Supplemental Appendix

The Matching Multiplier and the Amplification of Recessions

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A Data Appendix

A.1 LEHD Data

This project uses a 23-state subset of the LEHD. The LEHD is an unbalanced panel of states, and Table A2 reports the years for which each state is included in this analysis. I exclude individuals for whom industry and firm information is missing. For each state, I drop the first two years of available individual-level data, as lagged incomes are not well-defined for workers in those years. In addition, I drop the first two years in which an individual appears in the entire sample. For the majority of individuals, this is the same restriction as dropping the first two years of the state. However, for workers who appear in the sample in the later years (e.g., workers moving into the sample, young workers, etc.), this is an additional restriction that ensures that the lagged earnings, and thus MPCs, are well-defined for all workers. This two-year lag restriction excludes about 20 percent of the sample in each year. To abstract from schooling and retirement decisions, I exclude another 12 percent of the original sample who are not between the ages of 25 and 62.

One potential concern with the rolling-panel structure of the LEHD is that the magnitude of the measurement error in constructing the total earnings series is changing over time. Both in constructing lagged incomes for the MPC estimation and in defining income processes over the business cycle, I rely on the full set of earnings across all states for the individual. As states enter the sample over time, total earnings for individuals employed across multiple states may jump artificially. In order to address these issues, I supplement the baseline analysis with analysis run on the subset of states with data available by 1993. These states, listed in bold in Table A2, represent 70 percent of the workers in the full sample. While I only report the robustness for the key findings, this subsample produces very similar patterns throughout the entire analysis.

The LEHD provides a comprehensive snapshot of employment in each quarter, but it does not provide information on labor market activity for workers in periods when they are not employed within this sample. Therefore, I must take a stance on the labor market activity of workers who leave my sample. This assumption enters in both my measurement of labor market outcomes and my calculation of an individual's MPC, in so far as it affects the level of an individual's average earnings in the two previous years.

Throughout the main analysis, I assume that prime-age workers who leave employment in my sample make no labor market earnings in those quarters. This assumption would be violated if individuals moved to a job either outside the LEHD coverage (i.e., to the military, federal employment, or self-employment) or to a state that is not in my sample. Using the ACS subsample, I find that among workers who leave my LEHD sample between $t-1$ and t, and are in the ACS in year t, 24 percent report being employed elsewhere, suggesting that this margin is potentially non-negligible. However, this would be a serious problem for my covariance estimate only if workers of different characteristics were differentially likely to move outside the LEHD sample over the business cycle. For example, if younger workers were disproportionately likely to move to states outside of my sample during recessions, then I would overstate the unemployment of young workers in recessions, and thus erroneously conclude that the earnings of young workers were more sensitive to recessions, when in fact they are not. In addition to overstating the sensitivity of these workers' earnings to GDP, I may exaggerate the difference in MPCs between workers of different ages, as the lagged earnings of younger workers would be biased downwards (because they had positive earnings in other states, rather than the zero earnings that I assume). Note that since I mostly focus on the cross-section of employment, and since I remove the initial employment periods, this bias in the measurement of lagged earnings would only appear for workers who moved out of my sample to noncovered employment and then returned to my sample in a future period. However, both of these patterns together would lead me to potentially overstate the differential sensitivity of workers of different

MPCs to business cycles.

While I cannot fully address these concerns, I explore their importance in two ways. First, using the matched monthly basic Current Population Survey (CPS), I explore the probabilities that workers of different MPCs transition from private sector employment into the military, self-employment, or the federal government, all of which are sectors beyond the scope of the LEHD (Flood et al., 2021). The CPS features a rolling panel structure wherein individuals are interviewed for four months, have eight months off, and then are interviewed again for four months. I flag an individual as making a transition to noncovered employment at time t if they are newly self-employed, in the military, or in federal government at time t and were in the private sector in any previous survey. Table A15 shows how the probability of moving to noncovered employment varies over the business cycle. Column 1 shows that on average, high-MPC workers are less likely to move to employment outside the LEHD sample; Column 2 shows that on average, transitions from LEHD employment to noncovered employment are less likely during recessions; while Column 3 shows that there is no differential sensitivity in mobility by a worker's MPC.[33]

Second, within the PSID, I calculate the baseline LEHD regressions in Table 2 within the PSID. Since the PSID includes all states, I can directly compare the estimates using the actual observed change in earnings and then replacing worker earnings with 0 if they moved from one of the states in the LEHD sample to a state that is not in the LEHD sample. The second of these outcomes is the equivalent to what I assume within the LEHD, while the first includes the effects of mobility. The gap between these estimates should demonstrate the importance of these cross-state moves for my LEHD estimates. Table **??** shows the estimates for total earnings (columns 1 and 2), the extensive margin of employment (columns 3 and 4) and the intensive margin of earnings (columns 5 and 6). As you can see from comparing the estimates in column 1 to column 2, column 3 to column 4, and column 5 to column 6, I find that this assumption makes only a very small difference overall.

A.2 PSID Data

The PSID surveys households annually from 1968 to 1997 and every other year from 1997 to 2015. Each household in the PSID is interviewed once a year, primarily between March and June. In each year of the survey, households are asked about the demographics and labor market status of the household head and spouse. For the length of the survey from 1968 to 2015, households are also asked about how much their household spent on food in the average week. While this is not specific to the week of the interview, it likely refers to the recent period. The income measures, however, refer to the annual income for the previous tax year (i.e., 2007 income is collected in the 2008 survey), and I use the panel structure of the data to get a measure of annual labor market earnings in the year of the interview. This means that the income measure will capture all income in that calendar year, while the consumption and labor market variables will refer to the survey month.

Table A3 shows the summary statistics for the PSID sample. Columns 1 and 2 show the snapshot of employed workers in the PSID in the LEHD sample states and nationally, respectively. These two samples are very similar to each other, showing that the LEHD sample is largely nationally representative. A comparison of Column 1 in Table A3 and Column 3 of Table A1 also shows that the PSID sample is similar to the LEHD sample on all demographics. The only exception is that the average income in the PSID is higher than the average income in the LEHD. This is likely because the PSID is restricted to household heads and spouses who are employed full time, while the LEHD includes all workers who had any covered earnings in that quarter. Lastly, Column 3 shows summary statistics for the sample used in the baseline estimation

[33] Since the CPS does not record the lagged income over the previous two years, I impute the MPC of the individual using only demographic characteristics (race, age, and gender). Within the PSID, the MPCs that result from this modified imputation are similar to those that result from the baseline estimation used in the LEHD.

of MPCs. This sample differs from that in Column 2 along several dimensions. Most significantly, it includes workers who were employed in $t-2$ but makes no restrictions on employment status in time t. It also adds the SEO sample, which oversamples low-income households.

A key limitation of the PSID data is that the main measure of expenditure is food. Figure A1 shows that the fraction of total expenditures that is spent on food is changing across the income distribution. The upward slope at the low end of the income distribution reflects the phase out of food stamps, which subsidize the consumption of food for lower-income households.

The main method that I use to impute total consumption in the PSID closely follows the methodology laid out in Blundell, Pistaferri and Preston (2008). They propose a method to impute expenditures in the PSID using information in the CEX.[34] The approach involves estimating a demand system for food as a function of nondurable consumption, demographic variables, and relative prices. Under the assumption that food demands are monotonic, this demand function can be inverted to get an estimate of total consumption in the PSID. In order to deal with measurement error in expenditures, Blundell, Pistaferri and Preston (2008) instrument the nondurable consumption with the average (by cohort, year, and education) hourly earnings of the husband and wife.

I modify and simplify the Blundell, Pistaferri and Preston (2008) analysis along several dimensions. First, in order to be consistent with the second method described below, I estimate the reverse of the equation (i.e., estimate total consumption as a function of food consumption). This decision does not affect the estimates, as the resulting consumption series is nearly identical when using the reverse specification. Second, I estimate this relationship for both durable and nondurable consumption combined.[35] Third, I include households with single household heads. I do this because I am including those households within the PSID and LEHD. Fourth, I estimate the relationship using OLS, rather than using the instruments as the original paper does. Fourth, I use an updated sample, extending their sample to 2013. Table A4 shows the summary statistics for the CEX sample used in the imputation. The sample looks very similar to the PSID sample on demographics, except that on average, the workers have slightly lower incomes. Using this sample in the CEX, I estimate the following equation

$$\ln C_{ht} = Z_{ht}\beta + p_t\gamma + g(f_{ht}, X_{ht})\theta + u_{ht} \tag{A1}$$

where C_{ht} is total household consumption, Z_{ht} are household demographics, p_t are relative prices (i.e., Consumer Price Index, or CPI, series from U.S. Bureau of Labor Statistics, 2022b,c,d,e,f,g,h,i,j,k,l,m), f_{ht} is food consumption, and X_{ht} are demographic characteristics and time dummies that shift the relationship between food consumption and overall consumption. These time dummies allow the food share to shift over time and can be used because the PSID and CEX have overlapping time frames.[36] Figure A2 shows that imputed total consumption in the PSID closely captures the relationship between food consumption and total consumption across the income distribution in the CEX.

An alternative methodology for imputing total consumption in the PSID is to follow Attanasio and Pistaferri (2014) and use the relationship between food consumption and overall consumption in the later years of the sample to impute the total consumption in the previous years of the sample.[37] This imputation

[34] The CEX includes much more comprehensive measures of consumption. Indeed, it covers around 95 percent of all expenditures, excluding housekeeping, personal care products, and nonprescription drugs. In the interview survey data, consumption is recorded for each month in the three months preceding the interview. This is then aggregated to create measures of total quarterly consumption for each household in an array of spending categories.

[35] Specifically, I estimate this equation using total consumption, which is the sum of nondurable and durable consumption. However, results are very similar when I estimate it separately for nondurable and durable consumption and then aggregate.

[36] I follow Blundell, Pistaferri and Preston (2008) in my choice of controls. These include dummies for the number of children in the household; three education bins; a quadratic in age; region of residence dummies; an indicator for being white; 4 education bins; and year, and children dummies. All of these are interacted with food consumption.

