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**The Matching Multiplier and
the Amplification of Recessions**

Christina Patterson

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The Matching Multiplier and the Amplification of Recessions*

Christina Patterson[†]

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Abstract

This paper shows that the unequal incidence of recessions in the labor market amplifies aggregate shocks. I define the *Matching Multiplier* as the increase in the output multiplier stemming from the matching of high marginal propensity to consume (MPC) workers to cyclical jobs. Using administrative data from the United States, I document a positive covariance between worker MPCs and their elasticity of earnings to GDP. This covariance is large enough to increase shock amplification by 40 percent over an equal exposure benchmark. I provide additional evidence for this mechanism using local labor market variation and a dynamic incomplete-markets model.

Keywords: Marginal Propensity to Consume, Amplification, Labor Market Inequality

JEL Classification: E21, J11, J23

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[†]Northwestern Economics Department. Email: christina.patterson@northwestern.edu. All errors are my own.

1 Introduction

The postwar U.S. economy is characterized by periodic large recessions. In the 11 recessions since 1945, gross domestic product fell by an average of 2 percent, and the unemployment rate spiked by an average of 2.3 percentage points. Most recently, in the Great Recession – the most severe downturn in the post-war period – GDP contracted by more than 4 percent, consumption fell by almost 3 percent, and the economy shed 8.6 million jobs (Mian and Sufi (2014)). Recessions are also unequally distributed. In the labor market, the employment of small and young firms is particularly volatile, as are the earnings of both very low and very high earners (Fort et al. (2013), Guvenen et al. (2017)). This project proposes a link between the heterogeneous impact of cyclical shocks in the labor market and the size of recessions. I show that the unequal incidence of recessions increases the aggregate marginal propensity to consume and significantly amplifies recessions via this channel. I summarize the amplification coming from the matching of workers to different job types by the matching multiplier, and further show that local economies with greater matching multipliers experience more volatile business cycles.

The response of aggregate consumption to business cycle shocks has been a central focus of macroeconomic research (Mian et al. (2013), Kaplan and Violante (2014)). In both traditional and modern models of the business cycle, the aggregate MPC plays a critical role. For example, in the simplest Keynesian models, the Keynesian cross captures how the aggregate MPC amplifies recessions. The Keynesian cross captures a simple, intuitive feedback loop: when there is a shock that decreases aggregate demand in the economy, some of that translates into lower incomes, which leads to depressed demand, which again feeds back into incomes, *ad infinitum*. Through this feedback mechanism, the initial demand shock is amplified, and the size of each of these feedback loops is determined by the aggregate marginal propensity to consume, which measures what fraction of each unit of income is turned back into consumption. This cumulative effect is memorably summarized by the classic Keynesian output multiplier, $\frac{1}{1-MPC}$.

While the aggregate MPC is core to both Keynesian and New Keynesian models, it is not itself a fundamental parameter of the economy. Unlike time or risk preferences, which are inputs to a model, the aggregate MPC is a feature of the model that depends on the model's other assumptions. For example, in a representative agent New Keynesian model, the aggregate MPC in response to a transitory income shock is very small because the agent saves to smooth consumption, while in models featuring substantial heterogeneity (e.g., with constrained hand-to-mouth consumers), the aggregate MPC can be an order

of magnitude larger (Bilbiie (2018b), Galí et al. (2007), Kaplan and Violante (2014)). To elucidate the core mechanism through which the incidence of recessions in the labor market increases the aggregate MPC, consider the case where all income comes from labor earnings and thus the aggregate MPC is simply given by

$$MPC = \sum_i \frac{dC_i}{dE_i} \frac{dE_i}{dY} = \underbrace{\sum_i \frac{dC_i}{dE_i}}_{\text{Avg. MPC}} + \underbrace{Cov\left(\frac{dC_i}{dE_i}, \frac{dE_i}{dY}\right)}_{\text{Covariance}} \quad (1)$$

where E_i is the income of individual i , C_i is the consumption of individual i , and Y is aggregate output. The aggregate MPC is made up of two terms. First, it depends on the average *level* of individual MPCs, $\sum_i \left(\frac{dC_i}{dE_i}\right)$. When individual consumption responds more on average to changes in incomes, the MPC is higher. Second, and more importantly for this paper, it depends on the *covariance* between individual MPCs and the sensitivities of individual incomes to aggregate movements, $Cov\left(\frac{dC_i}{dE_i}, \frac{dE_i}{dY}\right)$. This covariance term captures how the matching of workers with different MPCs to jobs with different sensitivities to aggregate fluctuations affects the magnitude of the aggregate MPC – when shocks disproportionately hit the incomes of individuals whose consumption is more sensitive, the aggregate MPC is larger. This covariance also implies a simple summary measure, motivated by the models of the business cycle mentioned above, of how this type of matching amplifies business cycles – a mechanism I term the *Matching Multiplier*. Formally, I define the matching multiplier as the component of the overall output multiplier that comes from this covariance between worker MPCs and the sensitivity of their income to shocks. This term captures the additional output response generated by the unequal exposure of worker earnings to recessions, relative to a benchmark in which all workers face the average earnings elasticity.

In the first part of this paper, I estimate this key covariance term and quantify the degree to which the earnings of high-MPC workers are more exposed to recessions. The key challenge in estimating this empirical moment has been that it requires detailed information on both consumption and income, and very few national data sets include both well-measured, detailed longitudinal earnings data and measures of consumption at the individual level.¹ I overcome this challenge by combining information from two data

¹ One notable exception is the JPMorgan Chase data, analyzed in Ganong and Noel (2019), which includes data on both direct deposit earnings and detailed credit card spending. This data set, however, has two substantial weaknesses relative to the Longitudinal Employer-Household Dynamics. First, and most importantly, it covers a much shorter time series, beginning in 2012, making it impossible currently to explore any recession periods. Second, it does not include much information on the firms in which individuals work, limiting the scope to explore firm-level determinants of earnings heterogeneity. The PSID also

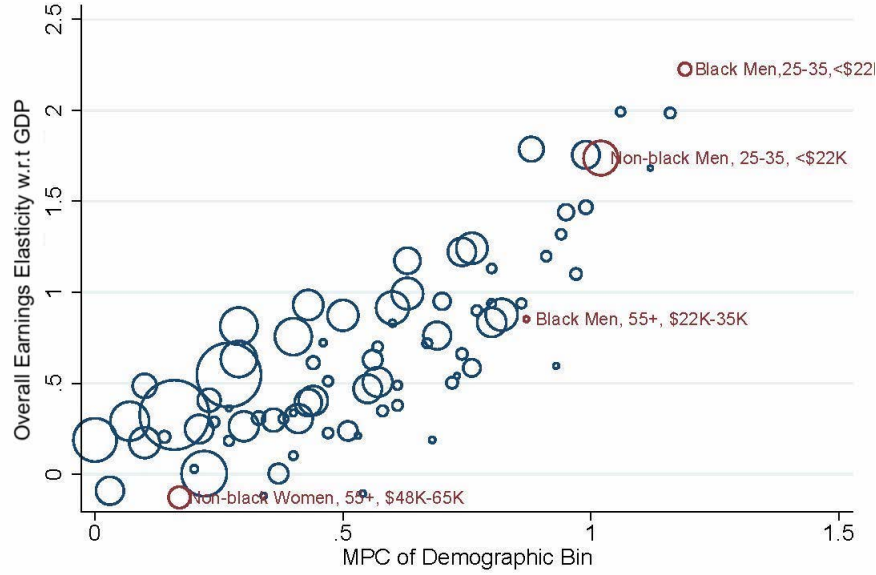
sets. I first use the Panel Study of Income Dynamics (PSID), which is a longitudinal survey that includes measures of both consumption and income, to estimate the MPC for individuals based on their detailed demographic characteristics. Then, using those sample demographic characteristics, I impute MPCs in the matched worker-firm earnings data recorded in the Longitudinal Employer-Household Dynamics data set (LEHD) from the U.S. Census Bureau. Using this imputation, I explore the degree to which workers with different MPCs are more exposed to movements in aggregate GDP.

Similar to prior literature, I find that individual MPCs, identified using unemployment as the shock to income, are sizable and heterogeneous. Unlike for most MPC estimates, this identifying shock is persistent but captures the income variation most similar to what is experienced by workers in recessions. Consistent with other patterns in the literature, I estimate an average MPC out of lost labor income of 0.5, with young, black, and poor workers having higher MPCs. Under several assumptions that I define and test, I am able to impute these MPC estimates in the LEHD, where I uncover a large, positive covariance between these estimates of a group's MPC and the sensitivity of the group's earnings to aggregate GDP. Figure 1 displays this key positive relationship. Each circle represents a detailed demographic group, the y-axis plots the average earnings elasticity to GDP within that group, and the x-axis plots the average MPC of that demographic group. Across groups, there is a strong positive relationship, with the earnings of high-MPC workers being more exposed to aggregate fluctuations than those of low-MPC workers.

In the second part of this paper, I show that the magnitude of this covariance between worker MPCs and earnings elasticities is large enough to have a meaningful effect on the response of the aggregate economy to shocks. I show this in three distinct ways. First, using the estimated covariance and a partial equilibrium model, I benchmark that the heterogeneous incidence of shocks increases the aggregate marginal propensity to consume out of labor income by 6 percentage points. Due to the non-linearity of the multiplier, this difference in MPCs leads to an estimate of the matching multiplier of 0.13, which implies that the amplification of demand shocks is almost 40 percent larger than it would be if all workers faced the earnings sensitivity of the average dollar in the economy. Since this multiplier captures the general equilibrium response to a broad class of demand shocks, this amplification mechanism has implications not only for the magnitude of recessions in general but also for the response of the economy to both fiscal

includes data on both income and consumption. Specifically, while the PSID does cover multiple recessions, its earnings measures are much worse than the administrative earnings data in the LEHD. The administrative earnings data are better measured, have a higher frequency, provide a much larger sample size, and include firm-level variables.

Figure 1: Recession Exposure and MPC by Demographic Group



Notes: Sample includes the set of all workers employed in a sample state in year $t - 1$ from 1995 to 2011. The dependent variable in the regression producing the y-axis estimates is the total change in log earnings for the demographic group. The subgroup is defined in year $t - 1$ and earnings are not conditional on the subgroup into which individuals move in period t . The size of each bubble represents the earnings share of that demographic group. The coefficient on the fitted line for this plot is 1.33. Appendix Figure A12 shows the corresponding figure separately for the intensive and extensive margin of earnings.

and monetary policy.

Second, in order to shed light on the empirical importance of this mechanism, I turn to the geographic variation in the administrative earnings data to test and validate the model's prediction that areas with a larger matching multiplier experience deeper recessions and larger booms. In the theoretical framework, the matching multiplier matters because, for a given shock, it leads to a larger consumption response, and thus amplifies aggregate fluctuations through the consumption multiplier. Therefore, under the assumption that a significant share of demand within a commuting zone (CZ) is derived locally, we should see more pronounced fluctuations in CZs with a higher matching multiplier. Indeed, this is what I find. I estimate significant local variation in the magnitude of the matching multiplier, and show the CZs with higher matching multipliers suffer deeper employment losses during recessions. I also find that this difference is entirely concentrated in nontradable industries, where the local consumption response should be much more important. Together, these local estimates provide additional important evidence for the empirical significance of this matching multiplier mechanism in explaining economic fluctuations.

Lastly, I demonstrate the importance of the estimated covariance by exploring the matching multiplier

mechanism in a dynamic model. The MPCs that I estimate capture the response of consumption to a potentially persistent shock. Under the assumption that the persistence of the aggregate shock is the same as the persistence of the unemployment shock, this is the correct measure to capture the effect that the unequal incidence of recessions has on the aggregate MPC. However, in a dynamic setting, the relationship between the empirical covariance and the multiplier is not straightforward and depends on the dynamic structure of the model. I explore the importance of these dynamic considerations by augmenting a standard Bewley-Huggett-Aiyagari model of consumer demand to include endogenous labor supply and rich cross-demographic group heterogeneity. I pair it with a simple supply side featuring sticky wages in the short run and exogenous labor rationing. Within this model, I derive an expression for the dynamic multiplier, and then calibrate the consumer side of the model to match the covariance that I measured in the first part of the paper. I show numerically that the 2-period approximation to the dynamic multiplier captures the amplification implied by the mechanism well even in a more structural dynamic setting.

The analysis in this paper adds to a large literature emphasizing that micro heterogeneity in the consumption responses to income changes is critical in determining aggregate dynamics. Important works in this area include empirical studies documenting substantial heterogeneity in MPCs at the individual level (Johnson et al. (2006), Fagereng et al. (2018a), Jappelli and Pistaferri (2014)) and quantitative models demonstrating the importance of agent heterogeneity in the determining the effectiveness of fiscal (Galí et al. (2007), Kaplan and Violante (2014)) and monetary policy (Auclert (2017), Kaplan et al. (2018), McKay et al. (2016)). Additionally, several other papers have highlighted the key role that the general equilibrium redistribution of income plays in the effectiveness of automatic stabilizers (McKay and Reis (2016)) or fiscal redistribution over the business cycle (Oh and Reis (2012)). This analysis builds on these papers but differs from them in two critical respects. First, I focus on a particular amplification mechanism coming from the covariance of worker MPCs and the sensitivity of their incomes to the business cycle. Second, I undertake a detailed empirical analysis of this channel of amplification using administrative microdata to both quantify this covariance and empirically evaluate its importance in the aggregate.

One important emphasis in the heterogeneous-agent New-Keynesian literature is that the introduction of constrained, high-MPC workers does little to increase the aggregate MPC, as when these models are calibrated to match the empirical distribution of wealth, high-MPC workers comprise a small share of the economy (Kaplan et al. (2014)). Recent works by Kaplan and Violante (2014) and Kaplan et al.

(2018) generate a larger aggregate MPC by introducing two types of assets, liquid and illiquid, which introduces “wealthy hand-to-mouth” individuals, who have substantial assets but high MPCs out of transitory shocks. Alternatively, Krusell and Smith (1998) and Carroll et al. (2017) show that incorporating preference heterogeneity generates large aggregate MPCs while matching the wealth distribution. The covariance between worker MPC and their earnings elasticity, which is the focus of this paper, is an alternate and complementary amplification mechanism that increases the aggregate MPC through heterogeneity in the incidence of the aggregate shock in the labor market. While high MPC workers may constitute a small share of the economy, if their income is most affected by the aggregate shock, they will become disproportionately important in determining the response.²

The importance of this particular mechanism is highlighted analytically in a series of papers by Bilbiie (2008, 2018a, and 2018b) and by Auclert (2017). In a two-agent New Keynesian model, Bilbiie (2008) derives the result that monetary policy shocks are amplified with agent heterogeneity only when the elasticity of income of the constrained agent is above 1. Extended to the case with multiple agents, Auclert (2017) similarly highlights the theoretical role that the covariance between worker MPCs and the sensitivity of their incomes to aggregate output plays in amplifying monetary policy shocks. This paper differs from those papers in its focus on the measurement of this key covariance and quantification of its aggregate consequences for the amplification of shocks. Additionally, while I focus on the importance of this moment for amplification, Bilbiie (2018a) shows this covariance may also have important implications for the determinacy of heterogeneous-agent New Keynesian models with interest rate rules and potentially exacerbates a wide class of New-Keynesian puzzles.

