantitatively significant effect, driven solely by government transfers targeted at low-income households. The effects on aggregate output amounted to 0.3 percent each year over 2020–2023.

Figure 10: State-Dependence of the Macroeconomic Effects of Transfers



Notes: All values are in percent. Panels show percent differences between the transfer and no-transfer paths, except for the EPOP ratios and type-*l* household savings, which show percentage-point differences. Type-*l* household savings are expressed as a ratio of type-*l* household income.

A central question for policy design is whether the effectiveness of government transfers depends on current economic conditions. The gap between the two lines $CF_h^X(pan)$ and $CF_h^X(ss)$ in Figure 10 highlights the state dependence of transfer policy. The responses in the pandemic state are stronger than those in the steady state. Specifically, in 2020, consumption of the low-income household increased, while its EPOP ratio declined more sharply along the pandemic path. The more pronounced movement in the aggregate EPOP ratio primarily reflects the behavior of the EPOP ratio for the low-income household.

We measure the degree of state dependence $SD_{h^*}^X$ by the peak relative gap:

$$SD_{h^*}^X = \frac{CF_{h^*}^X(pan) - CF_{h^*}^X(ss)}{|CF_{h^*}^X(ss)|} \times 100,$$

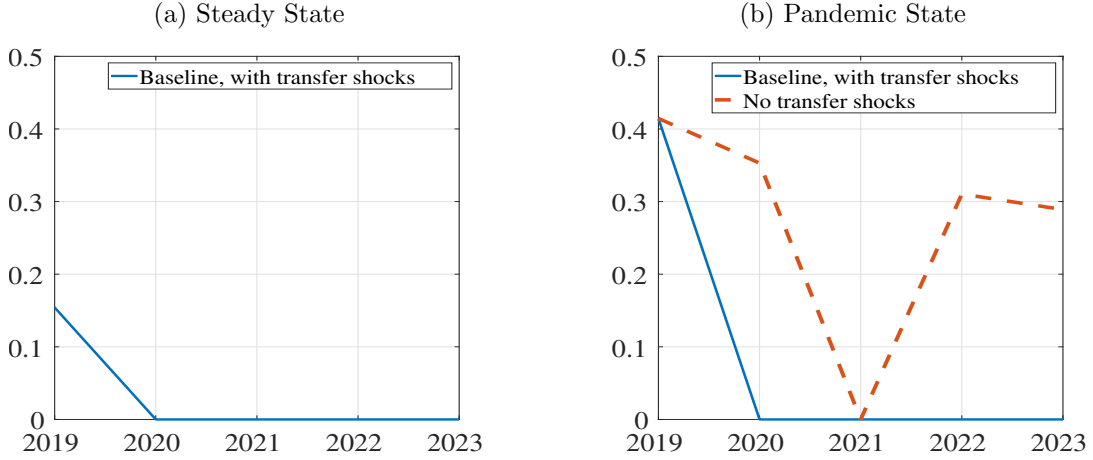
where h^* is the year in which $CF_h^X(pan)$ was the largest. Table 9 presents the peak year, the impact of transfers on the selected variables in the pandemic state, and the associated statistic $SD_{h^*}^X$. It turns out that the largest effect occurred in 2020 for most variables, as can be seen in Figure 10. Note that for $CF_h^X(ss)$, the largest effects tend to occur one year

Table 9: Maximum Effects of Transfers and State Dependence

Variable	Peak Horizon h^*	$CF_{pan}^X(h^*)$	$SD^X(h^*)$ (%)
Type- l Consumption	2020	6.00	36.9
Type- l EPOP	2020	-1.94	42.7
Aggregate EPOP	2020	-0.43	45.1
Aggregate Output	2020	-0.34	52.4

Notes: $CF_{pan}^X(h^*)$ for EPOP ratios are expressed as percentage point differences. $CF_{pan}^X(h^*)$ for consumption and output are expressed as percent difference in level.

Figure 11: Paths of the Lagrange Multiplier under Alternative Economic Conditions



Notes: Figure plots the paths of the Lagrange multiplier associated with the borrowing constraint of the low-income household under the observed sequence of transfer shocks when the economy is in steady state (panel a) and when the economy is in a pandemic state (panel b).

later. Because the economy was hit by large shocks in 2020, the effect of the transfers was larger. The state dependence statistic in Table 9 shows that responses of the four variables considered are magnified by 40 to 50 percent due to the economic conditions in 2020.

The major source of the state dependence is the fact that the borrowing constraint was tighter in 2020. Figure 11 presents the paths of the Lagrange multiplier associated with the low-income household's borrowing constraint. Panel (a) plots the path under the steady-state $\Theta_h^{\text{transfer}}(ss)$, while panel (b) plots the paths under the pandemic state with and without transfers, $\Theta_h^{\text{transfer}}(pan)$ and $\Theta_h^{\text{no transfer}}(pan)$, respectively. In the steady state, the shadow value was 0.15 in 2019 and dropped to zero in 2020 as a result of the large transfer payments, and the constraint remained slack for several years. In panel (b), actual economic conditions as of 2019 implied a higher shadow value, and then $\Theta_h^{\text{transfer}}(pan)$ dropped to zero as a result of transfers and remained slack, just as $\Theta_h^{\text{transfer}}(ss)$ did. What matters, however, is how tight

the constraint would have been without transfers. In the absence of transfers, $\Theta_h^{\text{no transfer}}(\text{pan})$ was 0.35 in 2020, more than twice its steady-state value of 0.15, implying a much tighter borrowing constraint for the low-income household at the height of the pandemic. Because the constraint was tighter, the household used more of the transfer for consumption and leisure and less for saving, producing a larger drop in the EPOP ratio, compared with the steady-state responses in 2020, as demonstrated in panels (a) and (f) in Figure 10. The increases in savings by the low-income household were accordingly smaller in the pandemic state (panel (e)).

There is a debate in the empirical literature regarding the state dependence of the effectiveness of fiscal policy. This literature focuses mostly on the effectiveness of government expenditures rather than transfers. In particular, [Auerbach and Gorodnichenko \(2012\)](#) find evidence of a much larger government spending multiplier, roughly double, in a recession. However, [Ramey and Zubairy \(2018\)](#) question the robustness of this evidence.²⁴ In any case, the existing state-dependence literature concerns spending and output multipliers. We document that the labor supply response to transfers, operating through wealth effects, is itself state-dependent, owing to the nonlinearity introduced by the borrowing constraint that becomes slack during transitions. To the best of our knowledge, our paper is the first to quantify state dependence in the employment response to transfers.