[37] The expanded consumption measure within the PSID includes home insurance, rent, electricity, heating, water and miscella-

approximates total consumption less food (i.e., net consumption) as a function of demographics and food consumption

$$\ln n_{ht} = Z_{ht}\beta + p_t\gamma + g(f_{ht})\theta + u_{ht} \tag{A2}$$

where n_{ht} is the net consumption of the household, Z_{ht} are various socioeconomic variables, p_t are prices, and f_{ht} is food consumption. I estimate this equation restricting the sample to one observation per household and include controls individually for the demographics of the head and spouse. The implicit assumption in this imputation is that the preferences of individuals are stable over time, and thus, the relationship between overall consumption and food consumption remains stable. This contrasts with the assumption in the CEX-based imputation that uses the same time period from two different samples.[38] Using the β, γ, and θ that result from estimating Equation A2 on the 1999 to 2013 subsample, I recover an estimate of total household consumption in each year using

$$\widehat{c_{ht}} = f_{ht} + e^{Z_{ht}\widehat{\beta} + p_t\widehat{\gamma} + g(f_{ht})\widehat{\theta}}$$

A.3 Additional Estimates of Marginal Propensities to Consume

In the baseline estimation of MPCs, I restrict the sample to those individuals who are employed in year $t-2$. I restrict to $t-2$ rather than $t-1$ so that I can include the later years of the PSID sample when the survey is collected every two years.[39] The changes in both income and consumption are also defined over a two-year period. From the entire PSID sample, I exclude observations that do not meet the panel structure necessary to define two-year changes in income and consumption, restrict attention to those between ages 25 and 62 in year t, and drop observations with missing race or education. In addition, in each regression, I exclude observations where the two-year change in log consumption or log income is more than 4.[40] I define an individual's lagged income as the labor market earnings for the individual in years $t-1$ and $t-2$. I group this average into five approximately equally sized bins: $< \$22,000$, $\$22,000 - \$35,000$, $\$35,000 - \$48,000$, $\$48,000 - \$65,000$, and $> \$65,000$. The measure of lagged income is intended to capture differences in permanent earnings capacity across groups. However, I find that patterns across lagged incomes are not sensitive to the particulars of how lagged earnings are defined; the same patterns for estimated MPCs appear when using additional income lags or fixing earnings at a given age, which may capture a more permanent measure of income.

Table A5 and Figure A4 display supporting statistics for the baseline estimates discussed in detail in the main text. Specifically, Figure A4 shows the first-stage and reduced-form estimates associated with Figure 2 in the main text. The left panel shows substantial variation in the effect of unemployment on the level of labor income, with the largest falls, unsurprisingly, being among the highest earners. The right panel shows that there is less, although still substantial, variation in the level of the consumption drop

neous utilities, car insurance, car repairs, gasoline, parking, bus fares, taxi fares and other transportation, school tuition and other school expenses, child care, health insurance and out-of-pocket health costs, and food.

[38] I closely follow Attanasio and Pistaferri (2014) in parameterizing controls in Z. Like them, I include a third-degree polynomial in total food consumption; dummies for age, education, marital status, race, state, and employment status; the hours worked by the household head; homeownership status; family size and the number of children in the household, and consumer price indices to capture relative prices (overall CPI, CPI for food at home, CPI for food away from home, and CPI for rent). I also include household income as a consumption shifter and the spouses' labor market variables as controls in Z.

[39] These later years are particularly important both because they overlap with the time period of the LEHD and because they represent a significant fraction of the years for which the CEX and the PSID overlap – and thus the years for which I have the expanded consumption measure.

[40] This restriction on outliers is similar to that in Hendren (2017), who excludes individuals with more than a threefold change in food consumption, and Gruber (1997), who excludes observations with a greater than 1.1 log change in food consumption.

across households. Table A5 shows the regression estimates for Equation 5 that produce the distribution of MPCs shown in Figure A3. The left column reports regression coefficients using food consumption only; the middle panel shows estimates using the PSID-based imputation measure, which is described in Appendix A.2; and the third panel shows the baseline estimates using the CEX-based imputation of total consumption, which is used as the baseline consumption measure throughout this analysis. The fourth panel shows results using unexpected job loss as the instrument. Unsurprisingly, these multivariate estimates echo the patterns displayed in Figure 2, in which black, lower-income, and young workers have higher MPCs.

The left panel of Figure A6 shows the overall estimates of the MPC that result from re-estimating Equation 5 using different identifying income shocks. First, the left-most point shows the OLS version of Equation 5. The coefficient is close to 0, suggesting a substantial downward bias and the need for an instrument to identify the causal relationship between consumption and income movements. However, while the use of an instrument matters critically, across the x-axis, estimates of the MPC are relatively stable to the type of income shock used as the instrument. For comparison, the second point shows the baseline MPC estimated using the unemployment shock. The next four estimates show the MPC estimated using either the change in state GDP or the national unemployment rate of the worker's industry. For an individual worker, these aggregate changes are plausibly exogenous to their own earnings and affect their earnings both positively and negatively and on both the intensive and extensive margins. While noisier, the average MPC estimates are only slightly smaller. This is true whether I include all workers (as in columns 3 and 4) or restrict to those workers who remain employed (as in columns 5 and 6). Those who remain employed across years experience a smaller income change yet a similar MPC.[41] Lastly, the farthest-right point shows the average MPC estimated using an indicator for whether the worker becomes employed between $t-2$ and t.[42] The average MPC is slightly higher with the positive income "shock," but this is an artifact of the different estimation samples – the hires estimation restricts to the nonemployed, who, on average, have higher MPCs than the employed. When averaged on the same sample, the estimates are similar. The right panel of Figure A6 shows that not only are the averages similar for these different shocks, but the alternate MPC estimates are also highly correlated at the individual level.

Figure A7 explores the stability of MPCs over the business cycle and plots the bivariate versions of Equation 5, modified to allow the MPC to vary with the state unemployment rate. The blue circles plot the MPC at the average unemployment rate in the state, and the red squares show the implied MPC at 4 percentage points above the average unemployment rate. Generally, the MPC is somewhat lower in recessions, but the differences are economically and statistically insignificant.

Table A6 shows the correlation between the baseline MPC estimates and those estimates including various job-level characteristics. In the first specification, I include the individual's tenure with their current employer. This variable is intended to capture some amount of private information on the riskiness of the individual's job, as workers with longer job tenures are less likely to lose their jobs (Farber, 1999). Column 3 adds the lagged variance of an individual's earnings. Columns 4 and 5 include the variance of an individual's lagged earnings, capturing the fact that individuals with a higher earnings variance may differ in their MPCs. This variable is calculated using the matched monthly basic CPS from 1976 to 2013 and is the sample average of the change in log earnings between interview 4 and interview 8, which are a year apart. This variable is intended to capture the expected variability of earnings of the job. Lastly, I include dummies for the census region of residence, allowing MPCs to vary geographically. As shown in Table

[41] I find that those who remain employed across surveys experience a drop in total hours worked when the unemployment rate is high, suggesting moves to part-time employment.

[42] This specification includes only those who were not employed in $t-2$; thus the control group is the set of individuals who remain nonemployed between $t-2$ and t. Patterns are robust to including only those who are unemployed, rather than nonemployed, in $t-2$.

A6, the resulting MPC heterogeneity does not change meaningfully when these variables are added.

A.4 Additional Results for $Cov(MPC_i, \gamma_i)$

A.4.1 Adjusted Standard Errors

Clustered standard errors for Equation 6 do not take into account the additional noise imposed by the imputation of a worker's MPC. Indeed, the worker MPC estimates rely on two imputations. I first impute total consumption in the PSID using the CEX, and then I impute the MPC in the LEHD using the MPC estimates from the PSID. In order to account for the additional noise injected at each of these steps, I implement multiple imputation techniques, as in Rubin (1987). Specifically, I take 100 draws in which I randomly sample with replacement both the CEX and the PSID. This produces 100 estimates of main-text Equation 5, which estimates the MPC for each demographic group x. In the LEHD, I then estimate main-text Equation 6 for each imputation, which results in 500 estimates of the degree to which workers of different MPCs are exposed to recessions. I combine these various estimates following the formulas derived in Rubin (1987):

$$\bar{\alpha}_2 = \sum_{i=1}^{100} \frac{\widehat{\alpha}_{2,i}}{100}$$

$$var(\alpha_2) = \sum_{i=1}^{100} \frac{var(\widehat{\alpha_{2,i}})}{100} + \sum_{i=1}^{100} \frac{(\widehat{\alpha}_{2,i} - \bar{\alpha}_2)^2}{99} + \sum_{i=1}^{100} \frac{(\widehat{\alpha}_{2,i} - \bar{\alpha}_2)^2}{99 * 100}$$

The point estimate is the average across imputation draws, while the variance of the estimate is the combination of the average within-draw variance and the between-draw variance.

A.4.2 Robustness of LEHD-based Estimates

Figure 1 clearly demonstrates that there is a positive relationship between the average earnings cyclicality of a demographic group and the average MPC of that group. The additional results presented in this section support the robustness of this pattern. First, Figure A8 shows this pattern separately for the intensive margin of earnings (i.e., earnings conditional on remaining employed between $t-1$ and t) and the extensive margin of employment. The figure clearly shows that higher-MPC workers are more likely to become unemployed during recessions and earn less conditional on remaining employed. Indeed, the same demographic groups that are exposed on the intensive margin are also exposed on the extensive margin of earnings.

Tables A7 and A8 probe the robustness of the positive relationship between a worker's MPC and the exposure of their earnings to recessions to several data decisions. Table A8 shows that the estimated relationship is robust to various methods of imputing MPCs. Since the magnitude of the MPCs changes with the imputation method, so does the magnitude of the coefficient, but the proportional relationship is fairly stable (see Table 3 in the main text for implied amplification for each measure).