Lastly, this project also connects to a growing empirical literature examining the incidence of recessions. Recessions can unequally distribute shocks through several channels, including the housing market (Mian et al. (2013)) or the asset market (Glover et al. (2011)). This project specifically focuses on heterogeneity coming through the labor market. In that context, Hoynes et al. (2012) show that the earnings of young, low-education men are more sensitive to business cycles, and, using high-quality administrative tax records, Guvenen et al. (2017) document that the earnings of both the very low and very high income

² It is important to note that the mechanism emphasized in this paper also differs from the amplification that comes from countercyclical income risk, featured in various ways in Werning (2015), McKay (2017), Heathcote and Perri (2018), and Ravn and Sterk (2017), among others. The matching multiplier mechanism explored here focuses instead in the distribution of realized income, rather than cyclical changes in income risk. Indeed, recent work by Bilbiie (2018a) clearly disentangles these two channels and shows that these two forces – countercyclical income risk and heterogeneous incidence of shocks – reinforce each other.

workers are particularly exposed.³ Similarly, Guvenen et al. (2014) find that the fortunes of individuals during recessions are strongly predicted by an individual’s past earnings history.⁴ I expand on these findings to understand their implications for macroeconomic stability.

The rest of the of the paper proceeds as follows. Section 2 defines the matching multiplier in a simplified two-period framework. Section 3 describes the two main data sets that I combine in my empirical analysis. Section 4 presents empirical estimates of the covariance between MPCs and earnings sensitivities to the aggregate. Section 5 provides estimates of the empirical matching multiplier and Section 6 uses geographic variation to empirically test the importance of this amplification mechanism. Lastly, Section 7 explores the importance of dynamics in affecting the amplification implied by this covariance. Section 8 concludes.

2 Defining the Matching Multiplier

The equilibrium assignment of workers to jobs affects the economy’s response to aggregate shocks in a wide class of models (Auclert (2017), Carroll et al. (2017)). In this section, I illustrate the effect of the equilibrium assignment of workers to jobs in a simple two-period framework. I return to a more dynamic setting in Section 7, where I more formally model the persistence of unemployment, which is the income shock that identifies the MPCs, and the effect this has on the relationship between MPCs and the multiplier. For now, I abstract from the effect those dynamics have on the multiplier and consider this a 2-period empirical approximation to a dynamic multiplier.

To begin, consider the simple case in which worker i has a consumption function given by

$$C_i = c_i(E_i(Y), \theta_i)$$

where E_i are the earnings of individual i , which are given as a function of aggregate output Y , and θ_i are

³ This evidence on the relationship between income sensitivities and lagged incomes does not have any immediate implications for the relationship between income sensitivities and MPCs. First, MPCs are not a direct function of income and vary with other characteristics such as time preferences (Parker (2017)) or liquid wealth (Kaplan and Violante (2014)). Second, since MPCs are generally linearly falling in wealth, there is not clear mapping to the nonlinear relationship between the elasticity of income to changes in aggregate output across the income distribution.

⁴ Relatedly, Coibion et al. (2017) explore the degree to which the heterogeneous effects of monetary policy shocks on earnings affect the level of inequality in the economy. Using the Consumer Expenditure Survey, they find that contractionary monetary policy increases earnings inequality, a pattern that is consistent with my finding that the earnings of low-income workers are more exposed to shocks. See Mian and Sufi (2016) for an extensive survey of the literature on the cyclical of incomes and consumption across individuals.

other parameters affecting the consumption of the individual, such as preferences, borrowing constraints, etc. I assume that all output is consumed by workers, meaning that the market clearing condition dictates $Y = C$. Since I am interested in understanding the importance of demand-side heterogeneity in propagating shocks, I assume that prices are fixed and that output is demand-determined. Therefore, the total derivative of the market-clearing condition yields

$$dY = \sum_i \frac{dc_i}{dE_i} \frac{dE_i}{dY} dY + \underbrace{\sum_i \frac{dc_i}{d\theta_i} d\theta_i}_{d\varepsilon}$$

where $d\varepsilon$ is the change in total demand in response to an exogenous shock before output adjusts. Define $\gamma_i = \frac{dE_i}{dY} \frac{Y}{E_i}$ as the elasticity of individual i 's earnings to the aggregate and $MPC_i = \frac{dc_i}{dE_i}$ as the marginal propensity to consume of individual i . Assuming that $\sum_i \frac{dc_i}{dE_i} \frac{dE_i}{dY} < 1$, this can be expressed as

$$\frac{dY}{d\varepsilon} = \frac{1}{1 - \sum_i \frac{E_i}{Y} MPC_i \gamma_i} \quad (2)$$

where $\sum_i \frac{E_i}{Y} MPC_i \gamma_i = \sum_i \frac{dC_i}{dE_i} \frac{dE_i}{dY}$ is the *actual* aggregate marginal propensity to consume (MPC^a) in the economy – it captures how much of an additional unit of output is translated into an additional unit of consumption demand, taking into account the distribution of the aggregate shock. The multiplier, which is given in this setting by $\frac{1}{1 - MPC^a}$, determines the economy's response to any demand shock $d\varepsilon$. Equation 2 can be rewritten to highlight the role of earnings heterogeneity as

$$\frac{dY}{d\varepsilon} = \frac{1}{1 - (\bar{\gamma} \overline{MPC} + Cov(MPC_i, \gamma_i))} \quad (3)$$

where \overline{MPC} is the earnings-weighted average MPC in the economy, $\bar{\gamma}$ is the elasticity of the average dollar in the economy to aggregate output, and $Cov(MPC_i, \gamma_i)$ is the earnings-weighted covariance between MPCs and earnings elasticities.⁵ In the benchmark case in which every worker has an earnings elasticity equal to the average, $Cov(MPC_i, \gamma_i) = 0$ and the aggregate MPC is $MPC^b = \bar{\gamma} \overline{MPC}$. However, when the labor earnings of high-MPC workers are more exposed to aggregate movements in output, $Cov(MPC_i, \gamma_i) > 0$, and the aggregate MPC is larger. To explicitly capture the contribution of the covariance term to the multiplier, I define the *matching multiplier, or MM*, as difference between the multiplier

⁵ In this simple model, the earnings-weighted average elasticity in the economy is 1, but in the data, this number will be different, as labor earnings may not move one for one with output due to various frictions.

when workers face their actual earnings elasticity and a benchmark multiplier where the covariance between worker MPCs and earnings elasticities is 0.

$$MM = \frac{1}{1 - MPC^a} - \frac{1}{1 - MPC^b} \quad (4)$$

3 Data description

3.1 Longitudinal Employer-Household Dynamics and American Community Survey

The main data set for this analysis is the U.S. Census Bureau’s Longitudinal Employed-Household Dynamics (LEHD) data set, a longitudinal data set that provides quarterly earnings for all workers covered by the state-level Unemployment Insurance Program. The data for this paper includes a subset of 23 states in an unbalanced panel from 1995 to 2011, a period that covers two recessions. Appendix Figure A1 shows the by the late 1990s, this subset contained almost 50 percent of total U.S. private employment.⁶ In addition to the quarterly earnings of these workers, the data set also includes information on the firm (location, industry, firm size, and age), as well as demographic information on the workers (age, race, gender, and education).⁷ Reported quarterly earnings in the LEHD include gross wages and salaries, bonuses, stock options, tips, and other gratuities, as well as the value of meals and lodging (Spletzer (2014)).

In implementing the analysis, I make several sample restrictions. First, I exclude the first two years an individual appears in any state within my sample, allowing me to construct earnings histories and thus impute MPCs for all workers in the sample. Second, to abstract from schooling and retirement decisions, I exclude workers who are younger than age 25 or older than age 62. Third, for computational reasons, I restrict my attention to a fourth-quarter snapshot of the data.⁸ Appendix Table A1 shows simple summary

⁶ In a given state, this data set covers about 95 percent of private sector employment. See Appendix Table A2 for the list of included states, as well as the years for which each state is in the sample. I include all states to which I was given access. Appendix Table A5 shows that the demographic and labor market characteristics of workers in the LEHD states are very similar to those nationally over the same sample period.

⁷ Data on worker demographics in the LEHD come from the internal Census Personal Characteristic file, which covers 95 percent of the sample and is used to identify individuals across all census transactions and the long- and short-form censuses, which cover 61 and 12 percent of the sample, respectively (Vilhuber and McKinney (2014)). Specifically, worker age and gender are recorded in the person characteristic file, race is sourced from the short-form census, and education is sourced from the long-form census. In all cases, missing demographic data are imputed by the Census Bureau. Because education is imputed for almost 90 percent of the sample, I use this variable only in robustness exercises but not in the baseline results reported throughout this analysis. See Abowd et al. (2009) for further details on the data construction.

⁸ It is common in the literature to restrict analysis of the LEHD to an annual snapshot. See Sorkin (2018) and Abowd et al. (2003). I explore the robustness of the results to using annual earnings data rather than fourth-quarter earnings and find that results are similar. See the discussion in Appendix A.4.

statistics for this sample. Over the full sample, I observe an average of 38 million workers each year, about half of whom are male and who earn an average of \$44,000 dollars per year.

In order to refine elements of my empirical analysis, I take advantage of an individual-level linkage between the administrative earnings data and the rich survey data contained in the American Community Survey (ACS). Beginning in 2000, the ACS has interviewed 1 percent of the population every year on an array of topics including labor market activities, educational decisions, and housing situations. I use the information in the ACS for two primary purposes. First, I expand the set of worker observables for a subset of workers, allowing for a richer analysis of worker heterogeneity. Second, I explore and validate my assumptions on the labor market activities of individuals as they transition in and out of the LEHD sample. While the LEHD provides a comprehensive snapshot of employment, it does not provide information on the labor market activity of those who are not currently employed in that sample. Throughout the analysis, I assume that prime-age workers who leave employment in my sample make no labor market earnings in those quarters. This assumption of zero earnings in periods of nonemployment would be violated if individuals move 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. While it is certainly true that not all workers leaving the LEHD sample transition to non-employment, in Appendix A.1, I show that these differences are uncorrelated with the worker's MPC and thus unlikely to meaningfully bias my results.

3.2 Panel Study of Income Dynamics

I supplement the detailed administrative data on earnings with marginal propensities to consume estimated using the PSID. Each household in the PSID is interviewed every year from 1968 to 1997 and every other year after that. Among other things, households are asked detailed questions on their demographics and labor market experiences of the household head and spouse. In order to include secondary earners in my analysis and estimate a MPC at the individual level for both household heads and spouses, I transform the data to have up to two observations per household, one for the head and one for the spouse. This transformation means that each individual within the household has the same consumption, but the head and spouse differ in their demographics and labor market variables. Appendix Table A5 shows summary statistics for the PSID sample that I include in the estimation.⁹ Because I include all samples within

⁹ I start with the source and SEO samples of the PSID from 1968 to 2015. I drop any observations that do not have two lags, used to define previous income, and one lead, used to define current income. As in the LEHD analysis, I also drop those individuals

the PSID to estimate MPCs (i.e., the nationally representative sample and the oversample of low-income groups), the sample has a higher share of black and low-income workers than the total population.

For most of the PSID sample, the main expenditure variable is food consumption. There are several reasons to suspect that the response of food expenditure to income changes is not representative of overall expenditure responses. First, as food is a necessity, its share of total consumption varies across the income distribution (see Appendix Figure A2). Second, the provision of food stamps potentially distorts food consumption decisions on the margin and likely dampens fluctuations in food expenditure relative to overall expenditures (Hastings and Shapiro (2017)). In order to address these issues, the main measure of expenditure I use throughout the analysis is total expenditure, which I impute using overlapping information in the Panel Study of Income Dynamics and the Consumer Expenditure Survey, or CEX, following the methodology introduced in Blundell et al. (2008) and expanded in Guvenen and Smith (2014). Using the CEX, I estimate a demand for food expenditure as a function of durable consumption, nondurable consumption, demographic variables, and relative prices. Under the assumption that food demands are monotonic, this demand function can be inverted to get predicted total consumption based on the food expenditures and demographics of the household in the PSID.¹⁰ Appendix Figure A3 shows that this imputation not only matches the time series and levels of consumption in the CEX but also captures important cross-sectional patterns in the CEX such as the food share of consumption and age profile of consumption. However, as I show in the Appendix, in percentage terms, I find that the amplification implied by the covariance term is similar when using only food, only durable consumption, or alternate imputations.

4 Measuring the Covariance between MPCs and Earnings Elasticities

The first part of this paper combines these two datasets to estimate the covariance between an individual's MPC and the sensitivity of individual earnings to aggregate shocks. In Section 4.1, I present estimates of MPCs by worker characteristic in the PSID, where there is both consumption and earnings data. In

younger than age 25 or older than age 62. I also drop observations with missing food consumption or missing income. Lastly, I drop observations where the two-year change in either food consumption or income is more than fourfold. These restrictions on outliers are similar to those 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.

¹⁰ An alternative method for imputing more comprehensive consumption measures in the PSID, proposed by Attanasio and Pistaferri (2014), is to use the expanded consumption categories in the later years of the PSID. Specifically, they impute relationship between food consumption and overall consumption in the 1999-2013 survey years to impute the total consumption in the previous years of the sample. Appendix A.2 discusses this imputation measure in more detail and shows that estimates of MPCs using this methodology show similar patterns to the CEX-based imputation.

Section 4.2, I impute these MPCs in the LEHD using overlapping information on worker demographics and uncover an estimate of this key covariance.