Our finding suggests that transfers reduced labor supply incentives and that this negative effect was larger during the pandemic than in normal times. This result does not make a normative case against transfers. If anything, it cautions against reading a larger employment decline as a larger distortion, at least in our model, since the deeper employment decline in the pandemic state is the optimal exercise of the wealth effect by low-income households whose borrowing constraint was relaxed by transfers. As we show in the next subsection, transfers even at the unprecedented level during the pandemic were welfare-improving in the pandemic state.

7.4 Welfare Effects

To study how government transfers affect the welfare of each household, we first define welfare for the type- j household in period t , $\mathcal{W}_{jt}^P$, as the discounted sum of utility generated by the household's stream of consumption and leisure in period t and every future period:

²⁴See also [Ghassibe and Zanetti \(2022\)](#) and [Jo and Zubairy \(2025\)](#) and references therein for more recent developments of this literature.

Table 10: Welfare Comparison of Counterfactuals Relative to the Baseline Economy

	No transfers	Double transfers
Type- l household	-0.84	0.49
Type- h household	0.03	-0.02

Notes: The table reports welfare differences between the “no transfers” or “double transfers” counterfactual economies relative to the baseline economy. All values are in consumption-equivalent terms in percent.

$$\mathcal{W}_{jt}^{\mathcal{P}} \equiv \sum_{s=0}^{\infty} \beta_j^s \left(\ln C_{jt+s}^{\mathcal{P}} + \Psi_{jt} \frac{(L_{jt+s}^{\mathcal{P}})^{1-\frac{1}{\nu}}}{1-\frac{1}{\nu}} \right). \quad (17)$$

The superscript $\mathcal{P}$ denotes the policy scenario, following the notation introduced in the previous subsection. $\mathcal{P}$ takes three values: ‘transfers’ (the observed economy, with all estimated shocks including transfers), ‘no transfers’ (all shocks except transfers), and ‘double transfers’ (all shocks, with transfers doubled from baseline). Note that all welfare comparisons are made within the pandemic state, the state in which these transfers were deployed.

To interpret these welfare differences, we compute a consumption-equivalent measure. For each type j , $\lambda_{jt}^{\mathcal{P}}$ is the fraction by which consumption in the observed-transfer economy would have to change in every period for its welfare to equal welfare under counterfactual $\mathcal{P}$. Because consumption enters utility in logs, this measure has the closed form:

$$\lambda_{jt}^{\mathcal{P}} = \exp((1 - \beta_j)(\mathcal{W}_{jt}^{\mathcal{P}} - \mathcal{W}_{jt}^{\text{transfer}})) - 1. \quad (18)$$

The reference point is the observed-transfer economy, so a negative value means the counterfactual delivers *lower* welfare than the economy with the observed transfers and a positive value means it delivers higher welfare.²⁵ Welfare reflects both consumption and leisure, and the consumption-equivalent measure expresses the combined effect in consumption units. We report welfare by type rather than in the aggregate. Because the two household types discount the future at different rates, there is no natural common discount factor with which to sum utilities across types. $\lambda_{jt}^{\mathcal{P}}$ is computed separately for each type using the type’s own discount factor β_j .

Table 10 reports the consumption-equivalent welfare effects evaluated at $t = 2020$. Removing transfers makes the type- l household substantially worse off, with a consumption-equivalent loss of 0.84 percent, while the type- h household is better off, gaining 0.03 percent.

²⁵This is the reverse of the sign convention in Section 7.3, where the object of interest was the transfer-minus-no-transfer contrast.

Part of the type- l welfare gain comes through leisure, since the deeper employment decline that transfers induce is utility-bearing rather than a cost, consistent with our reading of that decline as the optimal exercise of the wealth effect rather than as a distortion. The pattern of welfare gains reflects the relaxation of the borrowing constraint. Transfers are valuable to the type- l household precisely because the binding constraint keeps its marginal utility of consumption high. This is the welfare counterpart of the multiplier paths in Figure 11.

The double-transfer column illustrates the size dependence of these welfare effects. Doubling transfers from the pandemic state raises type- l welfare further by 0.49 percent, and lowers type- h welfare by 0.02 percent. The first increment of transfers, moving from zero to the observed level, operates in the region where the constraint binds and the marginal utility of consumption is high, so it delivers a large welfare gain per dollar. Further increments, moving from the observed level to double, operate in the region where the constraint has gone slack and the marginal utility of consumption is lower. Each additional dollar thus buys less welfare. The type- l gain from doubling is positive but smaller than the gain from the first increment, highlighting diminishing returns to transfers in welfare improvements.

Two caveats bear on the finding that doubling still improves welfare. First, this result depends on the lump-sum financing assumption. A lump-sum tax has no deadweight loss, so the cost to the type- h household is the tax itself plus general equilibrium effects, which are small at this transfer level. Under distortionary financing, the cost would be larger and the case for larger transfers much weaker. We view lump-sum financing as a clean benchmark that isolates the general equilibrium and constraint forces, but the comparison should be read with this in mind. Second, welfare does not rise without bound in the size of transfers. Larger transfers require a larger tax on the type- h household, which lowers investment and the future capital stock and in the limit would collapse production and thus reduce welfare for both types.

8 Conclusion

This paper studies the labor market and welfare effects of the large fiscal transfer programs implemented during the COVID-19 pandemic, with a focus on heterogeneity across household income groups. Using CPS/ASEC data, we document a pronounced income gradient in the dynamics of the employment-to-population ratio during and after the pandemic. The decline in employment was largest and most persistent for the low-income households that received the largest transfers, and was far more closely tied to transfer intensity than to

education, age, or race. This pattern stands in sharp contrast to the GFC, when employment dynamics were not aligned with income-based transfer exposure. These facts motivate a quantitative framework that incorporates household-level heterogeneity, an occasionally binding borrowing constraint, and sectoral labor markets.

We develop and estimate a two-sector heterogeneous-household model in which low-income households are borrowing-constrained in normal times but can save out of sufficiently large transfers. The model delivers three main findings. First, the transfers substantially raised the consumption of low-income households and reduced their labor supply, with a dollar of transfer divided roughly evenly between higher consumption and reduced earnings. The ability to save, which the pandemic transfers made possible for households that are constrained in normal times, spreads this response over time and contributes to the persistence of employment declines. Second, the effects of transfers are state-dependent. Because the borrowing constraint binds more tightly in a depressed economy, the same transfer relaxes a tighter constraint and delivers a consumption and labor supply response about 40 to 50 percent larger during the pandemic than when the same transfer is introduced in the steady state. Third, transfers were welfare-improving for recipients, and the welfare gains diminish as transfers grow, since additional transfers push households off the constraint, lowering the marginal utility of consumption.