Table A7 show that the covariance is relatively stable across specifications. When estimating the relationship between earnings sensitivities and MPCs at the individual level, taking the log of earnings will restrict to those who remain employed. Therefore, in the baseline analysis, I estimate an overall earnings elasticity at the individual level by replacing the change in log earnings with $\Delta E_{i,t} = \frac{E_{i,t} - E_{i,t-1}}{.5 * E_{i,t} + .5 * E_{i,t-1}}$, which bounds the earnings loss of the nonemployed at negative 2. However, column 2 shows that the patterns are similar when using a log transformation (i.e., $\Delta E_{i,t} = \log(E_{i,t} + 100) - \log(E_{i,t-1} + 100)$).

The following columns of Table A7 show that the estimated relationship is robust to various other modifications. Baseline estimates consider movements in fourth-quarter earnings, but Column 3 shows that patterns are still present when considering annual incomes. Column 4 restricts to a balanced panel from 1995 to 2011 and finds that in this subset, the estimate is similar but slightly larger. Column 5 replaces aggregate GDP with state-level GDP and shows that heterogeneity patterns are similar, suggesting that these patterns hold not only across states but also within states.

A.4.3 Relationship to Guvenen et al. (2017)

Using individual earnings data from the U.S. Social Security Administration, Guvenen et al. (2017) document that the earnings of both the lowest and the very highest earners are more sensitive to aggregate income fluctuations. In Figure A9, I largely replicate this finding using my sample within the LEHD. The left panel shows the elasticity of worker earnings to aggregate GDP by the income decile of the worker. As in Figure 1 of Guvenen et al. (2017), there is a U-shaped relationship; the sensitivity of worker earnings is decreasing through much of the earnings distribution, but it spikes again at the very top of the income distribution. The LEHD misses the income of top earners along two dimensions. First, it is topcoded, generally at the 99th percentile within the state. Second, it includes only UI-covered income, and therefore misses the high earning self-employed. I benchmark the degree to which this missing income may bias my result by noting the amount of potential missing income and reestimating Equation 6 assigning to that share of income 1) the lowest MPC estimate and 2) the highest earnings elasticity estimate. I find that this extreme case attenuates the relationship by around 20 percent, suggesting that this omission is potentially meaningful but not large enough to negate the mechanism.

How does this relate to the relationship between worker MPCs and earnings sensitivity documented in Figure 1? This U-shaped relationship in earnings does not directly imply any relationship between worker MPCs and earnings sensitivity – the bottom of the income distribution has high estimated MPCs but a small share of overall earnings; the top of the income distribution has both low MPCs and the majority of the earnings in the economy; and in my estimation, lagged income only explains 40 percent of the overall variation in MPCs. For a direct comparison, the right panel of Figure A9 shows earnings elasticities by the MPC decile of the worker. There are two important observations. First, the overall pattern is upward-sloping, meaning that workers in the top decile have the highest income sensitivity. Second, there is a nonlinear pattern in the bottom deciles, likely reflecting the increased earnings sensitivity of the very higher earners.

A.5 Alternate Estimates of $Cov(\gamma_i, MPC_i)$

A.5.1 PSID-Based Estimates

I complement the baseline analysis with estimates entirely contained within the PSID. While the sample is substantially smaller and it does not have the benefit of high-quality administrative data, the PSID allows me to extend the analysis along several dimensions. First, it includes more comprehensive coverage of the labor force, namely the inclusion of the federal government and the unemployed. Second, it provides a longer time period, allowing me to explore changes in this covariance over time. Third, it includes a more comprehensive measure of income (i.e., total income as opposed to labor market earnings and household income as opposed to individual-level income). This allows me to supplement the labor market analysis, which is the main focus of the paper, with an analysis of how other margins of income adjust as well. In Figures A10 and A11, I report the estimates using the PSID and explore the importance of these various dimensions. For the purposes of facilitating a direct comparison with the results in LEHD, I use the baseline MPC estimates that utilize the CEX imputation. In the left panel, I closely replicate the baseline analysis in the PSID by restricting to the set of incumbent workers in the private sector between 1997-2011. In the right panel, I extend the sample to include government workers and unemployed workers (top estimates), and earlier years in the sample (bottom estimates). I find that extending the sample to include other workers does not meaningfully affect the covariance estimate, but that the estimate shrinks substantially when including the full PSID sample from 1968-2011. While the noise in the sample makes it challenging to make a strong claim, this suggests that the covariance between MPCs and earnings elasticities has grown over time.

Figure A11 shows estimates of the covariance for household income, rather than individual income There are two main takeaways. First, results are similar when moving from the individual to the household level, suggesting that intra-household dynamics are not important for driving this moment. Second, the covariance is still large and positive when considering total household income, as opposed to just labor income. There is a slightly negative covariance for other income (i.e., transfers go up more for high-MPC households while capital income falls for low-MPC households) but this is comparatively small and the overwhelming effect comes from labor income.

A.5.2 Italian Survey on Household Income and Wealth (SHIW)

I use data from the 1998-2018 waves of the survey, when the survey is available every other year. The survey has a rotating panel dimension – each year, about 50% of respondents were there in the previous wave while about 50% are new. This means that some households are in the sample for many years while others are only in the survey once. Directly-reported MPC information is available in 4 years within the sample:

- In 2016, respondents were asked *"Imagine you unexpectedly receive a refund equal to the household's monthly income. How much of the sum would you save and how much would you spend?"*
- In 2012, respondents were asked *"Imagine you receive an unexpected inheritance equal to your household's income for a year. Over the next 12 months, how would you use this windfall?"*
- In 2010, respondents were asked *"Imagine you unexpectedly receive a reimbursement equal to the amount your household earns in a month. How much of it would you save and how much would you spend?"*
- In 2000, respondents were asked *"If you were informed that you had unexpectedly won the sum of 10 million lire, payable immediately, by how much would your consumption increase during 2001?"*

Using this information on self-reported MPCs, I construct several possible measures of household MPCs:

- Raw reported MPC: This is the simplest measure since it requires no imputation. This is available for 30 percent of the sample.
- 2010 MPC: I assume here that household MPCs are fixed over time and assign the 2010 reported MPC to all observations for the household that are in the sample in 2010. This provides an MPC estimate for 39 percent of the sample. This is unlikely to be a good assumption, since the MPCs within household over time are not highly correlated.[43]

[43] The correlation between the 2010 MPC estimates and the 2000, 2012, and 2016 MPC estimates are 0.04, 0.12, and 0.17, respectively. See also Jappelli and Pistaferri (2020).

- Fitted MPC: I project the self-reported MPCs from each year on cash-on-hand deciles and 4 age bins. I choose these variables since they are the variables shown to be most important in Jappelli and Pistaferri (2020). I then impute the MPC for all households based on these estimated relationships. This is available for 100 percent of the sample and allows MPCs to change over time within household.

I also supplement these self-reported MPCs with an MPC that I estimate following the methodology outlined in Section 4.1 using the panel-structure of the SHIW and the unemployment shock. Specifically, I estimate

$$\Delta C_{i,t} = \sum_x \beta_x \Delta E_{i,t} \times x_{i,t} + \gamma_t + \epsilon_{i,t}$$

where C is reported total household consumption, E is labor income for individual i, and x is a set of household characteristics. As in the U.S. analysis, I restrict the estimation to those employed in $t-2$ and I instrument the change in income with an indicator for whether the individual is unemployed in time t. The left panel of Figure A12 shows the resulting MPC estimates – interestingly, the patterns look very similar to those that I uncover in the United States, with younger and poorer workers having higher MPCs.

Lastly, using these various MPC estimates, I calculate the following regression:

$$\Delta \log E_{h,t} = \beta_0 + \beta_1 MPC_{h,t-2} + \beta_2 MPC_{h,t-2} \times \Delta \log(Y_t) + \epsilon_{h,t}$$

where $E_{h,t}$ is household income and $MPC_{h,t-2}$ is the MPC of the household in the previous survey. Households are weighted by their income in $t-2$. I use household income as the baseline because, with the exception of the unemployment-based MPCs, the MPCs are at the household level. However, I also show results for individual payroll income. Table A10 shows that the estimates of β_2 are generally large, positive, and statistically significant. The magnitudes are also meaningful – the standard deviation of the reported MPC is 0.34. The average elasticity of total household earnings to GDP is 0.58 and the coefficient in Panel A, column 1 suggests that households with 1 standard deviation higher MPCs have household earnings elasticities that are 0.28, or just about 50 percent, higher than average.

A.5.3 CEX Analysis using Tax Rebates

For this section, I closely follow Misra and Surico (2014a,b), Johnson, Parker and Souleles (2006) and Parker et al. (2013). Specifically, I pool observations across the 2001 and 2008 tax rebates and estimate MPCs as:

$$C_{h,t+1} - C_{h,t} = \sum_s \beta_{0_s} \times month_{s,h} + \beta_1 X_{h,t} + \beta_2 \text{Rebate}_{h,t+1} + \epsilon_{h,t+1}$$

where h is the household, s is the month, and C is nondurable household consumption. X represents a set of controls, including worker age, changes in the number of adults and children in the household, and a dummy for whether the data is from the 2001 or 2008 experiment. Following the literature, I instrument the size of the tax rebate with an indicator for whether the rebate is positive. The right panel of Figure A12 shows the resulting patterns. While the standard errors are large, the patterns are familiar, with lowest income workers having the largest MPCs. These broad patterns are consistent with those in Johnson, Parker and Souleles (2006) and Parker et al. (2013).