4.1 Estimating marginal propensities to consume

Since I do not observe the consumption behavior of individuals in the LEHD, I estimate the MPC for workers with different characteristics using the panel structure of the PSID and impute these values in the LEHD. While the strategy of imputing MPCs within the LEHD based on individual characteristics is novel, my estimation of MPCs borrows from a long line of literature that explores the response of individual consumption to income changes. A consistent finding within this large and heterogeneous literature is that households exhibit high MPCs out of unexpected income shocks and that the magnitude of these responses differs across the population.¹¹

I build most directly on a line of research beginning with Gruber (1997), who examines the consumption drop upon unemployment. Using the panel structure of the PSID, I estimate

$$\Delta C_{t,i} = \sum_x (\beta_x \Delta E_{t,i} \times x_{t,i} + \alpha_x x_{t-1,i}) + \delta_{t,s} + \epsilon_{t,i} \quad (5)$$

where $C_{t,i}$ is total household consumption of individual i at time t , imputed from the CEX as explained in Section 3.2;¹² $E_{t,i}$ is labor earnings of individual i ; $\delta_{t,s}$ are state-by-year fixed effects, which capture any time variation that is common to all individuals within a state and year; and $x_{t,i}$ is a characteristic of the individual.¹³ In order to include data from 1997 to 2015, when the PSID becomes every other year, I consider two-year changes in both income and consumption. If x are all common to both the PSID and the LEHD, then using the estimated β_x , I can impute the MPC in the LEHD as

¹¹ In particular, a series of recent papers estimate that upon receiving tax rebates, workers, on average, spend more than half of the windfall within two quarters but that individuals with few financial resources spend more than those with more cash on hand (Johnson et al. (2006), Parker et al. (2013)). See also Fagereng et al. (2018b), Gelman (2016), Gross et al. (2017), Jappelli and Pistaferri (2014), Kaplan and Violante (2014), and Jappelli and Pistaferri (2010) for a comprehensive survey.

¹² Figure A10 explores the sensitivity of these estimates to using alternative consumption measures. While the levels of the MPCs differ, the cross-sectional patterns are very similar. Appendix A.3 discusses an alternate estimation of MPCs that uses only the short panel structure of the CEX. While noisier, the patterns that result from this separate estimation are similar to the baseline estimates in Figure 2.

¹³ In baseline specifications, x includes: five lagged income bins, a quadratic in age, female and black dummies, black interacted with age, and female interacted with black. See Appendix A.3 for additional details on sample restrictions. I include both household heads and spouses separately in the regression. Birinci (September 2019) documents using the PSID that the spousal response to the displacement of the family head is minimal, and thus the potential within-household spillovers are unlikely to meaningfully affect these estimates.

$$\widehat{MPC}_{i,t} = \sum_x \hat{\beta}_x x_{i,t}$$

Since many factors that could simultaneously move income and consumption at the individual level, I identify the causal relationship between income and consumption in Equation 5 using an income shock as an instrument for $\Delta E_{t,i}$. In a general class of models, the MPC of the individual is a function of the type of income shock. My baseline estimates are identified using unemployment as the shock to income, which is a large and persistent shock (Gruber (1997), Hendren (2017), Jacobson et al. (1993)). The unemployment shock captures income variation that is most relevant for understanding recessions – indeed, if all aggregate fluctuations have the same persistence as unemployment, then this is exactly the correct MPC to answer the question of how the heterogeneous incidence of aggregate fluctuations affects the aggregate MPC. An MPC that is estimated using a purely transitory shock, such as a tax rebate, would fail to capture the consumption response to the type of income shocks that workers typically experience over the business cycle. In Section 7, I further investigate the importance of this shock persistence in a structural dynamic model and show that when combined with the 2-period multiplier in Section 2, these MPCs provide a good approximation for a dynamic multiplier in response to a persistent aggregate shock.¹⁴

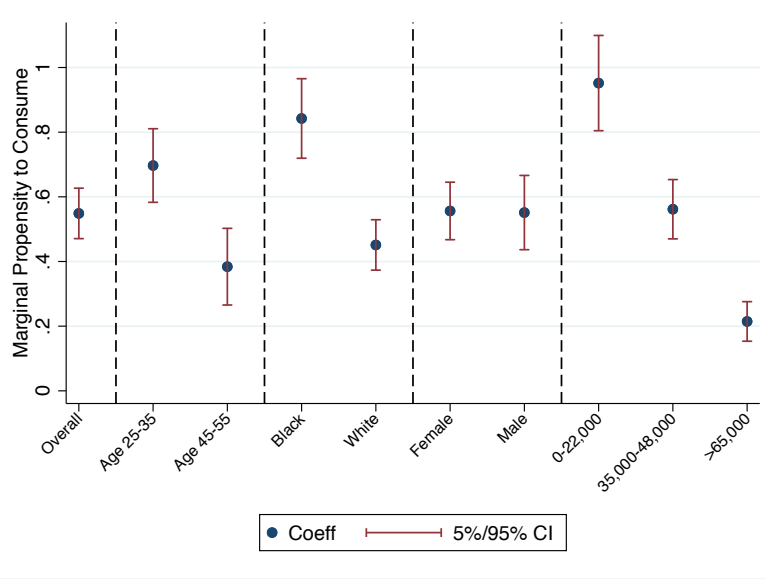
4.1.1 Description of MPC estimates

Before exploring the full distribution of MPCs that result from Equation 5, Figure 2 shows the patterns in MPC heterogeneity with bivariate regressions for select subgroups for the set of covariates that I include in the full estimation. The farthest-left estimate shows that the average MPC in the estimation sample is just more than 0.5. This average estimate is similar to other estimates in the literature that use comparable identifying variation.¹⁵ Importantly, the coefficients to the right show that there is substantial variation in MPCs around this average – younger, black, and poorer workers, on average, have a larger consumption

¹⁴ In estimating Equation 5 with unemployment as an instrument, I limit the sample to the set of individuals who are employed in the previous period and identify β_x by comparing the change in consumption between $t - 2$ and t of those who remain employed to the change among those who lose their jobs.

¹⁵ Using income and consumption data from JPMorgan Chase and similar identifying variation, Ganong and Noel (2019) estimate an average MPC of 0.4. They also find demographic patterns similar to those in the PSID – they find higher MPCs among individuals with lower incomes and assets, as well as among those who are younger. Similarly, using the Nielsen Consumer Panel, McKee and Verner (2015) estimate an MPC out of unemployment insurance benefits of between 0.6 and 0.9, and Jappelli and Pistaferri (2014) use survey data in Italy and find an average MPC out of transitory income of 0.48. See Appendix Figure A7 for a graphical comparison to other similar estimates in the literature and Jappelli and Pistaferri (2010) for a comprehensive review.

Figure 2: Heterogeneity in Marginal Propensity to Consume Estimates



Notes: Each estimate represents a separate regression including only the stated demographic group. In all cases, consumption is measured using total consumption, imputed using the method in Blundell et al. (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 marker earnings of the individual in $t - 2$ and $t - 3$. All regressions include year-by-state fixed effects and observations from 1992 to 2013. Appendix Figure A4 shows the reduced form and first stage for these regressions.

drop per dollar of lost income. The lagged income measure along which I allow MPCs to vary is the average earnings of workers in years $t - 2$ and $t - 3$, which is meant to capture differences in permanent income across workers stemming from different educations or other skills.¹⁶ Women and men in Figure 2 have similar MPCs, on average, but women also earn less than men, and Appendix Table A7 shows that once you control for differences in earnings levels, women have lower MPCs than men. These cross-demographic patterns are broadly consistent both quantitatively and qualitatively with other estimates of MPC heterogeneity by demographic group in the literature (Ganong and Noel (2019), Parker et al. (2013), Parker (2017), and McKee and Verner (2015)). Putting this all together, Figure 3 shows the full distribution of MPCs in the PSID that result from Equation 5.¹⁷ There is a substantial amount of variation, with the large mass between 0 and 1, and a small number of estimates above 1.

¹⁶ I use the average earnings over the previous two years to balance capturing a more permanent measure of earnings capacity against a loss of sample that comes with the more stringent within-individual panel. However, Appendix Figure A5 shows that the patterns are similar when using income either lagged further, averaged over longer intervals, or fixed at a given age.

¹⁷ Specifically, I include the following parametrization of the variables described in Figure 2: five approximately equally-sized lagged earnings bins ($< \$22,000$, $\$22,000 - \$35,000$, $\$35,000 - \$48,000$, $\$48,000 - \$65,000$ and $> \$65,000$); a quadratic in age; female and black indicators; an interaction between black and age; and an interaction between female and black. See Appendix Table A7 for the regression coefficients underlying the distribution in Figure 3.

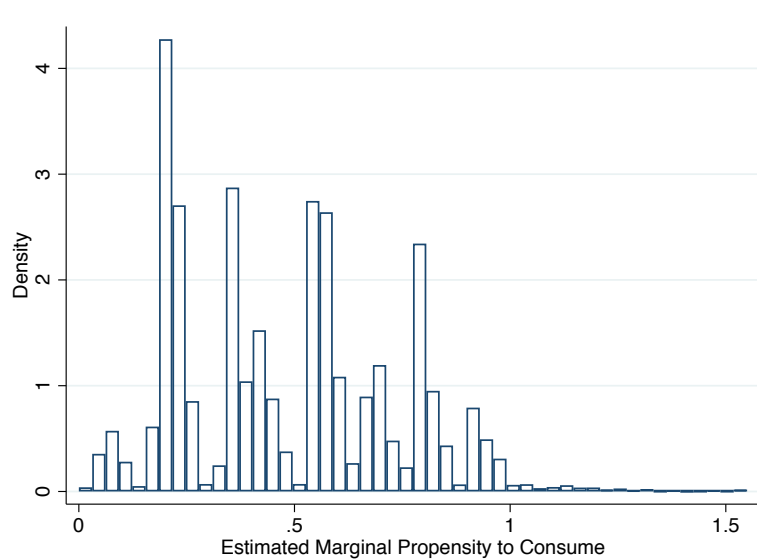
While I allow for heterogeneity in worker MPCs along only four demographic dimensions (race, age, gender, and earnings history), it is not necessary for the MPCs to be a direct function of those specific characteristics. Rather, it is likely the case that these characteristics are correlated with other underlying economic circumstances that directly affect MPCs. Specifically, in models of precautionary savings or credit constraints, a key source of heterogeneity in MPCs is the individual's cash on hand, and indeed, several studies find heterogeneity in MPCs along this margin (Jappelli and Pistaferri (2014), Kaplan et al. (2014), Parker et al. (2013), Fagereng et al. (2018b)). The demographic patterns in Figure 2 are consistent with that source of heterogeneity, as the literature has shown that young, black, and low-income workers also have less liquid wealth (Detting et al. (2017)).¹⁸ These differences in the amount of cash on hand across demographic groups may reflect different income processes across groups, which when combined with borrowing constraints or precautionary savings lead to different liquidity positions (Deaton (1991), Carroll (2001)). Alternatively, they may reflect differences in risk preferences or discount rates across demographic groups, or differences in access to credit (Gelman (2016), Parker (2017)). It is also possible that heterogeneity in $\hat{\beta}_x$ reflects differences in marriage rates across groups, as married workers have lower MPCs due to risk-sharing within the household. Lastly, heterogeneity in $\hat{\beta}_x$ may also reflect differences in the persistence of the unemployment shock across individuals, although the structural analysis in Section 7 suggests that this heterogeneity in persistence does not play an important role.

4.1.2 Assumptions for MPC imputation

While the above method for estimating MPCs closely follows existing methods in the literature, my subsequent imputation of these MPCs in the LEHD necessitates several important additional assumptions about the stability of the MPC estimates that warrant further discussion. First, in imposing that MPCs only vary by worker demographics, I assume that individual MPCs out of unemployment are similar to the MPCs out of business cycle income shocks of different signs and magnitude. This would imply both that the other business cycle shocks have a similar persistence to the unemployment shock and that the MPC does not depend on the magnitude or size of the shock. In a standard model in which agents maximize their expected utility subject to an intertemporal budget constraint, an individual's MPC depends on the persistence of the shock, not on the magnitude or sign. However, with liquidity constraints, the MPC

¹⁸Indeed, in Appendix Figure A5, I replicate the finding that households with assets below median have much larger MPCs than households with assets above median.

Figure 3: The Distribution of Estimated Marginal Propensities to Consume



Notes: See Appendix Table A7 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 et al. (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 $t - 3$. Regression includes year-by-state fixed effects and observations from 1992 to 2013.

out of small shocks may depend on the size of the shock as well as the sign (Kaplan and Violante (2014)). I explore the importance of the identifying shock by comparing MPC estimates that result from business cycle shocks of differing size and sign. Appendix Figure A8 shows that the average MPC is similar across these various identifying shocks. Specifically, the MPC is similar when using smaller income shocks, identified from movements in industry unemployment rates or changes in state gross domestic product, or when using the positive income shock of finding a job. Additionally, Appendix Figure A9 shows that not only are the averages similar but also the cross-demographic patterns are very similar. This does not mean that the MPC out of all different types of shocks is the same, but rather that the MPC out of labor market earnings is similar for changes in earnings over the business cycle of different signs and sizes.

A second key stability assumption embedded in the imputation of MPCs in the LEHD is that conditional on demographics, the consumption response is constant over the business cycle. This assumption could be violated for several reasons. It may be that liquidity constraints are more likely to bind in recessions, in which case the average MPC of a demographic group is likely to be higher. Conversely, unemployment insurance is higher in recessions, leading to lower realized MPCs out of lost labor income in

recessions. Existing empirical evidence on this cyclicalilty of MPCs is scarce – Gross et al. (2017) find that the MPC out of liquidity is higher in recessions, but a calibration by Carroll et al. (2017) finds that MPCs are roughly constant over time. I explore this in my setting by adding an interaction of changes in income with the state unemployment rate, thereby allowing the MPC by demographic to vary over the business cycle, and find that differences, both on average and for each demographic group, are statistically and economically small.¹⁹

Third, I impose that at the individual level, the marginal propensity to consume is a function only of the characteristics that I include in x (i.e., age, earnings history, gender, and race). While this is obviously an approximation, this assumption would be a problem for my analysis if within each demographic bin there is sorting across jobs such that it was precisely the higher-MPC workers within the group who are at cyclically insensitive jobs. If this were the case, I would be inaccurately capturing the heterogeneity in exposure of workers to business cycles by their MPC. While my data do not allow me to fully address this, I explore the sensitivity of my MPC estimates in the PSID to including job-level characteristics. If sorting across jobs of different characteristics were important in explaining MPC heterogeneity within demographic group, then these terms should have additional explanatory power. Appendix Table A8 shows that no additional job-level variables or regional controls meaningfully change the MPC estimates. While not ruling it out, these estimates do suggest that this cross-job sorting within demographic group is small and unlikely to be a meaningful source of bias in my estimates.