Two features of our approach are worth emphasizing. The labor supply margin, which much of the literature on transfers abstracts from, is quantitatively central once transfers are large, and our estimated response is consistent with independent quasi-experimental evidence on the earnings response to unearned income. Because the model is structural, we can trace the state dependence directly to the path of the shadow value of the borrowing constraint.

Our analysis abstracts from distortionary taxation in order to isolate the transmission of transfers to households that are borrowing-constrained in normal times. Under this lump-sum benchmark, the general equilibrium effects of financing on investment and output are modest, so the welfare gains to low-income households are large in consumption-equivalent terms, while the losses to high-income households are small. Incorporating distortionary financing would strengthen the adverse general equilibrium effects and would weaken the case for larger transfers, and we view this as an important avenue for future work. More broadly, while we quantify state dependence for the pandemic, the underlying mechanism operates in any state that tightens the borrowing constraint of low-income households, and quantifying its role in other downturns is a natural next step.

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Supplemental Materials

A Additional ASEC Evidence

Table S.1 shows the minimum income level for each quartile of the household income distribution.

Table S.1: Lowest Income Levels (\$) by Household Income Quartile

Calendar Year	First Quartile	Second Quartile	Third Quartile	Fourth Quartile
2015	0	28,001	56,307	102,562
2016	0	29,820	59,070	105,852
2017	0	30,021	61,001	110,597
2018	0	31,689	63,187	113,082
2019	0	34,746	68,637	123,701
2020	0	36,826	71,627	126,710
2021	0	37,965	74,900	133,875
2022	0	37,450	74,875	133,733
2023	0	40,527	80,286	145,001

Source: CPS/ASEC 2016–2024.

Table S.2 shows transfers as a share of household income, as well as the share of households receiving any transfers, during the 2007–2014 period.

Table S.2: Share of Transfer Income and Share of Households Receiving Any Transfers (2007–2014)

Calendar Year	First Quartile		Second Quartile		Third Quartile		Fourth Quartile	
	% of Income	% with Transfer	% of Income	% with Transfer	% of Income	% with Transfer	% of Income	% with Transfer
2007	6.0	24.5	1.2	11.2	0.4	6.5	0.1	3.9
2008	9.1	64.9	3.9	95.5	2.5	98.4	1.2	78.4
2009	10.9	32.7	3.7	20.4	1.8	14.9	0.7	9.2
2010	12.1	35.4	4.0	22.0	1.7	13.4	0.6	9.3
2011	11.6	35.2	3.2	20.7	1.2	12.2	0.4	7.0
2012	11.0	35.2	2.7	18.9	1.0	10.7	0.4	6.3
2013	9.7	34.0	2.2	17.5	0.7	9.3	0.3	5.4
2014	9.2	34.3	1.7	16.7	0.5	7.7	0.2	4.6

Notes: First column under each quartile: average shares (%) of transfer income in total household income; Second column: share (%) of households receiving any transfer income. Source: CPS/ASEC 2008–2015.

Table S.3 provides a breakdown of the average benefit amount per household.

Table S.3: Average Transfer Benefits by Income Quartile

	First Quartile	Second Quartile	Third Quartile	Fourth Quartile
<i>Panel A: Total household benefits</i>				
2015	943	544	322	229
2016	946	464	307	211
2017	790	436	278	200
2018	745	375	246	183
2019	688	363	255	206
2020	4,233	5,737	6,272	4,427
2021	3,658	5,034	5,205	3,190
2022	1,012	636	353	182
2023	971	572	348	254
<i>Panel B: Unemployment compensation</i>				
2015	102	153	204	185
2016	92	134	192	163
2017	71	137	191	158
2018	68	110	152	143
2019	76	123	156	174
2020	881	1,746	2,112	1,778
2021	413	749	759	737
2022	68	154	142	119
2023	70	144	177	195
<i>Panel C: Economic Impact Payments</i>				
2020	2,606	3,571	3,991	2,587
2021	2,197	3,180	3,538	1,739
<i>Panel D: Advance Child Tax Credit</i>				
2021	232	576	712	619

Notes: Values are expressed in current dollars. Source: CPS/ASEC 2016-2024.

B Industry Data

Data on the production side of the economy are based on the BLS Major Industry Total Factor Productivity dataset.¹ The dataset contains all the necessary information to construct TFP series. Specifically, we use (i) nominal gross output and its deflator; (ii) nominal capital cost and its deflator; (iii) nominal labor cost and its deflator; (iv) aggregate hours; and (v) the labor composition index. These series are provided at the two-digit NAICS level.

We assume a Cobb–Douglas production function for each of the two broad industries (high-wage and low-wage, as defined in footnote 16 in the main text). We build series for real output, capital inputs, and labor inputs for our high- and low-wage industries by chain-weighting the real values of their sub-industries, using nominal values as the weights.

¹The Excel spreadsheet can be downloaded [here](#).

Note also that the labor input series is “quality-adjusted,” meaning it is scaled by a labor composition index. This index is itself a chain-weighted index of the labor composition indexes of the sub-industries within the two broad industries, with aggregate hours used as weights. We compute the labor share as labor costs divided by the sum of labor and capital costs and use its average value over 2015–2023. Using these pieces of information in a Cobb–Douglas production function, we recover the TFP series for the two broad industries.

We construct the price index for each of the two sectors as a chain-weighted index of the underlying sub-industry price indexes, using nominal gross output as weights. We then express these sectoral price indexes relative to the aggregate price index, which is taken directly from the dataset.

We detrend sectoral output series using a deterministic trend that grows at a constant rate. This rate is assumed to be driven by exogenous population growth and economy-wide TFP growth, with the latter taken directly from the dataset. As noted in the main text, sectoral nominal wage series are constructed from the ECEC dataset, and we convert them to real wage series by dividing by the aggregate price index.