Since these MPCs are only directly observable for the households that are in the sample in 2001 and 2008 and the CEX only includes a short time series, I must project these MPCs onto household characteristics in order to explore the covariance between these MPCs and earnings elasticities for workers. Since the CEX has only a short panel, in order to do the analysis entirely within the CEX, I would need to use pseudo-cohorts. However, this would mean that I would be constrained to using the set of characteristics that are largely invariant over the business cycle to avoid endogenous movements of workers across cohorts. Therefore, I instead impute these MPC estimates for households in the PSID, where I do observe the same household over time. In order to facilitate a comparison with the unemployment-based MPCs in the main body of the paper, I project these tax-rebate MPCs onto the following household characteristics: 4 age bins, 2 race bins and 5 income bins. Note, again, that unlike the unemployment-based MPCs, these MPC estimates are at the household level, and therefore, within the PSID, I explore the elasticity of *household* earnings by the MPCs estimated using the 2001 and 2008 tax rebates. Table A11 shows the results. Columns 1 and 4 show the results using the labor income of the household head and spouse as the measure of household earnings, columns 2 and 5 use total household income as the dependent variable, and columns 3 and 6 use individual labor earnings. In all cases, the interaction term between MPCs and earnings elasticities is positive, although it is not precisely estimated. The magnitude is also meaningful – the estimates in column 1 show that being 1 standard deviation higher in the MPC distribution is associated with an elasticity of household income to aggregate GDP that is 0.17 higher than someone with the average MPC.

Comparing MPCs out of tax rebates to MPCs out of unemployment There are potentially many reasons that the MPCs in response to tax rebates and those in response to unemployment shocks could be different both in levels and in their distribution across the population. Tax rebates are positive income shocks while unemployment shocks are negative on average, tax rebates are temporary income shocks while unemployment shocks are more persistent, and tax rebates are generally small shares of household balance sheets while unemployment shocks have very large effects on annual incomes (see Figure A4). These differences are not only true on average, but they also potentially vary across demographic groups in important ways (e.g., unemployment is more persistent for some groups). Despite these many potential differences, I find that resulting MPC estimates are similar, both on average and across the distribution.

Specifically, to facilitate a direct comparison, I focus on the MPC for nondurable consumption. For MPCs upon unemployment, I estimate MPCs using the set of demographics characteristics as described in the main text (see Column 2 of Table 3 in the main paper). For MPCs out of tax rebates, I impute MPCs within the PSID using the households characteristics described above and used in Table A11. Despite the many differences, I find that the *average* MPCs within the PSID are somewhat different, with an average estimate of .25 for tax rebates and .41 for unemployment. However, the MPC estimates are positively correlated across demographic groups with a correlation of 0.34.

One particular concern with MPC estimates using unemployment is that the heterogeneity could be driven by differences in the duration of unemployment. If duration were driving the MPC heterogeneity, that would change the interpretation of the results. Indeed, within the PSID, I find that there is a positive correlation between the average duration of unemployment for a demographic group and the MPC estimate for that demographic group. However, I find a very similar correlation between MPCs calculated using tax rebate heterogeneity and the average unemployment duration of the demographic group as well. Specifically, Figure A5 plots estimates of the MPC versus average unemployment duration for income and age groups. There is a positive relationship for *both* estimates, with the slope of the relationship being nearly identical. Since tax rebates are clearly transitory, the correlation between the MPC and unemployment duration likely reflects other cross-sectional differences that correlates with average unemployment duration and affect MPCs such as time preferences, credit constraints or liquidity, rather than being a direct function of unemployment duration.

A.6 Details of Commuting Zone Analysis

A.6.1 Additional Data Definitions

Local control variables: I closely follow Kaplan, Mitman and Violante (2020) in defining household wealth measures in each local labor market. Specifically, I define housing wealth as the total number of housing units in a county, which are published by the U.S. Census Bureau (U.S. Census Bureau, 2012, 2018), multiplied by the Zillow Home Value Index for All Homes (Zillow, Inc., 2018).[44] Data on household debt come from the Federal Reserve Bank of New York Consumer Credit Panel (CCP), which provides the dollar values of mortgage, auto, and revolving credit debt annually in each county from 1999 to 2011 (New York Fed, 2016). I define household debt as the total value of both mortgage and non-mortgage debt. I construct data on financial assets by allocating total financial assets in a quarter from the Flow of Funds Balance Sheet of Households and Nonprofit Organizations to counties using the fraction of total financial assets in that county from the quarterly IRS Statistics of Income. Lastly, I aggregate these county-level measures to the commuting zone level, restrict attention to fourth-quarter estimates, and divide by population estimates to obtain per-capita values.[45]

The fraction of the commuting zone that is employed comes from the ACS. All other control variables – namely, demographic controls for the area and the average size and age of establishments by commuting zone – are calculated within the LEHD in each year.

Bartik shock: I construct a Bartik-style shock at the commuting zone level using

$$Shock_{c,t} = \sum_i \frac{L_{i,c,t_0}}{L_{c,t_0}} \Delta \log E_{i,t,-c}$$

where $t_0 = 1999$, L is employment, and $\Delta \log E_{i,t,-c}$ is the change in the log of total earnings in industry i within the states that are in the LEHD subsample in year $t-1$ but excluding earnings in commuting zone c. I exclude own commuting zones, since my LEHD sample is not national and thus any given commuting zone may represent a non-negligible fraction of the industry's total earnings. Additionally, because the LEHD is not balanced across states, the aggregated time series for any given industry are inconsistent due to the entry of states. Therefore, to be consistent over time, I define the change in earnings in an industry using only the incumbent states in each year. Unsurprisingly, this shock is very highly predictive of both changes in overall earnings in a commuting zone and movements in the GDP of the commuting zone's state.

In exploring the role of the local labor market multiplier in affecting local cyclicality using this Bartik shock, I *both* re-estimate MM_c using this shock and then re-estimate Equation 10 replacing aggregate GDP with this shock.

[44] This housing index is publicly available monthly for each U.S. county beginning in 1996. Housing units are available annually at the county level back until 2000. Prior to 2000, these counts are only released at the state-by-year level. I interpolate county housing units prior to 2000 by assuming that the fraction of houses in each county in the state is constant and by assigning total state housing units in each year to counties based on the 2000 distribution.

[45] CCP data are only released for counties with an estimated population of at least 10,000 consumers with credit reports in the fourth quarter of 2010. This restriction excludes 20 percent of counties. Since these are predominately small counties, I ignore these missing values in the aggregation from counties to commuting zones.

A.7 The Matching Multiplier and the Labor Share

While the matching multiplier is derived in a setting in which all output is earned by labor, in order to provide *empirical* estimates of the matching multiplier, I need to take into account the fact that in reality, not all output goes to worker wages. Since the focus of this paper is on quantifying a particular mechanism within the labor market, I do not explore potentially important heterogeneity in MPCs out of nonlabor income. Rather, I assume the covariance of MPCs out of non-labor income with the elasticity of non-labor income to the aggregate is zero and I make modest adjustments to the simple framework to rescale the contribution of this particular mechanism. Consider the case where output is given by $Y = E + K$, where E are labor market earnings and K are earnings from nonlabor income (e.g., profits, return on capital, etc). In this case, the aggregate MPC in the economy is given by:

$$MPC = \frac{dC}{dY} = \frac{\partial C}{\partial E}\frac{dE}{dY} + \frac{\partial C}{\partial K}\frac{dK}{dY}$$

Using $dY = dE + dK$, defining the labor share $\alpha_l = \frac{E}{Y}$, and $\overline{\gamma} = \frac{dE}{dY}\frac{Y}{E}$,

$$MPC = \frac{\partial C}{\partial E}\frac{dE}{dY} + \frac{\partial C}{\partial K}\frac{dY - dE}{dY}$$

$$MPC = \frac{\partial C}{\partial E}\frac{dE}{dY} + \frac{\partial C}{\partial K}\left(1 - \frac{dE}{dY}\right)$$

$$MPC = \frac{\partial C}{\partial E}\frac{dE}{dY} + \frac{\partial C}{\partial K}\left(1 - \alpha_l\overline{\gamma}\right)$$

The goal of this paper is to understand the importance of heterogeneous incidence of labor market earnings in determining the first term ($\frac{\partial C}{\partial E}\frac{dE}{dY}$). Therefore, rewriting this term as the sum across individuals, as in Section 2, we get:

$$MPC = \sum_i \frac{\partial C_i}{\partial E_i}\frac{dE_i}{dY_i} + \frac{\partial C}{\partial K}\left(1 - \alpha_l\overline{\gamma}\right)$$

$$MPC = \alpha_l\left(\sum_i MPC_i\frac{E_i}{E}\gamma_i\right) + \frac{\partial C}{\partial K}\left(1 - \alpha_l\overline{\gamma}\right) \tag{A3}$$

This simple total derivative highlights the importance of three terms that were in the definition of the aggregate MPC in the simple framework in Section 2 – the consumption response from changes in nonlabor income $\left(\frac{dC}{dK} = MPC_{nl}\right)$, the labor share $\left(\alpha_l = \frac{E}{Y}\right)$ and the average elasticity of labor earnings with respect to the aggregate $\overline{\gamma}$. The importance of the labor share is intuitive – a mechanism affecting labor market income matters more for the total economy when labor earns a higher share of total income.

The benchmark case is one in which all workers have the same elasticity of income (i.e., $\frac{\partial C}{\partial E}\frac{dE}{dY} = \overline{\gamma}\overline{MPC}$) as in Section 2. Plugging that into Equation A3, we get Equation 7 in the main text.