4.2 Heterogeneity in worker exposure

Using these estimates of an individual's MPC, I move to the LEHD and estimate the degree to which worker earnings of different MPCs are differentially sensitive to aggregate shocks. To do so, I estimate the following equation:

$$\Delta E_{i,t} = \alpha_1 MPC_{i,t-1} + \alpha_2 MPC_{i,t-1} \times \Delta \log G_t + \delta_t + \epsilon_{i,t} \quad (6)$$

where $E_{i,t}$ is a measure of the individual's fourth-quarter earnings; $MPC_{i,t-1}$ is the imputed MPC of individual i ; δ_t are year-fixed effects, soaking up any variation in earnings that is common across individuals

¹⁹ See Appendix Figure A8 for a graph showing the estimates of MPCs at different points in the business cycle.

in a given year; and $\Delta \log G_t$ is the annual change in the log of national GDP.²⁰ The sample includes the set of all workers employed in year $t - 1$. The coefficient of interest is α_2 , which captures the degree to which the earnings of workers of different MPCs are differentially sensitive to movements in aggregate GDP.

I explore the different dimensions of earnings cyclicalities with various specifications of the outcome variable $E_{i,t}$. I capture the intensive margin of earnings elasticity by using the log of earnings, thus restricting the sample to the set of individuals who remain employed across years, and I capture the extensive margin of employment using an indicator for whether the individual is employed in time t . Lastly, I combine the intensive and extensive margin into one estimate using $\Delta E_{i,t} = \frac{E_{i,t} - E_{i,t-1}}{.5 \times E_{i,t} + .5 \times E_{i,t-1}}$. This transformation defines and bounds the earnings losses of those who lose their job between periods, thus providing an estimate for overall earnings elasticities.²¹ Importantly, each individual in the regression is weighted by their share of overall earnings. What matters for the economy as a whole is not the differential elasticity of individuals but the differential elasticity of *dollars* earned in the economy.

Before going directly to estimates of α_2 from Equation 6, recall Figure 1 from the introduction to demonstrate the variation underlying this key relationship. Each point represents a demographic group aggregated to the level of heterogeneity in the MPC imputation (for example, white men, ages 25 to 35 with lagged earnings between \$22,000 and \$35,000) and shows the relationship between group MPCs and earnings elasticities to GDP. This figure clearly shows that there is a tight, almost linear relationship between these two variables – higher-MPC demographic groups are much more exposed to recessions. For example, the consumption of black men from ages 25 to 35 who earned less than \$22,000 in the previous year is very sensitive to changes in their earnings, with an average MPC of above 1, yet it is precisely these workers whose earnings are most sensitive to aggregate shocks.²² The elasticity of their earnings is just above 2, meaning that when GDP falls by 1 percent, their earnings, on average, fall by 2 percent. In con-

²⁰ For computational reasons, I estimate Equation 6 on a 5 percent random subsample of the data. Appendix Table A9 shows similar estimates with an aggregated estimation of Equation 6 that utilizes the full sample. I restrict attention to the set of employed workers for several reasons. First, the LEHD is a data set of employment and thus does not have complete coverage of the unemployed. I also earnings weight the regressions; thus, including the unemployed would necessitate an alternate weighting strategy. Finally, a large fraction of earnings is earned by the employed rather than the new hires. However, in Appendix Section A.4.4, I use the link between the ACS and the LEHD to provide estimates for the heterogeneity in the incidence of hiring from unemployment over the business cycle. I find that the differential sensitivities among the unemployed are small and contribute very little to the aggregate.

²¹ In Appendix Table A9, I explore alternate transformations for estimating the overall earnings elasticity. I show that the estimates using either $\log(E_{i,t} + 100)$ or normalizing the level of the earnings change by the average earnings in the individual's group produce similar patterns but in general produce larger variation in elasticities across workers.

²² In Appendix A.4, I replicate the findings in Guvenen et al. (2017) that the earnings of the very high and very low earnings are most exposed to GDP, as well as discuss how these patterns affect the relationship between MPCs and sensitivity to GDP.

Table 1: Earnings Elasticity to GDP by a Worker's Marginal Propensity to Consume

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Earnings Margin		Partialled Out MPC Components ($X_{i,t-1}$)				
	Overall	Intensive	Extensive	Gender	Race	Income	Age	All Together
$MPC_{i,t-1}$	-0.245 (0.001)	-0.061 (0.001)	-0.110 (0.000)	-0.244 (0.001)	-0.245 (0.001)	-0.136 (0.001)	-0.290 (0.001)	-0.103 (0.002)
$MPC_{i,t-1} * \Delta GDP_t$	1.300 (0.028)	0.586 (0.025)	0.482 (0.012)	1.257 (0.028)	1.324 (0.028)	1.662 (0.047)	1.310 (0.028)	1.140 (0.053)
$X_{i,t-1}$				0.008 (0.000)	0.008 (0.000)	0.033 (0.000)	-0.006 (0.000)	
$X_{i,t-1} * \Delta GDP_t$				-0.378 (0.015)	-0.131 (0.027)	0.163 (0.016)	0.004 (0.001)	
No. Observations (Million)	29.20	25.50	29.20	29.20	29.20	28.46	29.20	28.46
R-Squared	0.009	0.002	0.010	0.009	0.009	0.009	0.017	0.018
Avg. MPC	.431	.423	.431	.431	.431	.431	.431	.431

Notes: Each regression is estimated on a 5 percent random subsample. All observations are weighed by the individual's earnings in $t-1$. Earnings in each regression are defined as total quarterly earnings for each individual in the fourth-quarter of the year. The number of observations is rounded to the nearest 100 to comply with U.S. Census disclosure requirements. Standard errors are clustered at the individual level. The outcome variable in Columns 1 and 4 through 9 is $\Delta E_{i,t} = \frac{E_{i,t} - E_{i,t-1}}{.5 \times E_{i,t} + .5 \times E_{i,t-1}}$. The outcome variable in Column 2 is the change in the log of fourth-quarter earnings, and the outcome variable in Column 3 is an indicator for being employed in time t . Columns 4 through 8 add the noted demographic characteristic $x_{i,t-1}$, both independently and interacted with GDP. Gender is a dummy for whether the worker is female, race is a dummy for whether the worker is black, and income is the log of a worker's earnings in the time $t-2$ and $t-3$. See Appendix Tables A9 and A10 for alternate specifications of these estimates.

trast, the consumption of nonblack women over age 55 who earned \$48,000-\$65,000 in the previous year is, on average, much less sensitive to changes in their income, yet the earnings of these workers are almost completely insensitive to movements in aggregate GDP.

The slope of the fitted-value line in Figure 1 is precisely the estimate of α_2 from Equation 6. The first column of Table 1 reports the estimate corresponding to the slope of Figure 1.²³ Columns 2 and 3 show this overall estimate decomposed into the intensive and extensive margin of earnings. Demographic groups that are cyclically sensitive on the intensive margin also tend to be cyclically sensitive on the extensive margin of employment, and thus, there is a strong positive relationship between the sensitivity of a worker's income to GDP and a worker's MPC along both the intensive and extensive margins. Both margins contribute similarly to the overall heterogeneity in exposure.

²³ The standard errors reported in Table 1 are clustered at the individual level, which accounts for correlation in the error over time within individuals. However, they do not take into account the additional noise stemming from the two imputations in the MPC estimates – an imputation of total consumption in the PSID from the CEX, and an imputation of the MPC in the LEHD from the PSID. Appendix A.4 shows standard errors adjusted to incorporate the noise in these imputations using multiple imputation techniques from Rubin (1987). As expected, the adjusted standard errors are larger, but the point estimates are still highly statistically significant. Due to the large computational burden imposed by this bootstrapping procedure, I proceed with the clustered standard errors for the rest of the analysis.

The subsequent columns of Table 1 show the estimated relationship controlling individually for various worker characteristics (X_i) along which MPCs vary. I include the variable both individually and interacted with GDP. If all of the variations in the relationship between MPCs and earning elasticities were driven by heterogeneity along one dimension, the coefficient on the MPC and GDP interaction would drop to 0 when that characteristic was included. However, the coefficients on the main interaction term between MPCs and GDP are relatively stable across Columns 4 through 8 as each worker characteristic is added individually. Even in Column 9, when all individual controls are included, there is still a substantial coefficient on MPCs, showing that there no one dimension of heterogeneity is driving the relationship.

This positive relationship between the cyclical sensitivity of earnings and the MPC of the worker is also very robust across empirical specifications. Appendix Table A9 shows that both the direction and magnitude of the relationship is robust to the functional form of the earnings outcome variable as well as decisions about the level of individual earnings aggregation. Specifically, while earnings in Table 1 are measured at the worker level using aggregate fourth-quarter earnings, Column 5 of Appendix Table A9 shows that the patterns are robust to using annual rather than fourth-quarter earnings. Column 7 in Appendix Table A9 shows that patterns are similar when using state-level GDP as a cyclical indicator rather than aggregate GDP, suggesting that these patterns are present both across and within states. Appendix Table A10 shows that the relationship is also robust across the various methods for imputing MPCs. For all imputations, a 1 standard deviation increase in the MPC of the individual is associated with an increase in the elasticity of earnings with respect to GDP of between 0.33 and 0.39.

Lastly, in Appendix Table A11, I use the expanded information in the ACS subsample to explore the possibility that within demographic group sorting could bias the estimated relationship between worker MPCs and earnings elasticities. One possible concern would be that workers of the same demographic group but with different household structures sort into jobs with different sensitivity to aggregate movements. However, I find that the slope of the relationship between MPCs and earnings sensitivity to GDP is similar when I use an alternate MPC that is allowed to vary by the number of children in the household and an individual's marital status, or when I aggregate fully to the household level.

4.3 Discussion

Although the source of this relationship between MPCs and earnings elasticities is not immediately relevant for understanding its contribution to macroeconomic stability, it is an interesting object in its own right. The finding that the earnings of high-MPC workers are more exposed to aggregate conditions is at odds with a simple model of firm-worker risk-sharing, which would predict that workers for whom fluctuations in income are costly would sacrifice part of their expected earnings to enter into contracts in which their wages are less sensitive to aggregate demand fluctuations (Bailey (1974)). These patterns are not, at face value, inconsistent with the idea that workers sort across jobs according to their risk preferences (Schulhofer-Wohl (2011)). However, for this allocation to be privately optimal, there would need to be a very strong negative relationship between risk aversion and worker MPCs.

One probable explanation for the observed covariance between worker MPCs and aggregate earnings risk is that differences in either observed or unobserved skills drive the sorting across firms and are correlated with worker MPCs. However, as I discuss in more detail in Appendix Section A.4.3, I find that the large majority of the covariance is within the firm rather than between firms, suggesting that the sorting of workers across firms based on their geographic location or industry-specific skills is only a small part of the story. Within the firm, I find substantial heterogeneity in exposure by MPC even within an occupation, much of which is explained by differences in the earnings history of the workers, with low-income workers' earnings being more sensitive to changes in GDP than the earnings of higher-income workers.

The within-occupation correlation between worker MPCs and aggregate earnings risk may still reflect sorting across jobs based on the unobserved skills of the individual. However, the relative unimportance of firms and the importance of earnings history suggest that this pattern is also consistent with models where workers' exposure to aggregate shocks and their MPCs are explicitly linked. For example, these patterns are consistent empirically with a large literature showing that one unemployment spell increases the risk of future unemployment spells (Stevens (1997)). Theoretically, they could be consistent with a job ladder model as in Jarosch (2014), wherein workers search for both more productive and more secure jobs, and thus, as they climb the job ladder, they sort into higher-paying and more-secure jobs. This model of worker flows would result in a pattern where within the firm, the worker with higher lagged earnings, both because she is in a higher-paying job further up the ladder and because she has not recently experienced an unemployment spell, is less exposed to shocks than the lower-earning recently hired worker.

5 Matching Multiplier estimates

The previous section measured the covariance between MPCs earnings elasticities. In this section, I use the simplified framework in Section 2 to benchmark its importance in the aggregate. Recall from Section 2 that the matching multiplier is defined as the difference in the Keynesian multiplier with the empirical incidence of aggregate shocks and the multiplier in a benchmark case in which all workers faced the same earnings elasticity. In the framework used to derive Equation 4, all output is earned by workers in the form of wages. However, this is not true empirically, as workers earn income from other sources (e.g., capital and profits). Therefore, in the empirical estimates of the matching multiplier, I make adjustments for 1) the MPC out of non-labor income; and 2) the share of overall output going to workers in the form of wages.²⁴ In the baseline estimates, I assume that the labor share is two-thirds and I set the MPC out of nonlabor income such that the total benchmark MPC (MPC^b) is unaffected by nonlabor income, which means that I assume that the MPC out of nonlabor income is around 0.23.²⁵

Panel A in Table 2 shows the estimates. The top row shows the baseline matching multiplier. Column 1 shows the estimate of the benchmark MPC, defined as the earnings-weighted individual MPC (equal to 0.42) times the estimate for the earnings elasticity of the average dollar in the economy (equal to 0.6). Column 2 shows that the actual MPC is 0.06 higher than this benchmark, meaning that heterogeneity in worker exposure to recessions increases the aggregate MPC by 28 percent. Across the remaining columns of Table 2, I translate this difference in MPCs into a difference in the multiplier. Column 3 shows that these estimates imply a benchmark multiplier of 1.3, Column 6 shows that this multiplier increases by 0.13, or 10 percent, with the empirical incidence of shocks, bringing the overall multiplier to 1.42.

The subsequent rows of Panel A shows estimates of MM for different, more restricted benchmarks. The second row shows MM with a benchmark in which each worker is given the earnings elasticity of the

²⁴The formula for the matching multiplier with the empirical adjustment is given by

$$MM = \frac{1}{1 - \underbrace{(\alpha_l \overline{MPC} + Cov(MPC_i, \gamma_i) + MPC_{nl}(1 - \alpha_l))}_{MPC^a}} - \frac{1}{1 - \underbrace{(\alpha_l (\overline{MPC} + MPC_{nl}) (1 - \alpha_l))}_{MPC^b}}$$

where MPC_{nl} is the MPC out of non-labor income and α_l is the share of overall output going to workers in the form of wages. See Appendix B.1 for a derivation of this equation.

²⁵ While it is difficult to validate this assumption explicitly, recent empirical evidence from Sweden in Di Maggio et al. (2018) suggests that the MPC out of non-labor income is meaningful, with an MPC out of dividends of 0.35 and the aggregate MPC out of capital gains of 0.06, suggesting that an overall MPC of 0.23 is not unreasonable. This average estimate for the MPC out of capital gains comes from a back-of-the-envelope calculation based on Table 3 in Di Maggio et al. (2018). Individuals in the bottom half of the wealth distribution have an average MPC of 0.13, those in the top half have an MPC of 0.05, and the bottom half of the wealth distribution owns 7 percent of overall stocks.