C Excess Savings for the Bottom Income Quartile

To compute excess savings for households in the bottom quartile of the income distribution, we follow the approach developed by [Aladangady et al. \(2022\)](#) (henceforth ACFP), who estimate US household excess savings as those savings above and beyond what households would have saved if income and spending components had grown at recent, pre-pandemic trends. Their method builds on the national income accounting identity for the flow of household savings as defined by the Bureau of Economic Analysis (BEA) in the National Income and Product Accounts (NIPA):

$$\begin{aligned} \text{Flow of Savings} = & \text{Disposable Personal Income (DPI)} - \\ & \text{Personal Consumption Expenditures (PCE)} - \text{Other outlays.} \end{aligned}$$

To calculate aggregate excess savings, ACFP sum (i) the amount by which each component of DPI exceeds its pre-pandemic trend, and (ii) the amount by which PCE and other outlays fall below their pre-pandemic trend. These flows are then cumulated over time to obtain the stock of excess savings. Pre-pandemic trends are estimated using a log-linear trend fitted over the 2015–2019 period for each component.

To allocate aggregate excess savings across the income distribution, ACFP decompose detailed components of personal income and personal outlays across income quartiles. This decomposition relies on existing microeconomic data sources wherever possible. When gaps exist in the available data, the authors apply institutional knowledge and judgment to allocate the remaining components.

Their original analysis extends through 2022:Q2. To construct estimates for the bottom income quartile through 2023, we follow a three-step procedure. First, we compute aggregate excess savings and aggregate DPI using BEA data following ACFP’s methodology from

2022:Q3 to 2023:Q4. We maintain the same pre-pandemic trend assumptions (2015:Q1–2019:Q4) to ensure consistency with the original estimates. Second, we allocate aggregate excess savings across income quartiles using the shares reported in Figure 7a in the ACFP paper. For quarters beyond 2022:Q2, where the original analysis ends, we assume a constant share of 0.05 for the bottom quartile, close to the average of the previous few quarters of data. Third, we estimate disposable personal income (DPI) for households in the bottom quartile of the income distribution using the ASEC data. Because ACFP do not report DPI disaggregated by income quartile, we use income shares computed from the ASEC. We assign the bottom quartile an income share of 0.05 and hold this share constant over the period 2022:Q2 through 2023.

Our cumulative stock of excess savings for the bottom quartile expressed as a percentage of their disposable personal income equals: $\frac{\text{Q1 excess savings}_t}{0.05 \times \text{Aggregate DPI}_t} \times 100$.

D Details on the Steady-State Calibration

This appendix derives the steady-state values reported in Section 4 and Tables 5 and 6. The calibration targets and data sources are described in Section 4.

D.1 Employment

Using the targets described in Section 4.1 and the industry classification in footnote 16, equations (11) and (12) evaluated at 2015 values are:

$$\underbrace{N_1}_{0.236} = \underbrace{H_l - L_l}_{0.303 \times 0.25} + (1 - \phi) \underbrace{(H_h - L_h)}_{0.75 \times 0.657},$$

$$\underbrace{N_2}_{0.358} = \phi \underbrace{(H_h - L_h)}_{0.75 \times 0.657}.$$

Because there are two equations and one unknown, we choose ϕ to minimize the distance between the two sides. Repeating this for each year of the sample gives the series ϕ_t used in the estimation. We use the 2015 value, $\phi = 0.70$, as its steady-state value.²

D.2 Two Production Sectors

Taking the ratio of the optimality conditions for sectors 1 and 2 gives:

$$\frac{K_2}{K_1} = \left(\frac{1 - \alpha_1}{\alpha_1} \right) \left(\frac{\alpha_2}{1 - \alpha_2} \right) \frac{W_2}{W_1} \frac{N_2}{N_1}. \quad (\text{D.1})$$

Evaluated at the 2015 values $W_2/W_1 = 1.638$ and $N_2/N_1 = 1.519$, and the capital shares $\alpha_1 = 0.345$ and $\alpha_2 = 0.394$ (see Section 4.2), Equation (D.1) implies $K_2/K_1 = 3.075$.

²Sectoral employment levels are expressed as shares of the 16+ population, so the sum of N_1 and N_2 conceptually matches the aggregate EPOP ratio in 2015.

Thus, a large share of the capital stock is allocated to the high-wage sector. Combining the optimality conditions also gives:

$$\frac{P_2 Y_2}{P_1 Y_1} = \left(\frac{1 - \alpha_1}{1 - \alpha_2} \right) \left(\frac{\mathcal{M}_2}{\mathcal{M}_1} \right) \frac{W_2}{W_1} \frac{N_2}{N_1}, \quad (\text{D.2})$$

where $\mathcal{M}_s \equiv \frac{\theta_s}{\theta_s - 1}$ is the price markup in sector s . With the 2015 output ratio $P_2 Y_2 / P_1 Y_1 = 2.665$, Equation (D.2) implies $\mathcal{M}_2 / \mathcal{M}_1 = 0.991$. Setting $\mathcal{M}_2 = 1.6$ (see Section 4.2) gives $\mathcal{M}_1 = 0.991 \times 1.6 = 1.585$.

Normalizing aggregate output and the aggregate price level to 1, the output ratio implies $P_1 Y_1 = 0.273$ and $P_2 Y_2 = 0.727$. Wage levels can be calculated as:

$$W_1 = \frac{(1 - \alpha_1) P_1 Y_1}{\mathcal{M}_1 N_1} = 0.474, \text{ and } W_2 = \frac{(1 - \alpha_2) P_2 Y_2}{\mathcal{M}_2 N_2} = 0.776.$$

With $r = 0.02$ and $\delta = 0.1$ (so that $R = r + \delta = 0.12$), the optimality conditions for capital give $K_1 = 0.492$ and $K_2 = 1.508$. Consumption expenditures in each sector are then:

$$P_s C_s = P_s Y_s - \delta K_s.$$

From the demand function for each sector, the sectoral price levels are:

$$P_1 = [P_1 Y_1 (1 - \omega)^{-\epsilon}]^{\frac{1}{1-\epsilon}} \text{ and } P_2 = [P_2 Y_2 \omega^{-\epsilon}]^{\frac{1}{1-\epsilon}}. \quad (\text{D.3})$$

Given the estimated values $\omega = 0.73$ and $\epsilon = 4.45$ (see Section 6), Equation (D.3) implies $P_1 = 0.677$ and $P_2 = 0.415$. Output and consumption quantities follow:

$$Y_s = \frac{P_s Y_s}{P_s} \text{ and } C_s = \frac{P_s C_s}{P_s}.$$

Steady-state profits and TFP levels are then pinned down by:

$$\begin{aligned} \Pi_s &= P_s Y_s - W_s N_s - R K_s, \\ A_s &= \frac{Y_s}{K_s^{\alpha_s} N_s^{1-\alpha_s}}. \end{aligned}$$

D.3 Households

In the steady state, the borrowing constraint of the type- l household binds, so $B_l = 0$ and $C_l = (H_l - L_l)W_1 + F$. We choose F to match the 8.3 percent transfer share in 2015 (see Section 4.3):

$$\frac{F}{F + (H_l - L_l)W_1} = 0.083.$$

Given the type- l household's labor income, this gives $F = 0.0033$ and $C_l = 0.039$. The discount factor β_l is estimated (see Section 6).