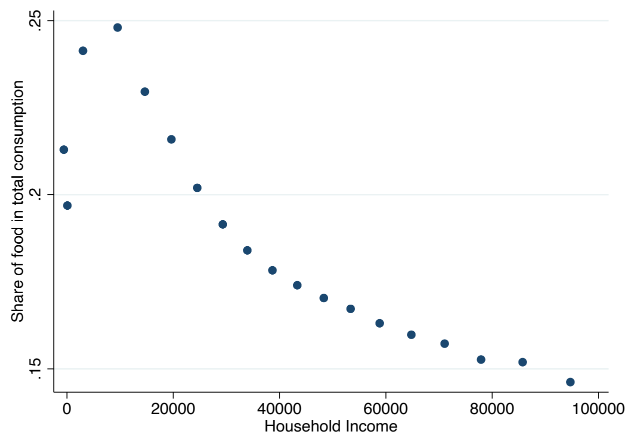
$$MPC^b = \alpha_l\overline{\gamma}\overline{MPC} + (1 - \alpha_l\overline{\gamma})MPC_{nl}$$

Similarly, the actual MPC is one with the empirical covariance (i.e., $\frac{\partial C}{\partial E}\frac{dE}{dY} = \overline{\gamma}\overline{MPC} + Cov(\gamma_i, MPC_i)$), and plugging this into Equation A3, we arrive at Equation 8 in the main text.

$$MPC^a = \alpha_l\left(\overline{\gamma}\overline{MPC} + Cov(\gamma_i, MPC_i)\right) + (1 - \alpha_l\overline{\gamma})MPC_{nl}$$

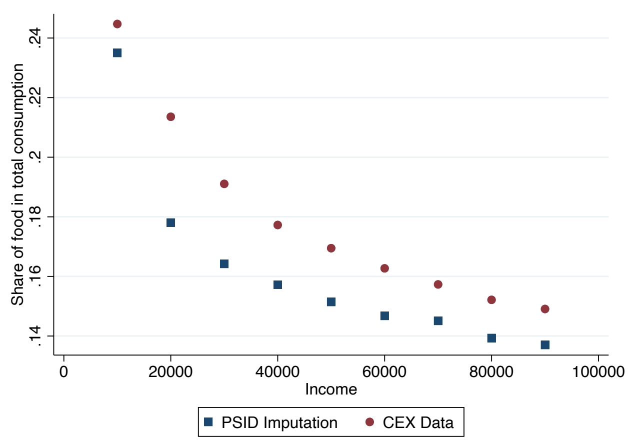
A.8 Appendix Figures

Figure A1: The Fraction of Food in Total Spending



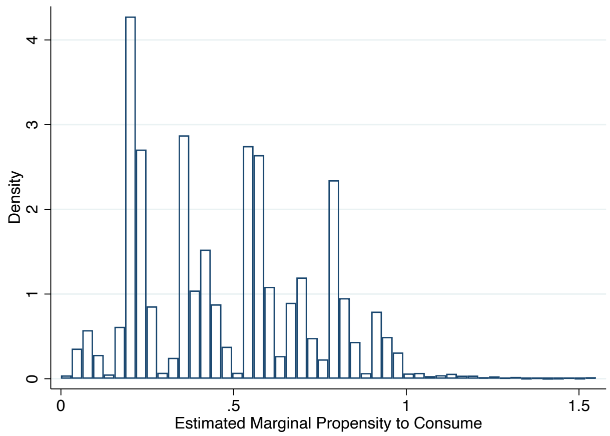
Notes: Data are from the Consumer Expenditure Survey and are pooled across 1984 to 2014 for all households with a head between the ages of 25 and 62. Household income is adjusted to 2010 dollars.

Figure A2: Imputed Total Consumption Using CEX-Based Imputation



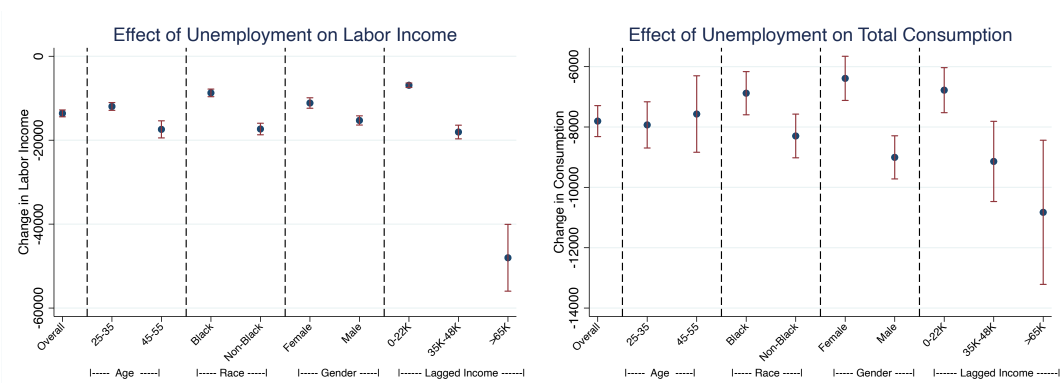
Notes: Average total consumption in the PSID is imputed using Equation A1. Averages are calculated using sample weights in the CEX and based on the nationally representative subsample in the PSID. Income refers to household income, adjusted to 2010 dollars.

Figure A3: The Distribution of Estimated Marginal Propensities to Consume



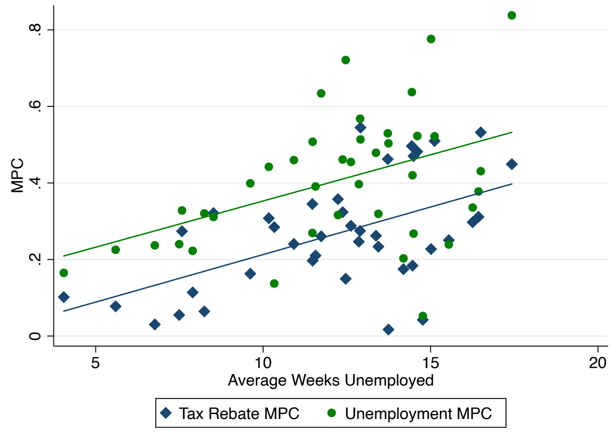
Notes: See Appendix Table A5 for the coefficients that underlie this imputation. Negative imputed MPCs are set to 0. Consumption is measured using total consumption, imputed using the method in Blundell, Pistaferri and Preston (2008). Income is measured using individual labor income. The instrument for income changes is unemployment. The sample includes the set of workers who were employed two years before the current year. The sample in the PSID excludes observations with more than a 400 percent change in food consumption or income over a given two-year period. Lagged income is measured as the average labor market earnings of the individual in $t-2$ and $t-3$. The regression includes year-by-state fixed effects and observations from 1985 to 2013.

Figure A4: Heterogeneity in the MPC: First Stage and Reduced Form



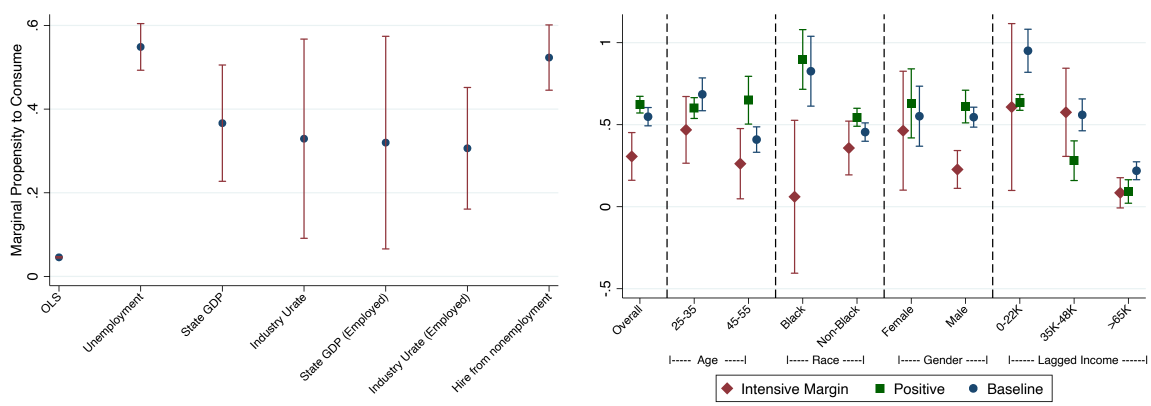
Notes: The left panel shows the first stage of unemployment on the level of labor earnings and the right panel shows the reduced form of unemployment on the level of consumption. These correspond to the instrumented regressions in Figure 2. Consumption is measured using total consumption, imputed using the method in Blundell, Pistaferri and Preston (2008). Income is measured using individual labor income. The sample includes the set of workers who were employed two years before the current month. The sample in the PSID excludes observations with more than a 400 percent change in food consumption or income over a given two-year period. All regressions include year-by-state fixed effects and observations from 1981 to 2013. Standard errors are clustered at the individual level.

Figure A5: The Importance of Unemployment Duration for MPC Heterogeneity



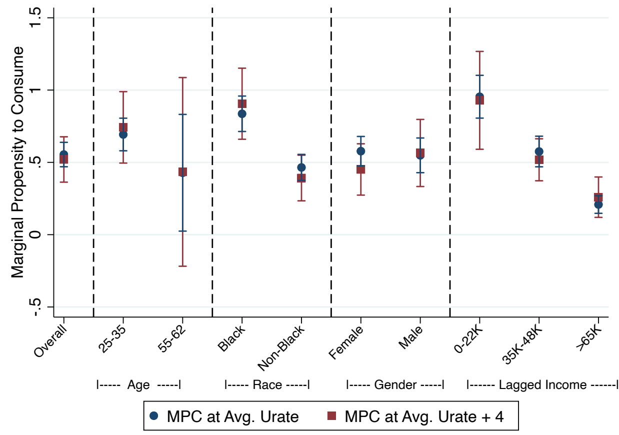
Notes: Each dot is the combination of five household income groups, 2 race groups, and four age groups. Average unemployment duration for each group is calculated as the average number of weeks of unemployment conditional on being unemployed. All averages are unweighted. Sample includes all individuals within the PSID, including both employed and unemployed workers. MPCs for tax rebates are estimated at the household level using five household income bins, four age bins and two race categories (as in Table A11). MPCs for unemployment are calculated as in the main text using individual-level income and five lagged income bins, a quadratic in age, female and black indicators, black interacted with age, and female interacted with black.