Table 2: National Estimates of the Matching Multiplier

	MPC^b	MPC^a	Pct. Increase in MPC	Actual Multiplier	Benchmark Multiplier	Matching Multiplier	Pct. Increase in Amplification
<i>Panel A: Main Estimates</i>							
Benchmark	0.23	0.29	28%	1.42	1.30	0.13	42.62%
Within Commuting Zone	0.23	0.29	26%	1.42	1.30	0.12	40.34%
Within Industry and Commuting Zone	0.24	0.29	22%	1.42	1.32	0.10	33.04%
<i>Panel B: Robustness</i>							
Non-linear Covariance	0.25	0.31	25%	1.46	1.33	0.13	40.05%
Non-Labor MPC of zero	0.15	0.22	41%	1.28	1.18	0.10	57.20%
Labor Share = 1	0.23	0.33	41%	1.48	1.30	0.21	70.09%

Notes: MPC^b is the earnings-weighted average MPC times the average elasticity of earnings. Linear estimates of earnings heterogeneity are taken from Table 1, demographic-group-specific estimates are taken from Figure 1, and decile-based estimates are presented in Appendix Figure A13. Panels B and C use the linear specification. The benchmark in Panel A and Panel C is that each worker faces the earnings elasticity of the average dollar in the economy.

average dollar in their commuting zone. For example, this equates the earnings elasticities of everyone in Detroit, allowing for the earnings of workers in Detroit to be more sensitive to recessions than those for workers in Austin. The estimate of the matching multiplier is very similar, suggesting substantial within-region heterogeneity in worker exposure. Row 3 shows the slightly more restrictive benchmark in which workers are given the average earnings elasticity of their industry and commuting zone. For example, this scenario equates the earnings elasticities of all workers in car manufacturing in Detroit but allows for different elasticities across industries within Detroit and across cities within car manufacturing. The matching multiplier falls only slightly, a finding that further illustrates the small role that the sorting of workers across industries plays in driving this pattern.

Lastly, Panel B of Table 2 probes the robustness of this benchmark to several data decisions. Row 1 shows MM estimated using the demographic-group-specific earnings elasticities from each point in Figure 1. This does not impose the strict linear functional form, yet the estimates are very similar. The next rows I re-estimate the matching multiplier under alternative assumptions for the importance of non-labor income, and show, intuitively, that the mechanism is increasing in the size of the labor share.

6 Commuting zone analysis

The benchmark discussed above shows that within the simplified framework in Section 2, the magnitude of the covariance between worker MPCs and earnings elasticities is large enough to imply sizable effects

on aggregate fluctuations. In this section, I empirically test the importance of the matching multiplier mechanism in determining the economy’s response to shocks. Under the assumption that demand in commuting zones is largely locally determined, the model in Section 2 would predict that output in areas with a higher measured matching multiplier would be more sensitive to shocks than output in areas with a smaller matching multiplier. I test this prediction by utilizing the fine geographic detail in the LEHD. If the mechanism were not important, whether because (a) consumption is not an amplification channel (b) this covariance term doesn’t matter or (c) the assumptions underlying my empirical analysis do not hold, we should see no relationship between the local matching multiplier and the size of local recessions. However, if, as I hypothesize, the matching multiplier is a meaningful amplification channel, I should find that areas with a higher matching multiplier have more severe recessions and that this effect is concentrated in nontradable employment, where demand is locally determined.

These local empirical tests of the strength of this mechanism are important because they do not rely on the simplifying assumptions embedded in the framework. Indeed, the ways in which a higher matching multiplier translates into aggregate output and employment outcomes in a local economy may depend on general equilibrium factors at the local level that are beyond the scope of the model in Section 2. In particular, the multiplier is not a deep structural parameter of a region, and thus, the ways in which the covariance between worker MPCs and income sensitivities affects output responses is potentially a function of other features of the economy. For example, while monetary policy and other national policies are held constant across regions, local prices may adjust in response to changes in local demand, partially offsetting the matching mechanism, or local fiscal authorities could respond to offset the amplification induced by this mechanism.²⁶ These local estimates will therefore include both the first-order effect of the matching multiplier on the local economy and any local general equilibrium responses to this mechanism.

I begin by separately estimating the matching multiplier in each commuting zone.²⁷ My LEHD sample includes 270 commuting zones, and in each one of those areas, I separately estimate the covariance between MPCs and earnings elasticities, which I use to calculate \widehat{MM}_c in each commuting zone.²⁸ There

²⁶ While both of these mechanisms would downward bias the true effect of the matching multiplier and therefore make the local estimate a lower bound for the full effect of the multiplier, factor mobility across local labor markets could upward bias the result (Chodorow-Reich (2017)).

²⁷ I restrict attention to commuting zones where the 23 states in the subsample cover at least 90 percent of employment in that commuting zone, excludes an average 12 percent of workers and earnings in each sample year.

²⁸ In adapting the national estimates to the CZ-level, I make 2 changes, First, since the multiplier is unbounded and the local estimation is noisy, I use the first order approximation to the matching multiplier from Equation 4. Second, I calculate each \widehat{MM}_c using the national estimate for γ , the average elasticity of earnings to GDP – as this exercise explores the relationship between

is substantial variation in this measure across local labor markets – the cross-commuting zone average covariance between worker MPCs and earnings elasticities is 0.076, but the standard deviation is 0.075. I also calculate the benchmark multiplier in each commuting zone (which I notate with \widehat{B}_c), which is the multiplier in each area in the case that the covariance between worker MPCs and earnings elasticities was 0. The total multiplier in a commuting zone is given by $\widehat{B}_c + \widehat{MM}_c$.

I explore the degree to which local markets with a higher matching multiplier are more sensitive to aggregate shocks by estimating variants on the following equation:

$$\Delta \log L_{c,t} = \phi_1 \widehat{MM}_c \times \Delta \log G_t + \phi_2 \widehat{B}_c \times \Delta \log G_t + X' \Phi + \delta_c + \delta_t + \epsilon_{c,t} \quad (7)$$

where $L_{c,t}$ is total employment in commuting zone c in year t , \widehat{MM}_c is the matching multiplier in commuting zone c , \widehat{B}_c is the benchmark multiplier in the area, δ_c are commuting-zone fixed effects, G_t is national GDP, and X is a series of additional CZ-level controls. The coefficient of interest is ϕ_1 , which the theory predicts is positive – all else equal, areas with a higher matching multiplier should be more sensitive to aggregate shocks. The matching multiplier is an amplification of a baseline local consumption multiplier, and thus the theory also predicts that ϕ_2 is positive, meaning that all else equal, areas with a higher benchmark multiplier should also more cyclical.

Causally identifying the relationship between \widehat{MM}_c and local cyclicity is challenging, as the size of the matching multiplier locally is likely correlated with many other features of the local labor market that also affect the cyclicity of the area. There are potentially many factors contributing to differences in the matching multiplier across commuting zones. The local industry mix could drive differences in the matching multiplier, since industries differ both in their sensitivities to recessions and in the average MPCs of their workers. Additionally, local labor markets may differ in the degree to which workers of different demographics are sorted across firms or in the within-firm incidence of shocks across workers.²⁹ The

\widehat{MM}_c and local cyclicity, \widehat{MM}_c should not be a direct function of the average cyclicity of earnings in the area. The resulting formula is

$$\widehat{MM}_c = \frac{MPC_c^a - MPC_c^b}{(1 - MPC_c^a)^2} = \frac{Cov(MPC_{i,c}, \gamma_{i,c})}{(1 - Cov(MPC_{i,c}, \gamma_{i,c}) - \bar{\gamma} \overline{MPC}_c)^2}$$

where \overline{MPC}_c is the earnings-weighted average MPC of the area, $Cov(MPC_{i,c}, \gamma_{i,c})$ is earning-weighted covariance within the CZ, and $\bar{\gamma}$ is the national average elasticity of earnings with respect to GDP.

²⁹ For example, some areas may have more cross-firm racial segregation or more assortative matching of high-wage workers to high-wage firms. Differences within the firm in the incidence of recessions could stem from differences in the power or scope of labor unions or from differences in fairness norms or managerial practices across regions (Bloom et al. (2017)).

Table 3: Employment Sensitivity to GDP and the Local Matching Multiplier

	(1)	(2)	(3)	(4)	(5)	(6)
$(MM_c + B_c) * \Delta \log GDP_t$	2.505 0.486					
$MM_c * \Delta \log GDP_t$		2.751 (0.473)	0.853 (0.303)	0.882 (0.319)	0.740 (0.344)	0.855 (0.370)
$B_c * \Delta \log GDP_t$		0.220 (0.911)	-1.748 (1.223)	-1.069 (1.368)	-3.562 (2.208)	-3.845 (2.983)
Year FE	X	X	X	X	X	X
Demographic Controls			X	X	X	X
Firm Controls				X		
Financial Controls					X	X
Year by State. FE						X
No. Observations	2245	2245	2245	2245	1658	1441
R-Squared	0.513	0.514	0.751	0.754	0.788	0.848

Notes: In all columns, the dependent variable is the change on log employment at the commuting zone level. All regressions include CZ-fixed effects, and observations are weighted by the share of employment in the commuting zone in $t - 1$. \widehat{MM}_c is winsorized at the 5th and 95th percentile to account for large outliers (\widehat{MM}_c is unbounded). Demographic controls include the share of employment in the two-digit industry; the average age and lagged earnings of the area; and the fraction of the CZ that is female, black, and in the labor force in $t - 1$, each included separately and interacted with $\Delta \log G_t$. Firm controls include average firm size and age in $t - 1$, included independently and interacted with $\Delta \log G_t$. Financial controls include the change in per-capita housing and financial wealth, the change in house prices, and lagged levels of debt per capita, each included individually and interacted with $\Delta \log G_t$. Standard errors are clustered at the commuting zone. See Appendix Table A15 for additional specifications.

estimates of the local matching multipliers will encompass all of these factors. My first empirical strategy is to estimate Equation 7 using an array of controls for other local characteristics that would affect the cyclicity of the area and may be correlated with the local matching multiplier. I then build on this with a second approach that explores additional interactions that further isolate the particular local demand channel through which the matching multiplier should operate. In particular, I test the prediction that the differential effects on employment across regions should be concentrated in nontradable industries, which are subject to local demand, rather than tradable industries, which are subject to a more national demand.

6.1 Local recessions and the Matching Multiplier

The results of estimating Equation 7 are presented in Table 3. Before moving to the full estimation of Equation 7, Column 1 first reports a specification that includes only the total multiplier ($\widehat{B}_c + \widehat{MM}_c$) and does not separately estimate the contribution of the matching multiplier. I find that, as predicted, areas with a higher overall multiplier are more sensitive to business cycles. Column 2 then breaks apart the overall multiplier into the two components that are the focus of this paper – MM_c and B_c . The positive coefficients

on each of these variables show that both components of the multiplier contribute to the overall descriptive relationship between local cyclicalities and the multiplier. Across the subsequent columns, I add a series of increasingly demanding CZ-level controls. The matching multiplier is a highly nonlinear function of the joint distribution of the firm and individual characteristics in an area, but the composition of firms and demographics could also affect the cyclicalities of an area through several other mechanisms. In Column 3, I include controls for these local demographic variables and the industry structure of the area, each on their own and interacted with aggregate GDP.³⁰ When these controls are added, the coefficient on \widehat{MM}_c drops by 70 percent, but remains large and statistically significant. Note that coefficient on the benchmark multiplier interacted with GDP becomes small and statistically insignificant. Given the methodology for constructing MPCs, the average MPC of an area is strictly a function of the distribution of local demographics, and were I to be able to control flexibly enough for these demographics, this term would drop out of the regression entirely. Therefore, it is not surprising that after controlling for the demographics of the area, there is not enough variation left to identify the effect of the average MPC on local cyclicalities. The matching multiplier, however, is a function not of the *level* of the controls but of the degree to which income changes are distributed across those groups, and therefore, these controls do not have the same effect on the matching multiplier. In Column 4, I include additional controls for the size and age composition of the firms in the area, again both alone and interacted with GDP, and find that the coefficient is insensitive to these additional controls. Since Mian et al. (2013) show the deterioration of household balance sheets played a significant role in explaining the cross-sectional patterns of employment declines during the Great Recession, in Column 5 of Table 3, I explore the possibility that the local matching multiplier is correlated with local household financial positions by including various controls for changes in the financial wealth of a commuting zone, both independently and interacted with aggregate GDP.³¹ I find that coefficients on \widehat{MM}_c are largely insensitive to these additional controls. Lastly, in Column 6, I add a full set of state-by-year fixed effects, thus controlling for any differences in cyclicalities that are common across states due to state-level economic policies and identifying the effect of \widehat{MM}_c by comparing the ex-

³⁰ Specifically, the demographic controls included are the share of CZ-level employment in each two-digit industry, the average worker age, percentage of workers who are black, average lagged worker incomes, the fraction of workers who are female, and the fraction of the area that is employed. I also include a control for the average cyclicalities of the area ($\bar{\gamma}_c$), which I include alone and interacted with GDP.

³¹ I follow Kaplan et al. (2016) in defining housing and financial net worth in each commuting zone. Specifically, I include separately changes in housing and financial wealth per capita, changes in house prices, and the initial level of household debt per capita. I include each of these variables independently, allowing for different employment trends along each dimension, as well as interacted with aggregate GDP, allowing for different cyclicalities along each dimension.

periences of commuting zones within the same state. I find that while the estimates are somewhat noisier, the coefficient on \widehat{MM}_c remains stable.³²

Across all columns, the magnitudes of the coefficients on the matching multiplier in Table 3 are substantial. The estimate in Column 3 implies that areas with the average matching multiplier have an elasticity to aggregate GDP that is 0.17 percentage points, or 27 percent, higher than, an area with a matching multiplier of 0.³³ This estimate is similar to, although somewhat smaller than, the estimates of the national matching multiplier in Table 2. Additionally, a CZ that has a matching multiplier in the 90th percentile of the cross-CZ distribution 1.5 times more sensitive to GDP than an area that is in the 10th percentile.