With $B = 1$, the government budget constraint gives steady-state taxes $T = F + rB = 0.023$. The budget constraint of the type- h household then gives its steady-state consumption:

$$C_h = N_h(\phi W_2 + (1 - \phi)W_1) - T + (R - \delta)K + rB + \Pi = 0.757.$$

The values of C_h and C_l determine Λ_h and Λ_l from Equations (2) and (6). We set Ψ_h and Ψ_l to satisfy Equations (3) and (7), respectively. Finally, given β_l ($< \beta_h$), the Euler equation (8) determines the steady-state Lagrange multiplier Θ_l on the borrowing constraint.

D.4 Fiscal Policy

In the tax rule (10), we set $\phi_B = 1$ and $q = 8$. These parameters affect only the timing of taxes and not the allocation (see footnote 15).

E Estimation Details

This appendix describes the estimation. We apply the methods of [Kulish et al. \(2017\)](#) and [Guerrieri and Iacoviello \(2015\)](#) and do not claim a methodology contribution.

We estimate the model using Bayesian techniques with an occasionally “nonbinding” constraint and sampling from the posterior with a Markov Chain Monte Carlo (MCMC). In our model, low-income households face binding borrowing constraints. In response to some shocks and especially in response to large transfers to the household, the borrowing constraint becomes slack temporarily. To deal with such a situation, we follow the literature on estimating DSGE models with occasionally binding constraints (e.g., [Kulish et al., 2017](#)). Here we consider the opposite situation where the constraint temporarily switches from binding to nonbinding and present the likelihood evaluation of the model in such a situation.

E.1 Occasionally Nonbinding Constraints

Following the notation of [Kulish et al. \(2017\)](#), up to a first-order approximation around the steady state, in which the borrowing constraint is binding for the type- l household, the system of linearized equations describing the equilibrium of the economy can be written as:

$$\mathbf{y}_t = \mathbf{J} + \mathbf{A}\mathbf{y}_{t-1} + \mathbf{B}\mathbb{E}_t[\mathbf{y}_{t+1}] + \mathbf{D}\zeta_t, \quad (\text{E.1})$$

where $\mathbf{y}_t$ is a vector of endogenous variables in t , ζ_t is a vector of exogenous variables at t , $\mathbf{J}$ is a vector of constants, and $\mathbf{A}$, $\mathbf{B}$ and $\mathbf{D}$ are coefficient matrices of conformable size. In this economy, the equilibrium is characterized by a policy rule of the following form:

$$\mathbf{y}_t = \mathbf{C} + \mathbf{Q}\mathbf{y}_{t-1} + \mathbf{G}\zeta_t \quad (\text{E.2})$$

Suppose now that, when the borrowing constraint is not binding, the system of linearized equations describing the equilibrium at t is given by:

$$\mathbf{y}_t = \bar{\mathbf{J}} + \bar{\mathbf{A}}\mathbf{y}_{t-1} + \bar{\mathbf{B}}\mathbb{E}_t[\mathbf{y}_{t+1}] + \bar{\mathbf{D}}\zeta_t. \quad (\text{E.3})$$

The difference between systems (E.1) and (E.3) is given by the Lagrange multiplier associated with the borrowing constraint, which is equal to 0 for the periods in which the constraint is not binding.

Suppose that at time t , the constraint is expected to be slack for r periods. From the period $t + r$ onward, the economy is described by the system (E.1) and the policy rules are given by (E.2). Thus, for period $t + r - 1$, the economy follows:

$$\mathbf{y}_{t+r-1} = \bar{\mathbf{J}} + \bar{\mathbf{A}}\mathbf{y}_{t+r-2} + \bar{\mathbf{B}}\mathbf{E}_{t+r-1}[\mathbf{y}_{t+r}] + \bar{\mathbf{D}}\zeta_t. \quad (\text{E.4})$$

Using the policy rules for $\mathbf{y}_{t+r}$, given by (E.2), in (E.4), we obtain:

$$\mathbf{y}_{t+r-1} = \bar{\mathbf{J}} + \bar{\mathbf{A}}\mathbf{y}_{t+r-2} + \bar{\mathbf{B}}\mathbf{E}_{t+r-1}[\mathbf{C} + \mathbf{Q}\mathbf{y}_{t+r-1} + \mathbf{G}] + \bar{\mathbf{D}}\zeta_t.$$

Solving this for $\mathbf{y}_{t+r-1}$ yields the policy rules for $\mathbf{y}_{t+r-1}$:

$$\mathbf{y}_{t+r-1} = \mathbf{C}_{t+r-1} + \mathbf{Q}_{t+r-1}\mathbf{y}_{t-1} + \mathbf{G}_{t+r-1},$$

where

$$\begin{aligned} \mathbf{C}_{t+r-1} &= (\mathbf{I} - \bar{\mathbf{C}}\bar{\mathbf{Q}})^{-1}, (\bar{\mathbf{J}} + \bar{\mathbf{B}}\bar{\mathbf{C}}), \\ \mathbf{Q}_{t+r-1} &= (\mathbf{I} - \bar{\mathbf{C}}\bar{\mathbf{Q}})^{-1}\bar{\mathbf{A}}, \\ \mathbf{G}_{t+r-1} &= (\mathbf{I} - \bar{\mathbf{C}}\bar{\mathbf{Q}})^{-1}\bar{\mathbf{D}}. \end{aligned}$$

Iterating backward, we see that the policy rule at t can be written as:

$$\mathbf{y}_t = \mathbf{C}_t + \mathbf{Q}_t\mathbf{y}_{t-1} + \mathbf{G}_t\zeta_t,$$

where

$$\begin{aligned} \mathbf{C}_t &= (\mathbf{I} - \bar{\mathbf{C}}\bar{\mathbf{Q}}_{t+1})^{-1}, (\bar{\mathbf{J}} + \bar{\mathbf{B}}\bar{\mathbf{C}}_{t+1}), \\ \mathbf{Q}_t &= (\mathbf{I} - \bar{\mathbf{C}}\bar{\mathbf{Q}}_{t+1})^{-1}\bar{\mathbf{A}}, \\ \mathbf{G}_t &= (\mathbf{I} - \bar{\mathbf{C}}\bar{\mathbf{Q}}_{t+1})^{-1}\bar{\mathbf{D}}. \end{aligned}$$

Note also that $\mathbf{C}_{t+r} = \mathbf{C}$ and $\mathbf{Q}_{t+r} = \mathbf{Q}$. Therefore, for a given sequence of expected durations of the state in which the constraint does not bind, denoted by r_t , we can compute the policy rules, following the procedure described above.