Figure A6: MPCs Using Different Identifying Income Shocks



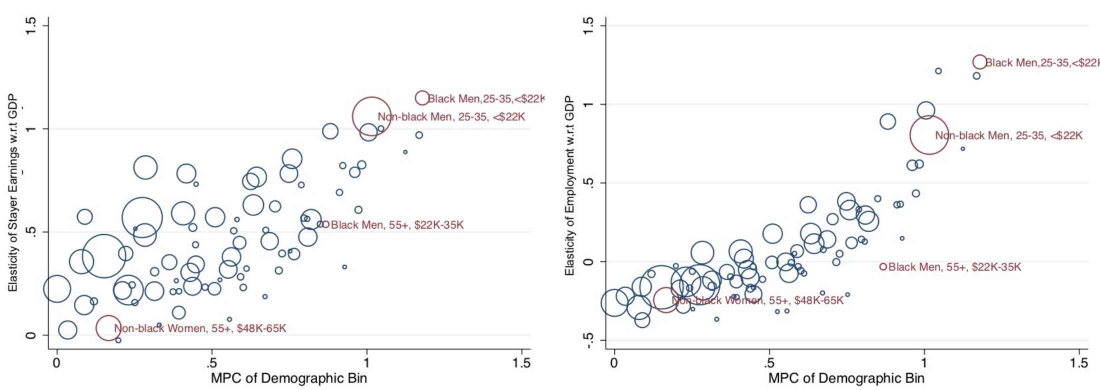
Notes: In the left panel, the instrument labeled "State GDP" is defined as the percentage change in state GDP, defined by the Bureau of Economics Analysis. The industry unemployment rate is calculated from the Basic Monthly Current Population Survey, pooled over months within the year, and defined using time-consistent 1990 census industry codes. In Columns 1, 3, and 4, the sample includes the entire sample (no work restriction); in Column 2, the sample includes those employed in $t-2$; in Columns 5 and 6, the sample is restricted to those who are employed in $t-2$ and t; and in Column 7, the sample is restricted to those who are not employed in $t-2$. In the right panel, the "baseline" shock is unemployment, the "intensive" series instruments the change in earnings with the unemployment rate in the industry in which the individual worked in $t-2$, and the "positive" series instruments earnings using hiring between $t-2$ and t. MPCs estimated using hires restrict the estimation sample to those not employed in $t-2$. MPCs estimated using unemployment restrict the sample to those who were employed in $t-2$. MPCs estimated using the industry unemployment rate are estimated without a restriction on employment status in $t-2$.

Figure A7: The Stability of MPC Estimates Over the Business Cycle



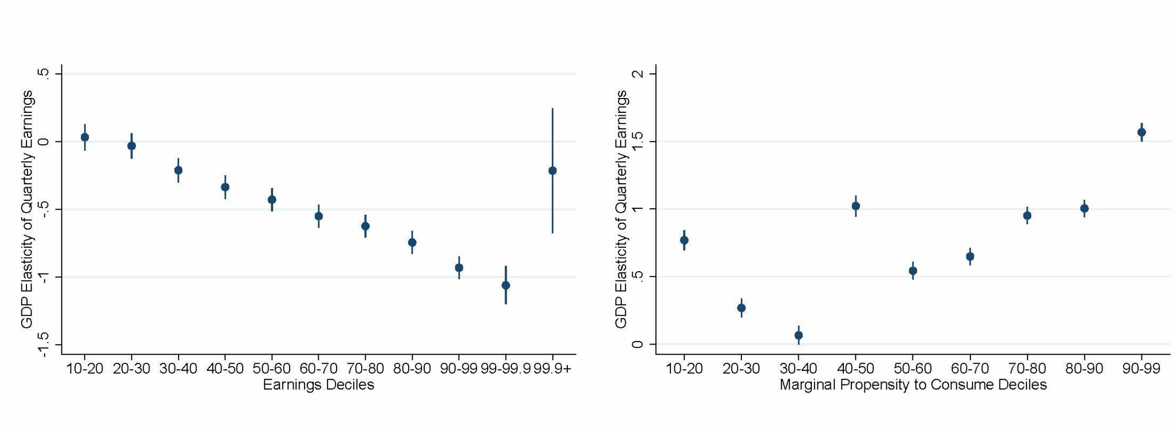
Notes: The unemployment rate is defined as the unemployment rate in the state in which the individual was employed in $t-2$. Blue dots show the average MPC for the specified bin at the average unemployment rate in the sample. The red squares show the average MPC calculated at the average unemployment rate for each subsample at the average unemployment rate plus 4 percentage points. Regressions are based on two-year periods. Bars reflect 90/10 confidence intervals.

Figure A8: Earnings Sensitivity to GDP and MPCs: Intensive and Extensive Earnings Margins



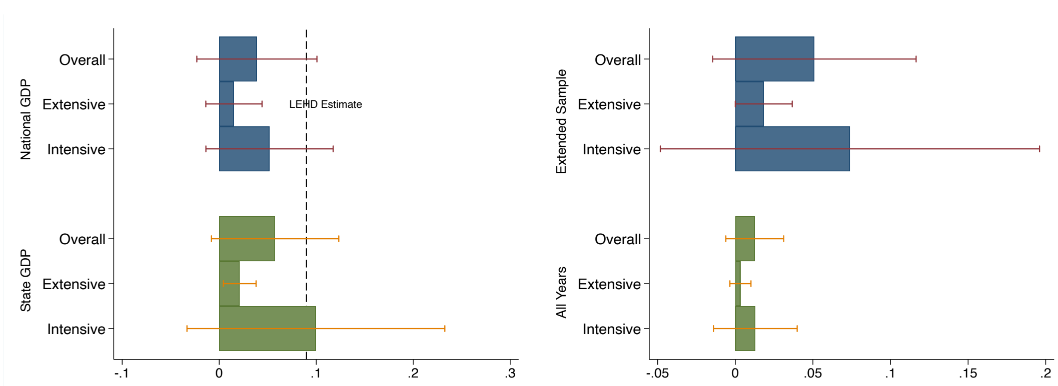
Notes: Sample includes the set of all workers employed in a sample state in year $t-1$ between 1995 and 2011. The dependent variable in the regression producing the y-axis estimates on the left graph is $\log(E_{i,t}) - \log(E_{i,t-1})$. The dependent variable in the regression producing the y-axis estimates in the right subplot is L_t, where L_t is an indicator for being employed in time t. The size of each bubble represents the earnings share of that demographic group. The demographic groups are defined as in Figure 1.

Figure A9: Earnings Sensitivity to GDP by Decile of the MPC and Income Distribution



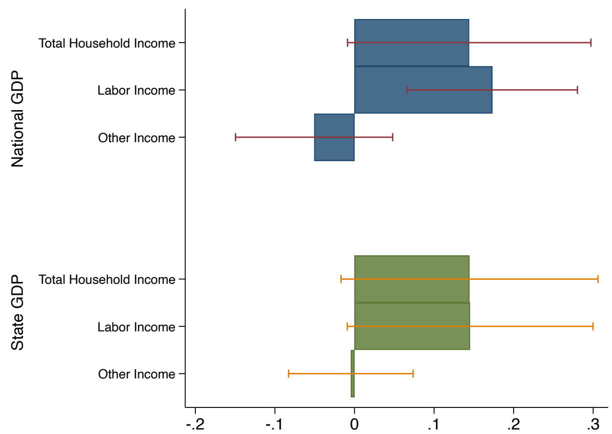
Notes: Sample includes a 5 percent random subset of all workers employed in a sample state in year $t-1$ between 1995 and 2011. The dependent variable in the regression is $\frac{E_{i,t}-E_{i,t-1}}{.5*E_{i,t}+.5*E_{i,t-1}}$. MPC decile bin cutoffs are defined on a sample pooled across all years and each bin represents an equal number of dollars of earnings, rather than individuals. Income deciles are also defined on a sample pooled across all years. Regressions include year fixed effects. Standard errors are clustered at the individual level. Blue bars reflect 95% confidence intervals.

Figure A10: PSID-Based Estimates of Covariance



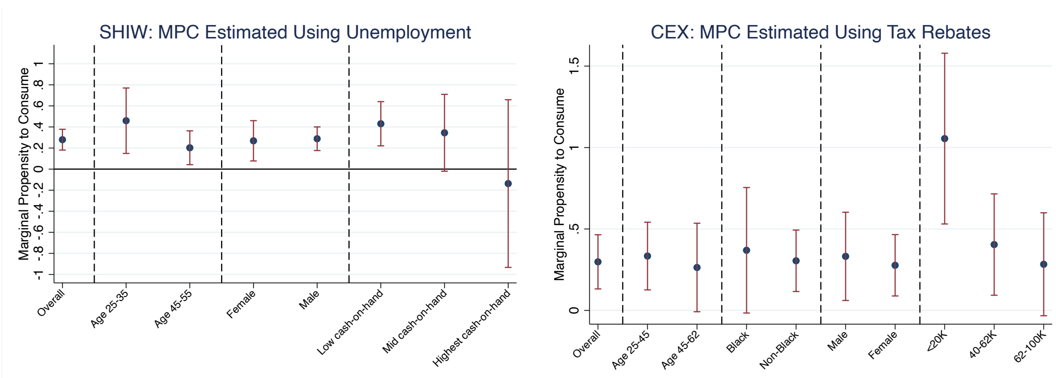
Notes: In all regressions, I restrict attention to the civilian population and drop those serving in the military. All regressions in the right panel use state GDP as the measure of output. In all regressions, observations are weighted by their share of labor income in $t-2$. In the left panel and the top bars of the right panel, the sample includes all years from 1997-2011. In the bottom of the right panel, the sample includes all years from 1971-2013. In the left panel, the sample is restricted to include those who are employed in year $t-2$. Standard errors are twoway clustered at the individual and year. Bars reflect 95% confidence intervals.

Figure A11: PSID-Based Estimates of Covariance: Beyond Labor Income



Notes: In all regressions, I restrict attention to the civilian population and drop those households were one of the primary members is serving in the military. In all regressions, households are weighted by the level of household income in $t-2$. The sample includes all households from 1997-2011. Household labor income is defined as the sum of the labor income of the household head and spouse. Other income is the difference between total household income and the labor income of the household head and spouse. The dependent variable is the change in the log of the income measure in all cases. Standard errors are twoway clustered at the individual and year. Bars reflect 95% confidence intervals.