All of the estimates in Table 3 explore the differential sensitivity of the commuting zones to the same aggregate shock. These estimates therefore include two dimensions of geographic heterogeneity – a first-order difference in the degree to which the local area is exposed to the aggregate shock and differences in the higher-order effect of the shock coming through the consumption response of households to the initial shock. An alternative approach is to use a standardized local labor demand shock, which eliminates potential differences in this first-order effect, and thus isolates the local amplification channel. Appendix Table A15 shows that the patterns are qualitatively and quantitatively similar when using a local Bartik-style shock rather than aggregate GDP as the demand shock.³⁴

6.2 Tradable industries and the Matching Multiplier

Since the matching multiplier affects the cyclicity of an area through its effect on local consumption, the relative employment effect of the local matching multiplier across regions should appear for nontradable industries, which are subject to local demand, rather than for tradable industries, which are subject to a more national demand. I explore the relative effect for tradable and nontradable industries by moving to

³² In this specification, I exclude commuting zones that include multiple states. Appendix Table A15 shows the robustness of the estimates in Table 3 to alternate functional forms of the multiplier. Specifically, I show that the patterns and magnitudes are similar when using only MPC differences rather than differences in the multiplier.

³³ The average elasticity of employment in an area to GDP is 0.799. The coefficient in Column 1 of Table 3 implies that the elasticity of an area with $\widehat{MM}_c = 0$ is $0.799 - 0.199 * 0.853$ and that an area with the average \widehat{MM}_c is 0.799. This implies that the average area has an elasticity that is $100 * \frac{0.199 * 0.853}{0.799 - 0.199 * 0.853} = 27$ percent higher.

³⁴ One additional feature of the above analysis is that both \widehat{MM}_c itself and the relationship between \widehat{MM}_c and employment cyclicity are estimated over the same sample period. It may be that the nature of the particular set of shocks in the sample period jointly generates a big recession in the area and a high matching multiplier. I explore this possibility by re-estimating \widehat{MM}_c in the pre-Great Recession period (i.e., 1995 to 2006) and look at the relationship between the change in employment in the Great Recession and the matching multiplier using the pre-recession \widehat{MM}_c as an instrument for the full-sample \widehat{MM}_c estimate. I find that that IV specification produces a similar but quantitatively larger relationship between the local matching multiplier and employment losses in the Great Recession. See Appendix A.5 for more details.

the three-digit industry by CZ level and estimating a modified version of Equation 7

$$\Delta \log L_{i,c,t} = \phi_1 \widehat{MM}_c \times \Delta \log G_t \times T_i + \phi_2 B_c \times \Delta \log G_t \times T_i + X' \Phi + \delta_{ci} + \delta_{it} + \epsilon_{i,c,t} \quad (8)$$

where $L_{i,c,t}$ is total employment in industry i in commuting zone c at time t , and T_i is an indicator for whether the industry is a tradable industry.³⁵ δ_{ci} are CZ-by-year fixed effects, which allow for each industry to have a different employment trend across commuting zones. δ_{it} are industry-by-year fixed effects, which flexibly control for any business cycle variation that is common to the industry. X includes all terms supporting the key triple interaction, as well as various CZ-level controls in time $t - 1$, all of which have been suppressed for notational brevity. The sample only includes the set of industries that are classified as tradable or nontradable, and the parameter of interest is ϕ_1 , which captures the differential effect of the matching multiplier on the cyclicalities of tradable industries relative to nontradable industries. Theory predicts that ϕ_1 is negative, meaning that the matching multiplier affects the employment of tradable industries less than the employment of nontradable industries.

Table 4 reports the results. Column 1 first reports the overall relationship between the matching multiplier and local cyclicalities using the industry-level specification, and shows a larger coefficient than in the aggregated CZ-level specification. Column 2 restricts only to the subsample of tradable and nontradable industries and shows that, on average, the overall relationship between local cyclicalities and \widehat{MM}_c is smaller for this subsample of industries. More importantly, Columns 3 and 4 estimate the regression separately for tradable and nontradable industries. Column 3 reports the relationship for employment in tradable industries, showing that the relationship is small, negative, and statistically insignificant. Conversely, Column 4 shows the relationship for employment in nontradable industries, where the relationship is positive, large, and statistically significant. A comparison of Columns 3 and 4 clearly shows that the overall effect of the matching multiplier on local cyclicalities is concentrated in nontradable industries. For completeness, Column 5 reports the full joint estimation in Equation 8 and shows that the coefficients are very stable, and the coefficient on the triple interaction is almost exactly the difference between the main coefficient in Columns 3 and 4. Column 6 shows that the magnitude of the coefficient is robust to a specification including a full set of CZ-by-year fixed effects, thus controlling for any employment move-

³⁵ Tradable industries are defined as in Mian and Sufi (2014). I use their “simple” definition in which retail and restaurants are nontradable and industries in global trade data are tradable. Each regression only includes the set of industries classified as either tradable or nontradable, and thus excludes those industries in the middle.

Table 4: Tradable and Nontradable Employment and the Local Matching Multiplier

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$MM_c * GDP_t$	1.503 (0.364)	0.425 (0.300)	-0.232 (0.637)	1.027 (0.246)	1.113 (0.294)		
$MM_c * GDP_t * Tradable_i$					-1.475 (0.658)	-1.427 (0.686)	-1.261 (0.716)
$B_c * GDP_t$	-0.326 (0.664)	-0.228 (0.489)	-0.085 (1.212)	-0.526 (0.300)	-0.824 (0.479)		
$B_c * GDP_t * Tradable_i$					1.327 (0.452)	1.243 (0.466)	1.445 (0.498)
Industry*Year FE	X	X	X	X	X	X	X
CZ*Industry FE	X	X	X	X	X	X	X
CZ*Year FE						X	X
Demographic Controls	X	X	X	X	X	X	X
Financial Controls							X
Included Industries	All	T + N	T	N	T	T + N	T + N
No. Observations	183789	50269	32979	17290	50269	50269	41173
R-Squared	0.408	0.392	0.317	0.470	0.394	0.434	0.439

Notes: The row labeled “included industries” specifies whether the regression includes all industries (All), tradable industries (T), nontradable industries (N), or both (T+N). The dependent variable in all regressions is the change in log employment in a three-digit NAICS within a commuting zone. The earnings change is winsorized at the 5th and 95th percentiles, as are the estimates of \widehat{MM}_c . Demographic controls include the average age and lagged earnings of the area, as well as the fraction of the CZ that is female, black, and in the labor force, each separately, interacted with G_t , and further interacted with T_i . Financial controls include the change in per-capita housing and financial wealth and lagged levels of debt per capita, each included individually, interacted with G_t and further interacted with T_i . All observations are weighted by the share of employment in $t - 1$. Standard errors are clustered at the commuting zone. See Appendix Table A16 for alternate specifications.

ments common to industries within a commuting zone in a given year and identifying only the degree to which the relative movement of tradable and nontradable employment covaries with the matching multiplier. Lastly, in Column 7, I also control for local financial positions, which also affect local demand and thus the relative employment of tradable and nontradable industries (Mian and Sufi (2014)). I include the housing and wealth variables alone, interacted with GDP, and triple-interacted with a tradable indicator. The coefficient identifying the relative effect of \widehat{MM}_c on tradable industries is largely unaffected by these additional controls.³⁶

³⁶ Appendix Table A16 shows that these patterns are also robust to the redefinition of several of the key variables in Equation 8. Specifically, the pattern that the matching multiplier affects the employment cyclicalities of nontradable industries more than tradable industries is robust to disaggregating to four-digit NAICS codes, which allows for an even more rigorous control for differences in industry experiences across commuting zones. It is also robust to using alternate functional forms for the multiplier or using different MPC imputations at the individual level.

7 The Matching Multiplier in a calibrated model

The previous two sections both demonstrate in different ways that the covariance between worker MPCs and earnings elasticities is large enough to have a meaningful effect on the aggregate response of the economy to shocks. In both sections, I used the formula for the matching multiplier from Section 2, which is derived in a 2-period model. In the following section, I explore the matching multiplier mechanism in a more dynamic setting. This is particularly important as I estimate MPCs using unemployment as the identifying income shock. Unemployment is a persistent shock, and therefore, the MPCs that I estimate include both the response of consumption today to income today, but also the response of consumption today to expected income shocks in all future periods. The empirical matching multiplier accounts for these dynamics only insofar as they are embedded in the empirical MPC estimate, but does not formally capture the role of these dynamics in the multiplier. Therefore, the empirical matching multiplier is a reduced-form approximation to a more complicated dynamic process.³⁷

I explore this mechanism within a standard Bewley-Huggett-Aiyagari model augmented along three dimensions. First, I introduce endogenous labor supply and rich consumer heterogeneity. Second, I pair this model of aggregate demand with fixed wages in the short run, which capture the role that this mechanism plays in demand-driven amplifications. Third, I introduce an exogenous labor rationing process that generates labor income fluctuations in the presence of fixed wages. Within the context of this model, I clarify the role that the persistence of the unemployment shock plays in shaping my estimates for the importance of the matching multiplier mechanism. I show that the persistence of the unemployment shock is important in determining the level of the multiplier and matching multiplier, but is not the driving force for the amplification coming from the covariance. Additionally, I show that the empirical approximation from Section 2 closely captures the dynamic estimates under the assumption that the aggregate shock has the persistence of the average unemployment spell.

7.1 Environment

The following setting is similar to the generalized setting in Auclert et al. (2018) and is a simplified version of the multisector model in Flynn et al. (2018). Since the focus of this exercise is to understand the

³⁷Alternatively, the empirical matching multiplier could be interpreted as the multiplier in which period 1 is the short run and period 2 is the long run.

role of heterogeneity in the demand side, I allow for rich heterogeneity among consumers and keep the supply side intentionally simple. Consider an economy in discrete time with T periods. The economy is populated by a continuum of agents of I types, where each type I has a mass ν_i of individuals such that $\sum_i \nu_i = 1$. Households within each group are ex ante homogenous, but households face idiosyncratic risk in their productivity or labor supply $e(s)$, a process that may vary across demographic groups I . Households across groups may differ both in the income process they face and in their discount rates (β_i). Households have preferences over both consumption and leisure, and agents have the ability to borrow and save into a real asset ($a_{i,t}$) to smooth consumption but are subject to a borrowing constraint that $a_{i,t} \geq b$. The household's problem therefore is to choose paths for their consumption $c_{i,t}$ and labor supply $l_{i,t}$ to maximize their utility taking wages, prices, and the real interest rate as given:

$$\max_{c_{i,t}, l_{i,t}} \sum_{t=0}^T \beta_i^t E[u(c_{i,t}) - v(l_{i,t})] \quad (9)$$

subject to

$$w_t l_{i,t} e(s) + r_t a_{i,t-1} - \tau_{i,t} = p_t c_{i,t} + a_{i,t} \quad , \quad a_{i,t} \geq b \quad (10)$$

where $\tau_{i,t}$ are lump sum taxes, and p_t is the price of the final good at time t . I assume that $u(c) = \frac{c^{1-\omega^{-1}}}{1-\omega^{-1}}$ and $v(l) = \frac{l^{1+\psi^{-1}}}{1+\psi^{-1}}$, where ω is the intertemporal elasticity of substitution and ψ is the Frisch labor supply elasticity.³⁸

While the demand side of the model features rich heterogeneity, the supply side of the model is simple.³⁹ All workers are employed by a representative competitive firm, which produces with constant returns to scale technology and takes labor as the only input:

$$Y_t = L_t \quad \forall \quad t \quad (11)$$

³⁸ These functional forms are used for the quantitative exercise in this section. However, the results in this section apply to a broader set of preferences. See Auclert (2017) or Flynn et al. (2018) for a discussion using more general preferences. These preferences have the advantage that they guarantee that the resulting labor supply and Marshallian demand functions are continuous and differentiable in r_t . The assumed CRRA utility function also exhibits sufficient diminishing marginal utility of consumption to guarantee the existence of an equilibrium. See Appendix B.2 for a discussion of the assumptions required to guarantee the existence of equilibrium.

³⁹ In a similar framework, Auclert et al. (2018) explore the importance of worker MPCs in a model with an enriched supply side that includes capital, sticky prices, and a Taylor rule for monetary policy. They show that while these modifications reduce the overall size of the multiplier, worker MPCs still remain crucial in determining the output response to fiscal policy. Specifically, they show that in a model that matches the empirical estimates of intertemporal MPCs and with deficit-financed spending, impact multipliers can be above 1, even with active monetary policy, distortionary taxation, and investment crowd out.

Firm profit maximization implies that

$$w_t = p_t \quad \forall t \quad (12)$$

The government sets potentially individual-specific lump sum taxes $\tau_{i,t}$ to finance government spending G_t . Rather than balance its budget strictly between periods, the government can issue bonds B_t to smooth fluctuations across periods and therefore is subject to an intertemporal budget constraint:

$$\sum_t \frac{\tau_{i,t}}{\prod_{i \leq t} (1 + r_i)} = \sum_t \frac{p_t G_t}{\prod_{i \leq t} (1 + r_i)} \quad (13)$$

I assume that government spending preferences are given exogenously by θ_G , such that $G_t = G(r_t, \tau_t, \theta_G)$. Even though this fiscal rule is specified exogenously, government spending still responds to interest rate changes in order to maintain the budget constraint in Equation 13.

7.2 Equilibrium and the output multiplier

Consider first the case where all prices are fully flexible. The household problem in Equation 9 results in a demand for consumption and a labor supply function given by

$$c_{i,t} = c_i(\{\lambda_t\}_{t \in T}, \{\tau_{i,t}\}_{t \in T}, \beta_i, b) \quad (14)$$

$$l_{i,t} = l_i(\{\lambda_t\}_{t \in T}, \{\tau_{i,t}\}_{t \in T}, \beta_i, b) \quad (15)$$

where $\lambda_t = \{r_t, w_t, p_t\}$ is the vector of prices. These are Marshallian demands, and thus these functions only depend directly on exogenous parameters $(\beta_i, b, \tau_{i,t})$ and prices (λ_t) . The goods and labor market clearing condition are given, respectively, by

$$Y_t = C_t + G_t = \sum_i \nu_i c_{i,t} + G_t \quad \forall t \quad (16)$$

$$L_t = \sum_i \nu_i l_{i,t} e(s) \quad \forall t \quad (17)$$

An allocation of $\{c_{i,t}, l_{i,t}, \tau_{i,t}, r_t, p_t, w_t, G_t, Y_t\}$ that satisfies Equations 12, 13, 14, 15, 16, and 17 characterizes the flexible price equilibrium.