E.2 Likelihood Evaluation

Given the procedure described in the previous section, we have the time-varying policy rules for all endogenous variables.

$$\mathbf{y}_t = \mathbf{C}_t + \mathbf{Q}_t\mathbf{y}_{t-1} + \mathbf{G}_t\zeta_t,$$

where $\mathbf{C}_t = \mathbf{C}$, $\mathbf{Q}_t = \mathbf{Q}$, and $\mathbf{G}_t = \mathbf{G}$ for all periods in which the constraint is binding, and for all periods in which the constraint is not binding, $\mathbf{C}_t$, $\mathbf{Q}_t$, and $\mathbf{G}_t$ are a function of r_t . We can then

use the time-varying coefficient Kalman filter to evaluate the likelihood function. Following [Hamilton \(1994\)](#) (Section 2.6), the state-space representation of this system is given by:

$$\begin{aligned}\mathbf{x}_t &= \mathbf{a}_t + \mathbf{H}_t' \mathbf{y}_t + \mathbf{w}_t, \\ \mathbf{y}_t &= \mathbf{C}_t + \mathbf{Q}_t \mathbf{y}_{t-1} + \mathbf{G}_t \zeta_t,\end{aligned}$$

where $\mathbf{x}_t$ is a vector of observables, $\mathbf{a}_t$ is a vector of intercepts, $\mathbf{H}_t$ is a coefficient matrix, and $\mathbf{w}_t$ is a vector of measurement errors with a variance-covariance matrix equal to $\mathbf{R}_t$. Note that the size of the vector $\mathbf{x}_t$ is also allowed to be time-varying. In our case, $\mathbf{x}_t$ does not include excess savings in periods in which the borrowing constraint is binding. The Kalman filter is implemented by iterating on the following equations:

$$\begin{aligned}\hat{\mathbf{y}}_{t|t} &= \hat{\mathbf{y}}_{t|t-1} + \mathbf{K}_t (\mathbf{x}_t - \mathbf{a}_t - \mathbf{H}_t \hat{\mathbf{y}}_{t|t-1}), \\ \hat{\mathbf{y}}_{t+1|t} &= \mathbf{C}_{t+1} + \mathbf{Q}_{t+1} \hat{\mathbf{y}}_{t|t}, \\ \mathbf{K}_t &= \mathbf{P}_{t|t-1} \mathbf{H}_t (\mathbf{H}_t' \mathbf{P}_{t|t-1} \mathbf{H}_t + \mathbf{R}_t)^{-1}, \\ \mathbf{P}_{t+1|t} &= \mathbf{Q}_t \mathbf{P}_{t|t-1} \mathbf{Q}_t' - \mathbf{Q}_t \mathbf{K}_t \mathbf{H}_t' \mathbf{P}_{t|t-1} \mathbf{Q}_t' + \mathbf{\Gamma}_t, \\ \mathbf{\Gamma}_t &= \mathbf{G}_t \mathbf{\Sigma}_\zeta \mathbf{G}_t', \\ \mathbf{\Sigma}_\zeta &= \mathbb{E} [\zeta_t \zeta_t'] .\end{aligned}$$

We initialize the Kalman filter with the unconditional variance of the model in which the borrowing constraint always binds, namely:

$$\mathbf{P}_{1|0} = [\mathbf{I}_{n^2} - (\mathbf{Q} \otimes \mathbf{Q})]^{-1} \text{vec}(\mathbf{\Gamma})$$

The likelihood function is expressed as:

$$\begin{aligned}\mathcal{L} &= \sum_{t=1}^T f(\mathbf{x}_t | \mathbf{x}^{t-1}; \Theta, \mathcal{D}) \text{ where} \\ f(\mathbf{x}_t | \mathbf{x}^{t-1}; \Theta, \mathcal{D}) &= -\frac{m_t}{2} \log(2\pi) - \frac{1}{2} \log | (\mathbf{H}_t' \mathbf{P}_{t|t-1} \mathbf{H}_t + \mathbf{R}_t) | \\ &\quad - \frac{1}{2} (\mathbf{x}_t - \mathbf{a}_t - \mathbf{H}_t' \hat{\mathbf{y}}_{t|t-1})' (\mathbf{H}_t' \mathbf{P}_{t|t-1} \mathbf{H}_t + \mathbf{R}_t)^{-1} (\mathbf{x}_t - \mathbf{a}_t - \mathbf{H}_t' \hat{\mathbf{y}}_{t|t-1}).\end{aligned}$$

$\mathbf{x}^t$ is the vector of observables through t , Θ is the vector of model parameters and $\mathcal{D}$ is the expected duration of the state of the constraint being slack.

E.3 Estimation Assumptions

We estimate the model parameters using Bayesian techniques by combining the likelihood function with time-varying coefficients and our priors over the parameters. In addition to the prior distributions on the model parameters, we impose the following two restrictions on the estimation.

First, we impose that the borrowing constraint was binding before 2020 and could be slack from 2020 onward. That implies that for a given set of parameters, we impose that the filtered vector of endogenous variables implies that (1) the expected level of assets for the type- l household is greater than zero for r_t periods, and (2) that the value of the Lagrange multiplier before 2020 is always greater than zero.³

Second, given the period for which the borrowing constraint was not binding, and for a given set of parameters, we use the sequence of expected durations of the nonbinding constraint that is model-consistent. In other words, we impose that r_t is equal to the expected duration of the nonbinding constraint at time t given the filtered shocks up to time t . To check this, for each period t in which the constraint is not binding, we filter the model's shocks given the data up to period t . Hence, given the expected duration r_t , we check that the expected level of assets for the type- l household is greater than 0 for exactly r_t periods.

Given these restrictions and assumptions, we sample from the posterior distribution using Markov Chain Monte Carlo methods. In particular, we implement the Metropolis-Hastings algorithm with a multivariate normal random-walk proposal whose variance-covariance matrix is set equal to the inverse of the Hessian of the log posterior evaluated at the optimization mode. We scale this matrix to target an acceptance rate of 24 percent. We then generate 2 million draws and compute posterior statistics based on these draws.