Figure A12: Cross-Demographic Heterogeneity MPCs: SHIW and Tax Rebates



Notes: The left panel shows MPCs estimated upon unemployment using the SHIW. The sample is restricted to those employed in $t-2$ and consumption is total household consumption, reported directly within the survey. The right panel shows estimates of MPCs for nondurable consumption out of tax rebates using the 2001 and 2008 waves of the CEX.

A.9 Appendix Tables

Table A1: Summary Statistics for the LEHD Sample

	1995 Snapshot	2011 Snapshot	Full Sample
Number of workers	22,680,000	45,380,000	38,078,235
Number of establishments	1,015,000	3,464,000	2,772,529
Worker Characteristics			
Fraction Male	0.53	0.51	0.52
Average Worker Age	40.61	43.05	42.10
Average 2-year Lagged Income	36,600	42,210	40,373
Fraction Black	0.09	0.11	0.10
Fraction College Educated	0.30	0.28	0.29
Job Characteristics			
Average Total Quarterly Earnings	10,650	11,920	11,794
Average Annual Earnings	40,140	45,430	44,119

Notes: Sample includes all individuals in the baseline sample. Averages are unweighted, and nominal values are expressed in 2010 dollars. Column 1 shows the data in 1995, Column 2 shows the data in 2011, and Column 3 shows the sample averaged from 1995 to 2011. Counts for the number of workers and the number of establishments are rounded to comply with U.S. Census disclosure requirements.

Table A2: Years in the Estimation Sample by State

State	**Sample Years**
Arkansas	2004-2011
Arizona	2006-2011
California	**1993-2011**
Colorado	**1995-2011**
Washington DC	2007-2011
Delaware	2000-2011
Florida	**1994-2011**
Iowa	2000-2011
Illinois	**1992-2011**
Indiana	2000-2011
Kansas	**1995-2011**
Maryland	**1992-2011**
Maine	1998-2011
Montana	**1995-2011**
New Mexico	1997-2011
Nevada	2000-2011
Oklahoma	2002-2011
Oregon	**1993-2011**
Pennsylvania	1999-2011
South Carolina	2000-2011
Tennessee	2000-2011
Washington	**1992-2011**
West Virginia	1999-2011

Notes: Sample years exclude the first two years for which there are individual-level data available. Bold states are those included in the balanced-panel subset of the data.

Table A3: Summary Statistics for the Panel Study of Income Dynamics

	LEHD Comparison Sample	**National Sample of Employed**	**Previously Employed Sample**
Worker Characteristics			
Fraction Male	0.549	0.540	0.527
Average Worker Age	42.70	42.30	41.30
Average 2-year Lagged Income	57,295	57,458	51,153
Fraction College Educated	0.365	0.373	0.308
Fraction Black	0.0469	0.0536	0.265
Average Income	60,692	60,312	52,683
Change in Income	3,013	2,734	1,552
Household Characteristics			
Household Size	2.995	3.060	3.134
Food Consumption	9,033	9,163	8,795
Total Consumption	63,052	63,266	58,430
Change in Food Consumption	36.13	59.42	84.12
Change in Consumption	1,020	1,097	1,600
Number of Individuals	12,189	32,832	72,078

Notes: This table shows summary statistics for the PSID sample used in the analysis. The sample in all columns restricts to individuals ages 25 to 62 who are also observed in $t-2$ and $t+1$, who have nonmissing changes in food or income over two years, and whose consumption and income change over two years is less than 400 percent. The third column restricts to the set of individuals employed in $t-2$ and all individuals with non-missing data for all variables from 1985 - 2013. Column 2 instead restricts to those currently employed who are in the nationally representative subsample of the PSID. Column 1 further restricts to those living in the set of state-years available in the LEHD sample.

Table A4: Summary Statistics for the Consumer Expenditure Survey

	CEX Sample	**PSID Sample**
Worker Characteristics		
Fraction Male	0.509	0.491
Average Worker Age	42.73	41.00
Fraction College Educated	0.394	0.327
Fraction Black	0.0929	0.0578
Average Income	46,202	45,931
Household Characteristics		
Household Size	3.096	3.138
Food Consumption	8,421	9,109
Total Consumption	60,682	60,382
Number of Individuals	100,901	80,040

Notes: The first column shows summary statistics for the CEX sample used to impute total consumption. The second column shows the same statistics for the similarly constructed PSID sample. All nominal variables are adjusted to 2010 dollars.

Table A5: Coefficient Estimates for Individual Marginal Propensities to Consume

Dep. Var.	Food Consumption	PSID Imputation	CEX Imputation	CEX Imputation
< 22000*Labor Income	0.027	0.230	0.917	0.917
	(0.103)	(0.218)	(0.717)	(0.718)
(22,000-35,000)*Labor Income	0.015	0.150	0.682	0.682
	(0.104)	(0.219)	(0.731)	(0.732)
(35,000-48,000) *Labor Income	-0.016	0.081	0.557	0.557
	(0.108)	(0.222)	(0.726)	(0.727)
(48,000-65,000) *Labor Income	-0.031	0.015	0.347	0.347
	(0.106)	(0.220)	(0.721)	(0.721)
$> 65,000$ *Labor Income	-0.035	-0.026	0.189	0.189
	(0.107)	(0.221)	(0.734)	(0.734)
Age*Labor Income	0.003	0.004	-0.001	-0.001
	(0.005)	(0.011)	(0.035)	(0.035)
Age^2 *Labor Income	-0.033	-0.023	0.041	0.042
	(0.062)	(0.130)	(0.411)	(0.411)
Female*Labor Income	-0.022	-0.085	-0.135	-0.135
	(0.012)	(0.023)	(0.059)	(0.059)
Black*Labor Income	0.042	0.197	1.231	1.231
	(0.060)	(0.114)	(0.509)	(0.507)
Black*Age*Labor Income	-0.001	-0.003	-0.024	-0.024
	(0.001)	(0.003)	(0.010)	(0.010)
Black*Female*Labor Income	-0.005	-0.018	-0.253	-0.253
	(0.027)	(0.052)	(0.182)	(0.183)
No. Observations	123439	86669	69788	69788
Year FEs	X	X	X	X
Identifying Shock	Unemployment	Unemployment	Unemployment	Job Loss

Notes: The table shows the regression estimates from PSID imputations. The dependent variable in the first column is total food consumption. The dependent variable in the second column is extended consumption imputed from the later years of the PSID. The dependent variable in the third and fourth columns is total consumption imputed using the CEX data. The fitted values of the regression in Column 3 are plotted in Figure A3. Income is measured using individual labor income. The instrument for income changes is unemployment in Columns 1 through 3 and unexpected job loss in Column 4. The sample includes the set of workers who were employed two years before the current year. The sample in the PSID excludes observations with more than a 400 percent change in food consumption or income over a given two-year period. Lagged income is measured as the average labor market earnings of the individual in $t-2$ and $t-3$. All regressions include state-by-year fixed effects. Columns 1 and 2 include years from 1971 to 2013 while Column 3 and 4 includes data from 1985 to 2013. All standard errors are clustered at the individual level.

Table A6: MPCs Estimated Using Job-Level and Geographic Variables

Variables	Baseline	w/ Tenure	w/ Lagged Variance	w/ Ind. Variance	w/ Occ. Variance	w/ Region
Baseline	1.000					
w/ Tenure	0.978	1.000				
w/ Lagged Variance	0.974	0.956	1.000			
w/ Ind. Variance	0.988	0.965	0.963	1.000		
w/ Occ. Variance	0.971	0.952	0.954	0.961	1.000	
w/ Region	0.998	0.975	0.973	0.986	0.970	1.000

Notes: The table shows the pairwise correlation between the baseline MPC estimate and estimates including the stated additional characteristic. The dependent variable is total consumption imputed using the CEX data. All regressions include state-by-year fixed effects and include individuals employed in time $t-2$. The expected variance of earnings at the industry or occupation level are calculated using the matched CPS monthly data and averaged over the sample period. These capture the average within-individual variance in earnings over a one-year period. Tenure is defined as the number of months the worker has been with the firm in which they were employed in time $t-2$. The lagged variance is the variance of an individual's earnings between $t-3$ and $t-2$. See appendix text for more details on data construction.

Table A7: Robustness of Relationship Between MPCs and Earnings Elasticities: Alternate Specifications

	(1) Baseline Estimate	(2) $\log(E_{it}+100)$	(3) Annual Income	(4) 1993 State Subsample	(5) State GDP
$MPC_{i,t-1}$	-0.229	-0.362	-0.080	-0.246	-0.221
	(0.049)	(0.116)	(0.013)	(0.049)	(0.048)
$MPC_{i,t-1} * \Delta Y_t$	1.228	2.550	1.091	1.540	0.837
	(0.383)	(0.829)	(0.249)	(0.459)	(0.219)
No. Observations	29,204,700	29,204,700	29,204,700	20,859,200	29,204,700
R-Squared	0.009	0.004	0.003	0.010	0.012
$Var(MPC_i)$	0.083	0.080	0.080	0.084	0.083
$Cov(MPC_i, \gamma_i)$	0.099	0.200	0.084	0.126	0.068
Fixed Effects					
Year	✓	✓	✓	✓	
Year by State					✓

Notes: Column 1 shows regression estimates from Table 2, estimated on a 5 percent subsample of the data set. Column 2 specified the outcome variable as the change in the log of earnings plus 100. Column 3 defines income as the annual income in the calendar year, rather than quarterly income in the fourth quarter. This analysis, however, still restricts the sample to the set of individuals employed in the fourth quarter of the previous year. Column 4 restricts to the subsample of states that are present in 1993, meaning that there is a balanced panel of states over time. Column 5 replaces aggregate GDP with state-level GDP. This specification includes state-by-year fixed effects, rather than simply year fixed effects. Across all columns, the number of observations is rounded to comply with U.S. Census Bureau disclosure requirements. In all columns, coefficients and standard errors are calculated using multiple imputation techniques, as explained in the main text.