The exercise in this paper will be to consider the response of an economy, initially at this flexible price

equilibrium, to an unanticipated demand shock when wages are fixed for $k + 1$ periods.⁴⁰ Equation 12 immediately implies that prices are also fixed over this period. With fixed wages, the interest rate does not adjust to clear the labor market, and thus, workers are off their labor supply curves for the first k periods (i.e., in response to a negative shock, there are workers who would like to work more but cannot because a firm is not willing to hire them). Rather, in those periods, labor supply is rationed, and a worker's labor supply is imposed exogenously as

$$l_{i,t} = n_{i,t}(Y_t) \quad (18)$$

such that $\sum_i \nu_i n_{i,t} = L_t$.⁴¹ This rationing function takes as inputs the aggregate change in output and the amount workers would like to work given the wage $l_{i,t}^*$, and returns a labor supply $n_{i,t}$ for each individual. This function is what determines the change in the worker's earnings in response to an aggregate demand shock. This reduced form specification, similar to Werning (2015), captures the notation that, for example, in response to a negative demand shock, workers are not able to work as much as they would like. In order to capture the relationship between the exposure of worker earnings to aggregate shocks and worker MPCs documented in Section 4.2, I parametrize the rationing function $N(Y_t) = \{n_{i,t}\}$ as

$$n_{it} = \frac{Y_t}{L_t^*} (1 - \chi \overline{MPC} + \chi MPC_i) l_{it}^* \quad (19)$$

where $L_t^* = \sum_i \nu_i l_{i,t}^*$, \overline{MPC} is the earnings-weighted average MPC in the economy and χ is the slope of this incidence function with respect to GDP. This formulation of the rationing function implies that the elasticity of worker i 's earnings to the aggregate is linear in the worker's MPC and is given by $\gamma_i = 1 - \chi \overline{MPC} + \chi MPC_i$.

Since the interest rate is not pinned down by the labor market clearing condition, it must be set by monetary policy. Assume for simplicity that the central bank targets fixed real interest rate, $r_t = \bar{r}$.⁴² In this rationing equilibrium, consumer demand becomes

⁴⁰ See Auclert (2017) for the case where wages are sticky indefinitely.

⁴¹ A more complete alternative to this rationing function is to explicitly model heterogeneity in the labor market through search frictions. See Ravn and Sterk (2016) for a recent example. Additionally, while the resulting mechanism is similar, the endogenous redistribution mechanism here differs from that in Bilbiie (2008) and Bilbiie (2018b). In his setting, cyclical inequality comes from the redistribution of firm profits – the government taxes firm profits (held by the unconstrained agents) and rebates them lump-sum to the constrained agents. I allow for a rationing function that is reduced form but disciplined by labor market data.

⁴² Since my focus is on quantifying the importance of heterogeneity in the labor market, I abstract from potential offsetting effects coming from countervailing monetary policy.

$$c_{i,t} = c_i(\{y_{i,t}\}_{t \leq k}, \{\lambda_t\}_{t \in T}, \{\tau_{i,t}\}_{t \in T}, \beta_i, b) \quad (20)$$

This is similar to the flexible price conditions (Equations 14), except that now it is a function of incomes in periods 1 through k , as these are now *exogenously* given by the rationing function.

Definition *The rationing equilibrium is defined as the set of $\{c_{i,t}, l_{i,t}, \tau_{i,t}, r_t, p_t, w_t, G_t, Y_t\}$ such that firms optimize as in Equation 12, consumers optimize consumption according to Equation 20 and supply labor according to $N(Y_t, l_{i,t-1})$ for periods 1 through k and according to Equation 15 for $t \geq k$, and goods and labor markets clear in each period as in Equations 16 and 17.*

Using bold variables to represent vectors of aggregate variables (i.e. $\mathbf{Y} = \{Y_t\}$), I derive the response of the economy to shocks in Proposition 1. I define the partial equilibrium effect of the shock on output as the response of the economy to a shock to any of the parameters of the model, before accounting for any of the general equilibrium responses of the economy.⁴³ In this economy, this amounts to all effects on the economy *before* incomes or interest rates change. Let $\partial \mathbf{Y}$ be the vector of the partial equilibrium change in output in each period. Define C_Y to be a matrix where the k, j entry is given by $\frac{dc_k}{dY_j} = \sum_i \frac{dc_{i,k}}{dy_{i,j}} \gamma_i \frac{l_{i,j}}{L_j}$, which is the aggregate response of consumption at time k to income in time j .

Proposition 1. *Under the assumption that wages are sticky for $k + 1$ periods, for any shock to parameters (θ, τ, θ_G) , the total change in output from an initial flexible price allocation is given to first order by:*

$$d\mathbf{Y} = (I - \mathbf{C}_Y J_k - (\mathbf{C}_r + \mathbf{G}_r) J_{T-k} (\mathbf{L}_r)^{-1})^{-1} \partial \mathbf{Y} \quad (21)$$

where subscripts denote partial derivatives (i.e. \mathbf{C}_r is the partial derivative of consumption with respect to r), and J_k and J_{T-k} are diagonal matrices with 1s in the first k or the last $T - k$ entries, respectively.

The proof for the proposition can be found in Appendix B.2. The first term (i.e. $C_y J_k$) captures the heterogeneous agent intertemporal version of the traditional Keynesian multiplier and embeds the mechanism that is the key focus of this paper. This matrix of intertemporal MPCs features prominently in Auclert et al. (2018), who argue in a similar setting that these moments are essential for determining general equilibrium effects in heterogeneous agent models. Due to the forward-looking nature of the consumer's

⁴³ See the proof of Proposition 1 in Appendix B.2 for a more detailed delineation of partial and general equilibrium effects.

problem, what matters for the total consumption response today is not just the change in today's income but also the change in future period incomes. The matrix J_k simply captures the fact that wages are only fixed for some period; thus, the consumer only responds directly to income changes in those periods. The heterogeneous incidence of labor shocks directly affects the magnitude of C_Y – when high-MPC workers have higher γ_i , the components of the C_Y matrix are larger.

The second term (i.e. $(\mathbf{C}_r + \mathbf{G}_r)J_{T-k}(\mathbf{L}_r)^{-1}$) captures the movements in the interest rate in periods after k . In those periods, the interest rate will adjust to bring workers back onto their labor supply curves and clear the labor market. Workers anticipate the future adjustment, and thus, consumption today will depend on the future change in the interest rate. Proposition 1 shows that this matrix is a sufficient statistic for characterizing the first-order general equilibrium effect on output of a demand shock.

Using Proposition 1, I define the matching multiplier in Corollary 1 as a special case of the model that abstracts from the potentially offsetting price effects far in the future.

Corollary 1. *The Matching Multiplier is defined as the difference in the output response to any small unanticipated shock to parameters (θ, τ, θ_G) between the actual case where γ_i varies across i and the case where $\gamma_i = 1$. Under the assumption that $C_r + G_r = 0$ and under the assumption that wages are sticky for $k + 1$ periods, this is given by:*

$$MM = \left[(I - \mathbf{C}_Y(\gamma_i))J_k)^{-1} - (I - \mathbf{C}_Y(\gamma_i = 1))J_k)^{-1} \right] \quad (22)$$

where subscripts denote partial derivatives (i.e. \mathbf{C}_Y is the partial derivative of consumption with respect to y) and J_k is a diagonal matrices with 1s in the first k entries. $\mathbf{C}_Y(\gamma_i)$ denotes the aggregate intertemporal MPC matrix when γ_i varies by individual and $\mathbf{C}_Y(\gamma_i = 1)$ reflects the case where $\gamma_i = 1$ for all individuals.

A comparison of Corollary 1 with the empirical matching multiplier derived in Section 2 demonstrates that the empirical moment from Equation 4 is a reduced form approximation of the multiplier in this dynamic setting. Recall that the k, j entry is given by $\frac{dc_k}{dy_j} = \sum_i \frac{dc_{i,k}}{dy_{i,j}} \gamma_i \frac{l_{i,j}}{L_j}$, which is the aggregate response of consumption in period k to an income shock in period j . Were the MPC estimates (\widehat{MPC}_i) in Section 4.1 based on a purely transitory shock, then $\widehat{MPC}_i = \frac{dc_{i,1}}{dy_{i,1}}$ and the empirical matching multiplier from Section 2 would be exactly the sufficient statistic in Proposition 1 in the case that wages were only sticky for 1 period. However, as discussed above, the MPCs that I estimate capture the consumption response to unemployment, which is a more durable shock, and therefore $\widehat{MPC}_i \neq \frac{dc_{i,1}}{dy_{i,1}}$. In the dynamic setting,

there is no direct analytical mapping between the empirical covariance, the empirical matching multiplier, and the matching multiplier defined in Corollary 1. Therefore, the exercise in the following sections will be to calibrate the dynamic model below using the average empirical MPC and the estimated covariance between MPCs and earnings elasticities as targeted moments and compare the matching multiplier in the dynamic setting to the reduced-form approximation used throughout the empirical analysis.⁴⁴

7.3 Model calibration

In order to match the empirical exercise, where I consider heterogeneity in MPCs and earnings sensitivities across both demographic and income groups, I calibrate an economy with eight demographic groups characterized by the combination of two genders, two education bins, and two race bins. Within each demographic group, agents are ex ante homogenous, but across demographic groups, agents differ along several ex ante dimensions.

First, and most importantly, I allow each demographic group to have a different income process that captures differences in the overall riskiness of income, features earnings shocks that mirrors the unemployment shock that I use to estimate the MPC in Section 4.1, and allows for heterogeneity in the persistence of that unemployment shock. I adopt a 2-part income process, where total earnings are given by

$$Y_{it} = e_{it} * w_{it}$$

where e_{it} is scalar for the number of months employed and w_{it} are the monthly earnings among the employed. I assume that these two processes are independent and calibrate them separately for each group.

I model the unemployment process as a discrete-time Markov process with two states – employed for the whole year ($e_{it} = 1$) and unemployed for some fraction of the year ($e_{it} = X$, where X is the average fraction of earnings lost in the year of unemployment). The transition probabilities between these two states are determined by the job-finding (f) and job-separation (s) rates, which I calculate for each demographic group using the measured job flows in the monthly basic Currently Population Survey (CPS).⁴⁵

⁴⁴An additional dynamic consideration is that while the empirical measure of the matching multiplier treats the MPCs of different demographic groups as fixed, in practice, consumption behavior will be determined as a function of current and future income shocks, and thus, will change as a function of the shock and its incidence. In Appendix B.3, I use the model estimates to relax this assumption and numerically show that the potential endogeneity of MPCs to the incidence of the aggregate shock does not meaningfully affect the estimates.

⁴⁵In calculating the labor market flow rates, I abstract for non-participation and define $f = \frac{UE}{UE+UU}$ and $s = \frac{EU}{EE+EU}$ where UE is the number of people transitioning from unemployment to employment across months, UE is the number from unemployment

Panel A of Table 5 reports the estimates. Consistent with prior literature, I find that, on average, job finding rates are higher for the more educated and for men. Appendix Table A17 demonstrates that the unemployment rate and unemployment durations implied by these labor market flows closely capture the empirical heterogeneity in these variables across demographic groups. Under the assumption that one earns nothing in the periods of unemployment, the differences in the job-finding and job-separation rates fully characterize the heterogeneity in the persistence of unemployment across demographic groups.⁴⁶

I assume that the earnings of the employed (w_{it}) follow an AR(1) process with persistent and transitory shocks, the parameters of which are the persistence parameter, the variance of the persistent shock, the variance of the transitory shock, an initial variance in earnings, and an average earnings level. I estimate these parameters following the methodology in Heathcote et al. (2010) and using the earnings of those who report being employed in the Panel Study of Income Dynamics.⁴⁷ Panel B of Table 5 reports the level and variance of earnings produced by these estimates for each demographic group. I capture the well-documented differences in the average earnings by gender, race, and education.

For each group, I set the intertemporal elasticity of substitution to be 1.5, assume that agents cannot borrow (i.e., $b = 0$), and set the interest rate to be 1.02.⁴⁸ Taking the earnings process for each demographic group as given, I choose the discount rate such that I match the average “empirical MPC” for each demographic group. In other words, I choose the discount factor such that the earnings-weighted average consumption drop per dollar lost upon transitioning to the unemployment state equals the earnings-weighted average MPC that I estimate in the PSID using the unemployment shock. The magnitude of this “empirical MPC” will in part reflect the persistence of the unemployment shock – all else equal, when the unemployment shock is more persistent, the average MPC is higher. Column 6 of Table 5 shows the resulting annual discount rates, which vary from 0.85 to 0.98. Empirically, groups with higher MPCs (Column 6) and more volatile incomes (Column 5) have lower discount rates (Column 7). Since agents are risk-averse,

to employment, and so on. See Appendix B.3 for more details on the construction of these labor market flows.

⁴⁶ See Appendix Table A17 for a comparison of these X values and those directly estimated within the PSID.

⁴⁷ See Appendix B.3 for the parameter estimates for each demographic group and further details on the estimation of the income process. In the baseline estimates, I restrict attention to those individuals who report being employed at the time of the PSID survey, are between the ages of 30 and 40, and for whom I can impute an MPC (i.e., observations with at least two lags of earnings).

⁴⁸ I follow Kaplan and Violante (2014) in choosing a value for the EIS above 1. While empirical studies using aggregate consumption data typically find very low values for the elasticity of intertemporal substitution, or EIS, (Hall (1988)), as is discussed in Bansal et al. (2012) and Kaplan and Violante (2014), this traditional approach may be downward-biased because of attenuation or endogeneity bias. Empirical studies that deal with this bias tend to find much larger estimates. For example, Gruber (2013) leverages exogenous variation in the after-tax interest rate using shifts in the tax rate and estimates an EIS of 2.