E.4 Additional Estimation Results

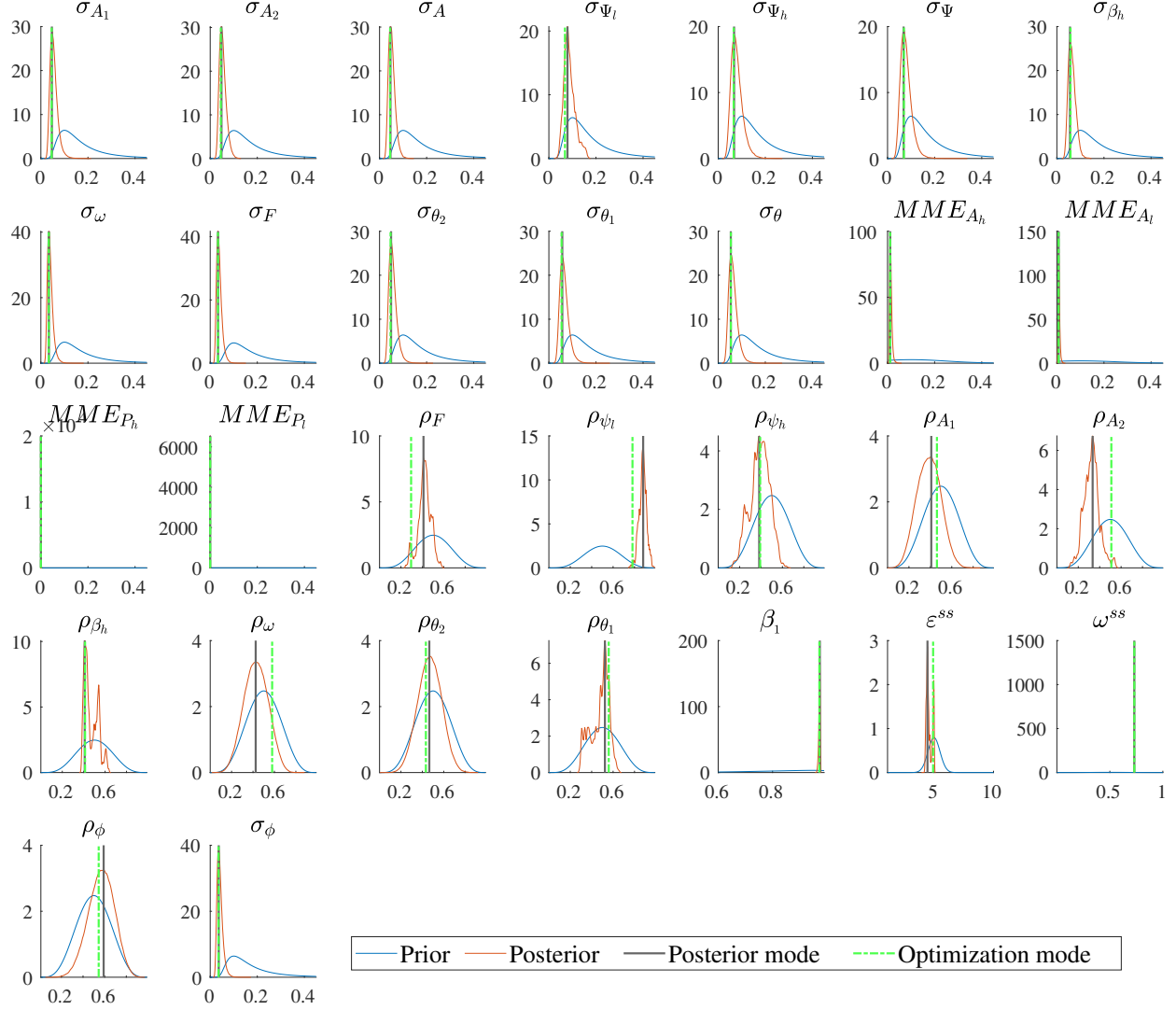
Table S.4 presents the prior and posterior distribution for all of our estimated parameters.

We next present two types of post-estimation checks. First, the prior and posterior distributions of the parameters are presented in Figure S.1. For most parameters, the posterior is more concentrated than the prior, indicating that the data are informative. Specifically, for most parameters, the posterior distribution is less dispersed than the prior and is concentrated around a specific value, indicating that the data have provided meaningful information about the parameter. In contrast, for some parameters like ρ_ϕ , the posterior distribution overlaps significantly with the prior, suggesting that the data are not very informative about this parameter.

Second, Figure S.2 presents the trace plots. Importantly, most of the plots exhibit a stable mass around the mode, with no indication of drift or movement over time. This suggests that the chain has converged to a stationary distribution, with the draws being representative of the posterior distribution. Furthermore, the plots are consistent across different sections of the chain, including the early iterations, indicating that the chain has reached a stable equilibrium and is not exhibiting any transient behavior.

³A negative multiplier would be inconsistent with a binding constraint.