Table A8: Robustness of Relationship Between MPCs and Earnings Elasticities: Alternate MPC Estimates

MPC Definition:	(1) Baseline Estimate	(2) Food	(3) Nondurables	(4) PSID-Based Consumption	(5) Hires Instrument
$MPC_{i,t-1}$	-0.229	-2.060	-0.306	-0.821	-0.260
	(0.049)	(0.750)	(0.072)	(0.168)	(0.110)
$MPC_{i,t-1} * \Delta \log Y_t$	1.228	12.470	1.755	3.945	1.086
	(0.383)	(4.536)	(0.543)	(1.250)	(0.509)
No. Observations	29,204,700	29,204,700	29,204,700	29,204,700	29,204,700
R-Squared	0.009	0.006	0.008	0.013	0.002
Avg. MPC_i	0.431	0.029	0.210	0.169	0.246
$Var(MPC_i)$	0.083	0.001	0.041	0.009	0.051
$Cov(MPC_i, \gamma_i)$	0.099	0.009	0.070	0.034	0.051
Fixed Effects					
Year	✓	✓	✓	✓	✓

Notes: Each column defines the MPC in a different way. Column 1 is the baseline MPC estimate. Column 2 uses the MPC defined only using food consumption. Column 3 uses the CEX imputation but includes only nondurable consumption. Column 4 uses the MPC calculated using the PSID-based imputation of expanded consumption. Column 5 uses the MPC estimated using hires, rather than unemployment, as the instrument for changes in income. The outcome variable in all regressions is the annual change in quarterly earnings across all jobs. All regressions include year fixed effects, and all regressions are estimated using multiple imputation techniques, as defined in the main text. Across all columns, the number of observations is rounded to comply with U.S. Census Bureau disclosure requirements.

Table A9: Amplification in Recessions versus Expansions

	(1) MPC from unemp.	(2)	(3) MPC from hires
$MPC_{i,t-1}$	-0.221	-0.215	-0.247
	(0.048)	(0.048)	(0.109)
$MPC_{i,t-1} * \Delta GDP_{s,t}$	0.837	0.663	0.660
	(0.219)	(0.243)	(0.354)
$MPC_{i,t-1} * \Delta GDP_{s,t} * Rec_{s,t}$		0.576	0.309
		(0.398)	(0.465)
No. Observations	29.2 M	29.2 M	29.2 M
$\overline{MPC}_i$	0.43	0.43	0.246
$Var(MPC_i)$	0.083	0.083	0.051

Notes: Regressions include year*state fixed effects and are estimated on a 5% subsample of the data. All coefficients and standard errors are calculated using multiple imputation techniques as described in the main text.

Table A10: Earnings Elasticities by MPCs: Evidence from Italy

	Reported MPC	2010 MPC	Fitted MPC	Unemployment MPC
Panel A. Household Income				
MPC * Change in GDP	0.822	0.648	22.987	3.067
	(0.345)	(0.661)	(5.854)	(0.804)
MPC	-0.048	-0.023	0.761	0.052
	(0.011)	(0.018)	(0.310)	(0.050)
Change in GDP	0.092	0.461	-9.816	0.074
	(0.394)	(0.511)	(2.596)	(0.170)
Average MPC	.45	.45	.45	.12
Std. Dev. MPC	.34	.35	.03	.21
Observations	7497	12720	20095	20095
R-Squared	0.002	0.004	0.016	0.012
Panel B. Individual Labor Income				
MPC * Change in GDP	0.669	0.876	7.937	0.309
	(0.382)	(0.239)	(3.201)	(0.443)
MPC	-0.037	-0.033	0.158	0.019
	(0.019)	(0.012)	(0.222)	(0.029)
Change in GDP	0.428	0.290	-3.013	0.542
	(0.353)	(0.190)	(1.389)	(0.064)
Average MPC	.45	.46	.46	.17
Std. Dev. MPC	.34	.35	.03	.22
Observations	7419	13060	19705	19705
R-Squared	0.005	0.005	0.005	0.004

Notes: All observations are weighted by their income in the beginning of the period. For panel A, this means weighting by total household income in t-2 and in panel B, this means weighting by individual payroll in t-2. MPCs range from 0 to 1. With the exception of the MPC in column 1, all MPCs refer to the MPC in the initial period. All standard errors are twoway clustered at the household and year.

Table A11: Elasticity of Income by MPS Estimated Using Tax Rebates

	(1)	(2)	(3)	(4)	(5)	(6)
MPC	0.128	0.111	-0.093	0.044	-0.009	-0.119
	(0.107)	(0.129)	(0.103)	(0.134)	(0.134)	(0.084)
MPC * Change in Aggregate GDP	1.351	0.488	0.951			
	(1.243)	(1.042)	(0.852)			
MPC * Change in State GDP				2.845	1.968	1.468
				(2.594)	(2.478)	(1.319)
Earnings Definition	HH Labor	Total HH	Ind. Labor	HH Labor	Total HH	Ind. Labor
Average MPC	.191	.192	.192	.191	.192	.192
Std. Dev. MPC	.122	.123	.122	.122	.123	.122
Observations	25476	25182	39171	22702	22154	34755
R-Squared	0.282	0.272	0.090	0.294	0.287	0.098

Notes: Households are weighted by their household's income in t-2. All regressions include year*state fixed effects. The dependent variable in all columns is the 2-year change in the log of the stated income variable. For Columns 1 and 4, this income variable is the sum of labor income for the head an spouse. For Columns 2 and 5, the income variable is total household income. For columns 3 and 6, the income variable is indiviudal labor income. Columns using household income measures use only 1 observation per household while columns using indiviudal income use 1 observation per head and one per spouse, if present. Sample is restricted to include 1997-2011. Standard errors are twoway clustered at the individual and year level in columns 1 through 3 and at the individual and state*year level in columns 4 through 6.

Table A12: Unemployment Probabilities over the Business Cycle

	LEHD Sample	Extended Sample	Non-employment	All Years
MPC	0.084	0.161	0.567	0.124
	(0.010)	(0.033)	(0.039)	(0.017)
MPC * Change in Aggregate GDP	-0.540	-0.735	-0.777	-0.238
	(0.181)	(0.281)	(0.327)	(0.114)
Observations	29422	34977	42137	108663
R-Squared	0.034	0.040	0.128	0.042

Notes: All regressions use MPCs estimated using CEX imputation. All regressions include state*year fixed effects. Changes are defined across 2-year periods. The LEHD sample restricts the sample to 1997-2011 and restricts attention to the set of workers employed in year t-2 in non-government industries. Since unemployment is measured in the month of the survey, which is mostly concentrated in March, the change in GDP is taken from Q1 in each year. Standard errors are twoway clustered at the individual and year level.

Table A13: Employment Cyclicality and the Local Covariance: Robustness

	Baseline		Financial Controls	Bartik Shock	CZ-level Variation
$\widehat{Cov}_c * \Delta \log Y_t$	4.858		3.966	2.171	1.887
	(1.098)		(1.203)	(1.543)	(1.119)
$\widehat{Cov}_c * \Delta \log Y_t * Tradable_i$	-5.710	-4.741	-5.431		
	(2.297)	(2.114)	(2.589)		
$\widehat{MPC}_c * \Delta \log Y_t$	-2.100		-1.304	3.736	0.033
	(2.407)		(2.893)	(1.409)	(2.479)
$\widehat{MPC}_c * \Delta \log Y_t * Tradable_i$	5.080	5.080	5.489		
	(1.271)	(1.271)	(1.444)		
Demographic Controls	X	X	X	X	X
CZ*Year FE		X			
Financial Controls			X		
Included Industries	T&N	T&N	T&N	All	–
No. Observations	130000	130000	96000	332000	2000
R-Squared	0.319	0.339	0.348	0.370	0.746

Notes: Each regression is calculated using multiple imputation techniques using 100 draws of MPC estimates. Regressions in columns (1)-(4) include an unbalanced panel of 270 commuting zones and 313 NAICS codes from 2001 to 2011. Column (5) includes an unbalanced panel of 270 commuting zones from 2001 to 2011. In columns 1 through 3, all controls are included separately, interacted with GDP, and triple interacted with GDP and a tradable indicator. Data for controls in column 3 is from U.S. Census Bureau (2012, 2018); Zillow, Inc. (2018); New York Fed (2016) (see Section A.6.1 for details). Column 4 shows results using the Bartik shock rather than GDP. See Appendix A.6 for details on the construction of the shock. In each regression, observations are weighted by the share of employment in $t-1$. Observations are rounded to the nearest 1000 due to Census disclosure rules.

Table A14: Mobility Patterns: Cross-Sector

MPC	-0.0036		-0.0032
	(0.0002)		(0.0004)
$\Delta \log GDP$		0.0087	
		(0.0043)	
MPC * $\Delta \log GDP$			-0.0412
			(0.0301)
No. Observations	11104884	11104884	11104884

Notes: Data are from the Basic Monthly Current Population Survey from 1990 to 2011. The dependent variable is an indicator for moving from employment in the private sector to self-employment, employment in the military, or federal employment. MPC is imputed using PSID estimates based on age, gender, and race. The sample includes all adjacent periods in which an individual is employed. Standard errors are clustered at the individual level. Column 1 includes quarter fixed effects, and all other columns include year-by-month fixed effects.

Table A15: The probability of moving outside of LEHD sample by worker marginal propensity to consume.

Marginal Propensity to Consume (MPC)	-0.0036		-0.0032
	(0.0002)		(0.0004)
$\Delta \log GDP$		0.0087	
		(0.0043)	
MPC * $\Delta \log GDP$			-0.0412
			(0.0301)
No. Observations	11104884	11104884	11104884

NOTES: Data is from the monthly basic current population survey 1990-2011. The dependent variable is an indicator for moving from employment in the private sector to employment in self-employment, the military, or federal employment. MPC is imputed using PSID estimates based on age, gender and race. Sample includes all adjacent periods in which an individual is employed. Standard errors are clustered at the individual level. Columns includes quarter fixed effects, and all other columns include year-by-month fixed effects.