Figure S.1: Prior and Posterior Distributions



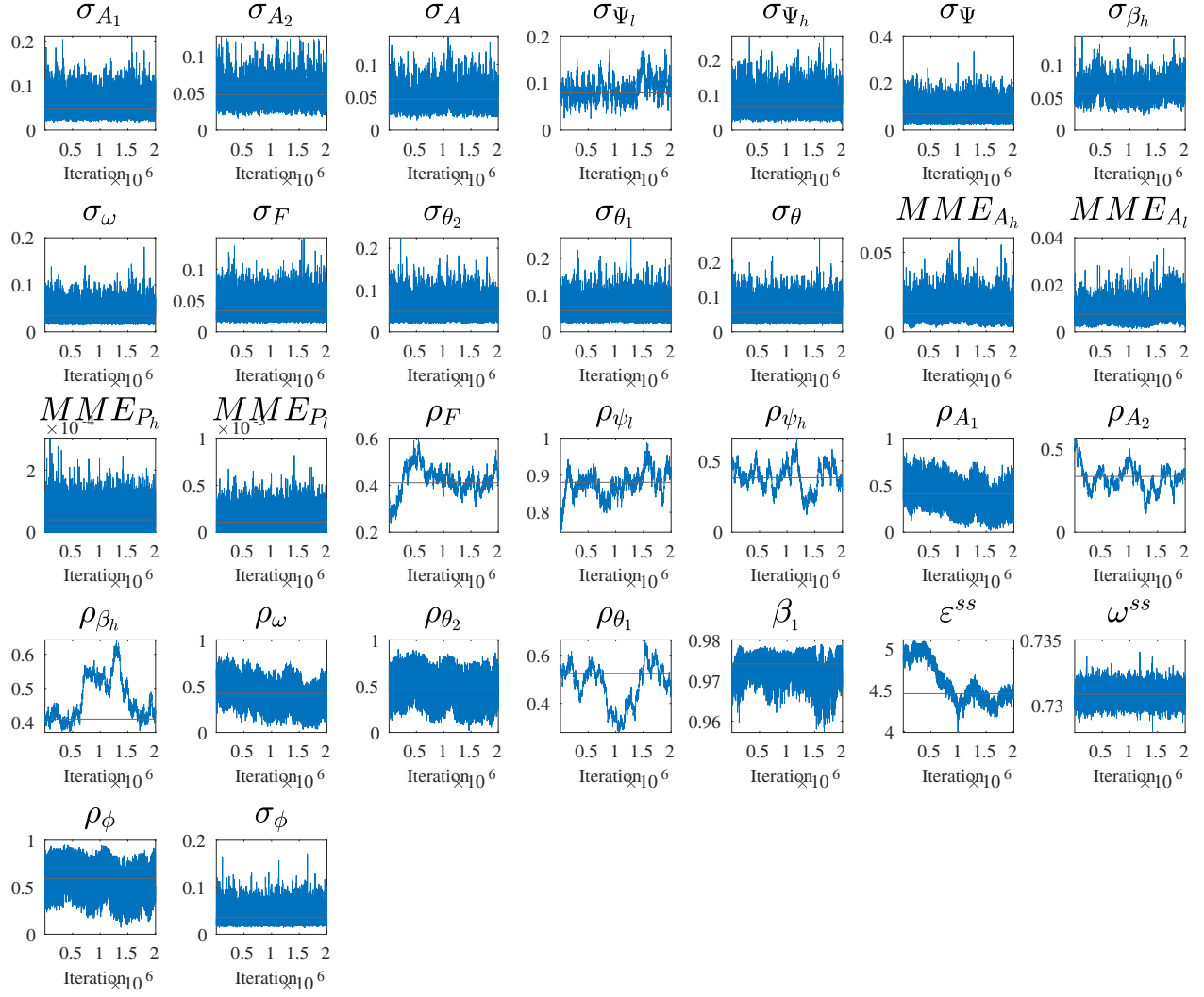
Notes: This figure plots the prior distributions (blue lines) along with the posterior distributions based on 2 million draws. The black vertical lines represent the posterior mode while the dashed vertical lines represent the optimization mode.

Table S.4: Model Priors and Posteriors

Parameter Name	Parameter	Prior			Posterior			
		Dist	Mode	SD	Mode	SD	90 % HPD	
<i>Standard deviation of shock innovations (x100)</i>								
Productivity sector 1	σ_{A_1}	invg	0.100	0.150	0.047	0.017	0.037	0.077
Productivity sector 2	σ_{A_2}	invg	0.100	0.150	0.048	0.015	0.037	0.073
Aggregate productivity	σ_A	invg	0.100	0.150	0.046	0.014	0.036	0.071
Labor supply type-l household	σ_{Ψ_l}	invg	0.100	0.150	0.079	0.024	0.060	0.121
Labor supply type-h household	σ_{Ψ_h}	invg	0.100	0.150	0.067	0.025	0.052	0.112
Aggregate labor supply	σ_{Ψ}	invg	0.100	0.150	0.068	0.024	0.052	0.109
Discount factor type-h household	σ_{β_h}	invg	0.100	0.150	0.056	0.016	0.046	0.085
Weight on sector 2 goods	σ_{ω}	invg	0.100	0.150	0.034	0.012	0.027	0.055
Transfers	σ_F	invg	0.100	0.150	0.033	0.012	0.026	0.054
Markup sector 2	σ_{θ_2}	invg	0.100	0.150	0.049	0.017	0.038	0.079
Markup sector 1	σ_{θ_1}	invg	0.100	0.150	0.057	0.019	0.044	0.091
Aggregate markup	σ_{θ}	invg	0.100	0.150	0.053	0.019	0.043	0.088
Type-h household composition	σ_{ϕ}	invg	0.100	0.150	0.036	0.012	0.028	0.057
<i>Autocorrelation</i>								
Transfers	ρ_t	beta	0.500	0.150	0.411	0.060	0.348	0.498
Labor supply type-l household	ρ_{ψ_l}	beta	0.500	0.150	0.881	0.035	0.831	0.920
Labor supply type-h household	ρ_{ψ_h}	beta	0.500	0.150	0.383	0.092	0.254	0.504
Productivity sector 1	ρ_{A_1}	beta	0.500	0.150	0.409	0.111	0.241	0.529
Productivity sector 2	ρ_{A_2}	beta	0.500	0.150	0.334	0.072	0.232	0.414
Discount factor type-h household	ρ_{β}	beta	0.500	0.150	0.410	0.063	0.400	0.552
Weight on sector 2 goods	ρ_{ω}	beta	0.500	0.150	0.425	0.112	0.282	0.574
Markup sector 2	ρ_{θ_2}	beta	0.500	0.150	0.465	0.110	0.325	0.610
Markup sector 1	ρ_{θ_1}	beta	0.500	0.150	0.524	0.085	0.340	0.571
Type-h household composition	ρ_{ϕ}	beta	0.500	0.150	0.591	0.118	0.412	0.719
<i>Measurement Error</i>								
Productivity sector 2	MME_{A_2}	norm	0.100	0.150	0.011	0.005	0.008	0.020
Productivity sector 1	MME_{A_1}	norm	0.100	0.150	0.007	0.003	0.005	0.014
Price index sector 2	MME_{P_2}	norm	0.100	0.150	0.000	0.000	0.000	0.000
Price index sector 1	MME_{P_1}	norm	0.100	0.150	0.000	0.000	0.000	0.000
<i>Structural Parameters</i>								
Discount factor type-l household	β_l	beta	0.950	0.150	0.974	0.003	0.969	0.976
Elasticity of subs, sectors 1 and 2	ϵ	norm	5.000	0.500	4.455	0.242	4.337	4.982
Weight on sector 2 goods	ω	beta	0.500	0.150	0.731	0.000	0.730	0.731

Notes: norm, beta, and invg refer to normal, beta, and inverse gamma distributions, respectively.

Figure S.2: Trace Plots



Notes: This figure plots the sampled values of the model parameters at each iteration of the MCMC process. Black horizontal lines represent posterior mode values.