Table 5: Model Calibration by Demographic Group

	A: Unemployment		B: Earnings		C: Model Calibration			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	f	s	$\log(w)$	Std. $\log(w)$	Std. $\log(y)$	Empirical MPC	β	Transitory MPC
<i>High School or Less</i>								
Non-Black Men	0.35	0.02	10.76	0.75	0.75	0.46	0.96	0.23
Black Men	0.26	0.03	10.44	0.79	0.80	0.79	0.85	0.57
Non-Black Women	0.31	0.01	10.12	0.87	0.87	0.55	0.94	0.29
Black Women	0.23	0.02	10.07	0.89	0.90	0.59	0.93	0.29
<i>Some College or More</i>								
Non-Black Men	0.32	0.01	11.17	0.84	0.85	0.31	0.98	0.11
Black Men	0.29	0.01	10.77	0.73	0.73	0.73	0.89	0.45
Non-Black Women	0.34	0.01	10.58	0.98	0.98	0.36	0.96	0.17
Black Women	0.27	0.01	10.44	0.84	0.85	0.47	0.96	0.20

Notes: Panel A reports the job-finding (f) and job-separation (s) rates calculated from the monthly basic Current Population Survey from 1994-2018 and defined as $f = \frac{UE}{UU+UE}$ and $s = \frac{EU}{EE+EU}$, where UE is the number of people transitioning across months from unemployment to employment, UU is the number of people from unemployment to unemployment, etc. Panel B reports the average log of earnings and the standard deviation of that log of earnings from the model's income process for the employed. This AR(1) income process is estimated to match the PSID data following the methodology in Heathcote et al. (2010). Panel C shows parameters for the steady-state of the model. Column 5 reports the standard deviation of the overall earnings process for each group in the model. The empirical MPC in Column 6 is the earnings-weighted average MPC estimated in the PSID as described in Section 4.1. Column 7 reports the discount factor that is needed to match the earnings-weighted average MPC given the other parameters. Column 8 reports the earnings-weighted average transitory MPC in the model, which is defined as the increase in consumption per dollar increase in income.

agents facing more income volatility want to accumulate assets, which pushes them away from their borrowing constraint and brings down the average MPC of that group. However, since it is precisely those groups that have higher measured MPCs, a higher degree of impatience is needed to match the MPC of the group in the model. The discount rates in the model need not reflect pure differences in time preferences across individuals and may also capture unmodeled differences in access to the banking sector or costs of borrowing. Even so, the estimates of the discount factor are actually in line with empirical estimates, both on average and in their patterns across demographics. For example, using experimental evidence in Denmark, Harrison et al. (2002) estimate higher discount factors for the rich, skilled, and educated. The last column of Table 5 shows the MPC in the model out of an unanticipated and transitory income shock. Unsurprisingly, for all demographic groups, this MPC is lower than the empirical MPC, but the two are highly correlated ($\rho = 0.97$), suggesting that heterogeneity in the persistence of the unemployment shock across groups is not a key driver of MPC heterogeneity in the model.

Lastly, having matched the average MPC with the discount factor, I match the covariance between MPCs and earnings elasticities with the parameter χ in the rationing function. I estimate this parameter

such that the $Cov(\widehat{MPC}_i, \gamma_i)$ is equal to 0.09, which is the empirical estimate from Section 5. I get that $\chi = 1.95$, which is similar to the empirical estimate in Table 1 as well.

7.4 Model estimates

I begin exploring the model-based estimates of the matching multiplier mechanism by looking at the importance of the incidence of the shock on the response of aggregate consumption. The left panel of Figure 4 shows the aggregate MPC in two scenarios. In the “actual scenario,” I consider an aggregate shock to incomes that is distributed to workers such that the earnings elasticity of each worker is exactly equal to the γ_i , calibrated as described above. In the “benchmark scenario,” I consider an aggregate shock to income of the same size that is distributed such that the earnings elasticity of all workers is equal to 1. I derive the aggregate MPC by aggregating the response of consumption and dividing by the size of the aggregate change in incomes in period 1.

Before reporting those estimates, the first column in the left panel of Figure 4 reports, for comparison, the increase in the aggregate MPC coming from the covariance that I estimated in Section 4. The benchmark scenario in this case is simply the earnings-weighted average MPC in the data. As in Section 2, the aggregate MPC in the actual scenario is the benchmark MPC plus the estimated covariance between the empirical MPC and the earnings elasticity, which is 0.09.⁴⁹ With this specification, the estimated covariance increases the aggregate MPC by 24 percent.

The last two columns in the left panel of Figure 4 show how this empirical estimate compares to those from the model and demonstrate the key role played by the persistence of the unemployment shock in determining this mechanism. The second column shows first the increase in the aggregate MPC that results from a 1-period aggregate shock.⁵⁰ Since this is a 1-time purely transitory cash drop, the aggregate MPC is determined not by the *empirical* MPC but rather by the *transitory* MPC, which Table 5 showed was far below the empirical estimates. However, Table 5 also shows that these transitory MPCs are highly correlated with the empirical MPCs, and thus, the aggregate MPC in the actual case is larger than the

⁴⁹ These numbers differ from those in Table 2 because they do not account for the existence of non-labor income. Therefore, I do not scale the benchmark MPC by the empirical average elasticity of income to GDP and I do not rescale the covariance by a measure of the labor share. This results in a larger baseline MPC and a larger level increase between the actual and benchmark scenarios. However, the percent increase in the MPC in Figure 4 is similar to that in Table 2.

⁵⁰ While I focus on the magnitude of this mechanism in the initial period, in Appendix Figure A18, I show the full dynamic path for the consumption differential in the simulated case. I find that the consumption boost coming from the empirical distribution of the shock is temporary, and in fact, in future periods, consumption in the benchmark case is higher.

aggregate MPC in the empirical case. Indeed, while the levels are lower than the empirical estimates, the percent increase in the aggregate MPC is even larger at 30 percent. In this model, while the persistence of the shock matters for the level of the aggregate MPC, it is not critical for the amount of amplification implied by the heterogeneous incidence of the shock.

Lastly, the final columns in the left panel of Figure 4 shows the aggregate MPC in response to a persistent aggregate shock. In period 1, agents receive their period 1 shock, but also anticipate that the shock will decay slowly and therefore may respond today to expected future changes income. I choose the persistence of the aggregate shock to match the persistence of the average unemployment spell, which is given by $\rho = 1 - 2\bar{f} = 0.34$.⁵¹ With this persistent shock, the aggregate benchmark MPC is much larger than with the transitory shock and very close to the empirical estimate in column 1. Importantly, the increase in the aggregate MPC across scenarios is large, similar in magnitude to the empirical estimate, and larger than in the transitory case in Column 2. When the shock is persistent and unevenly distributed in multiple periods, the same workers who face a large shock today also anticipate facing a larger shock in the next period, and thus the drop in their consumption today is even larger. The heterogeneous exposure of the future shock amplifies the heterogeneity today, and thus, the overall strength of this mechanism increases.⁵²

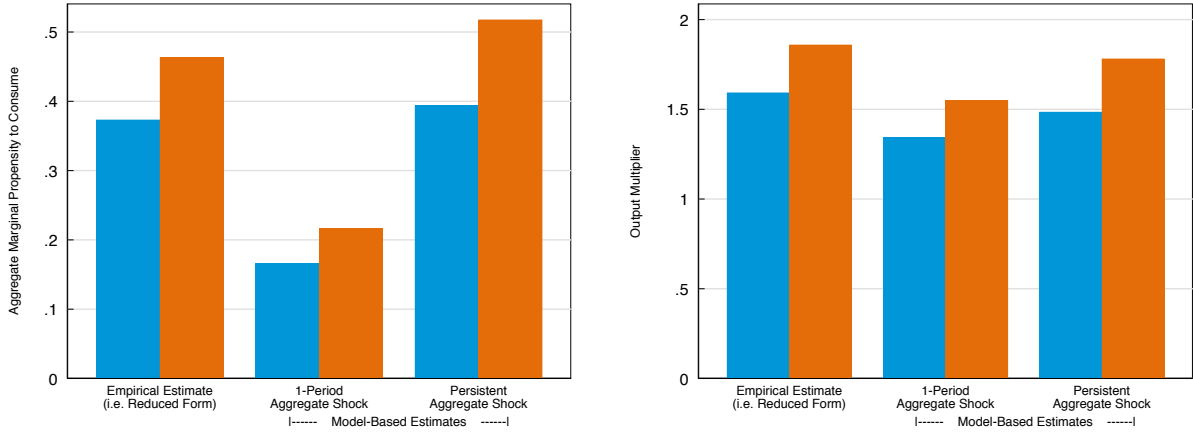
The right panel of Figure 4 uses the simplified structure of the model and the derived expressions for the multiplier in Proposition 1 to explore how well the empirical matching multiplier from Section 2 captures the general-equilibrium effects on *output* in this dynamic setting. First, column 1 in the right panel reproduces the empirical estimate, which uses the empirical MPCs and the simplified 2-period formula for the multiplier. The following columns compare this to the model-based multipliers that take the dynamics of the model seriously, and are therefore based on the model-implied estimates of the intertemporal MPC matrix as in Auclert et al. (2018). Column 2 in the right panel corresponds to the scenario in column 2 in the left panel and shows multiplier in response to a 1-period partial-equilibrium shock.⁵³ Since the level

⁵¹This formula comes from the relationship between the properties between of an AR(1) process and a markov process. An alternative is to estimate this persistent directly from the PSID as the income loss 1 year after an unemployment incidence relative to the earnings loss in the initial year of unemployment. This number in the PSID is 0.25, and results using this alternative measure are very similar.

⁵²It is important to note that this experiment captures the average persistence of the unemployment shock as in the data, but does not capture the heterogeneous persistence of the unemployment shock across individuals. If a large part of the heterogeneity in empirical MPCs across groups were driven by heterogeneity in the persistence of the unemployment shock, the amplification of the consumption response in the actual scenario in the model would be smaller than in the data. However, the amplification from the heterogeneous incidence is slightly larger in the model than in the data, suggesting, if anything, that the heterogeneous persistence of unemployment across individuals dampens the matching multiplier mechanism.

⁵³For the estimates in both columns 2 and 3 of the right panel of Figure 4, I assume that wages are rationed (and thus prices are fixed) for 10 periods. Appendix Figure A19 shows that as in Auclert et al. (2018), as the degree of price stickiness increases, so too

Figure 4: The Matching Multiplier in the Model



Notes: The blue bars refer to the “benchmark scenario” in which the shock is distributed such that all workers have an elasticity of 1. The red bars refer to the “actual scenario”, where the shock is distributed such that the each worker has an elasticity determined by the empirical covariance between elasticities and empirical MPCs. The left panel shows the aggregate MPC across the two scenarios and the right panel shows the output multiplier across the two scenarios.

of the MPC is much lower, the level of the dynamic multiplier is also much lower in both the baseline and actual scenarios. However, still, the amplification implied by the heterogeneous incidence is meaningful, increasing the baseline multiplier by 21 percentage points, or 15 percent. Lastly, Column 3 in the right panel of Figure 4 shows the multiplier in response to a shock that has the persistence of the average unemployment spell. This column looks very similar to column 1, with a baseline multiplier of about 1.5 that is amplified by 20 percent with the heterogeneous incidence of the aggregate shock.

The analysis in both panels of Figure 4 demonstrate that the empirical matching multiplier used throughout the analysis, which was derived using MPCs out of persistent unemployment and a simplified 2-period multiplier closely approximates a dynamic multiplier of a persistent shock. Additionally, while the persistence of the shock is important for determining the level of the amplification, it is not the driver of the matching multiplier mechanism. Thus, the covariance estimated in this paper also implies a meaningful amplification of more transitory shocks that have a similar incidence to aggregate GDP.

8 Conclusion

This paper explores the link between inequality in the labor market and macroeconomic stability. I demonstrate that the aggregate MPC is higher when there is a positive covariance between worker MPCs and the does the level of the mutiplier and the matching multiplier.

elasticity of their earnings to aggregate output, a mechanism I call the matching multiplier. Empirically, it is precisely the high-MPC workers whose earnings are most exposed to recessions, and this relationship is large enough to have meaningful effects on the response of output to shocks. This mechanism matters empirically – employment in areas with a higher matching multiplier is more sensitive to shocks, particularly in nontradable industries, where local demand channels should be operative. Lastly, I find that the empirical matching multiplier approximates the strength of the channel in a dynamic setting and therefore these estimates inform the amplification coming from similarly distributed but more transitory shocks.

Uncovering the linkages between labor market inequality and the consumption multiplier has potentially important implications for macroeconomic stabilization policy. Indeed, policies can be made more effective in part by explicitly targeting this covariance between earnings heterogeneity and worker MPCs. For example, the government could consider this covariance when deciding how to target fiscal stimulus across industries or firms. While much of the covariance between MPCs and earnings sensitivities to GDP occurs within the firm, there is still some scope for targeting particular industries or firm types (e.g., young and small firms), where higher-MPC workers are more likely to be employed. Additionally, unemployment insurance that is targeted toward high-MPC workers could provide greater aggregate consumption stabilization benefits. Several countries, such as Germany, make unemployment insurance more generous for older workers, but the results in this paper suggest a rationale for making unemployment insurance benefits more generous for young workers, who have higher MPCs and more volatile earnings.

Lastly, these results may suggest another reason for policymakers to be alarmed by rising inequality in the economy. As wealth becomes more unequally distributed, MPCs in the population may become more dispersed, with a wide swath of consumption being greatly affected by aggregate shocks. A concurrent economic phenomenon of the past decade is that workers have become increasingly sorted across firms, occupations, and even types of employment contracts. These two economic forces could combine to further strengthen this mechanism and contribute to more instability in the future.

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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 I am missing industry and firm information. 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. Additionally, in order to abstract from education and retirement decisions, I also restrict my attention to workers between 25 and 62 years old. This excludes around another 12 percent of the original sample.

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 a balanced panel of states using 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 transition to unemployment and 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 in the sample, 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, I would 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 downward (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, the following two pieces of evidence suggest that the differential mobility of workers outside the LEHD sample over the business cycle will not substantially affect my results. First, Table A3 explores the cross-state mobility patterns across the 23 states in my sample. These states are geographically and economically diverse, and therefore, they should reflect the mobility patterns in the United States as a whole. The results in Columns 4 and 5 show that workers with higher MPCs are more likely to move on average, but their mobility is *less* sensitive to GDP, meaning that in recessions, the change in the probability of moving is smaller than for those with higher MPCs. This pattern suggests that differential geographic mobility over the business cycle, if anything, biases the estimate of the heterogeneity in exposure downward.

Second, 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. 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 non-covered 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 A4 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.⁵⁴

Together, Tables A3 and A4 suggest that the assumption that workers who leave the sample make no labor market earnings is reasonable and if anything, the tables imply that my estimates of the heterogeneity in exposure to business cycles by a worker's MPC are underestimates.

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.⁵⁵ 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 A5 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 A5 and Column 3 of Table A1 in the main text also shows that the PSID sample is similar to the LEHD sample on all demographics. The only exception is that the average income

⁵⁴ 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.

⁵⁵ From 1999 to 2015, when the survey becomes every other year, the data include variables on twice-lagged incomes.

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 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 A2 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 downward slope across the rest of the income distribution suggests that estimates of the heterogeneity in marginal propensities to consume food by the individual's lagged earnings may not generalize well to estimates for total consumption. Therefore, while I show the robustness of my main findings to the use of food consumption only, I instead use the information on food consumption, as well as the richness of the PSID, to impute more comprehensive measures of consumption.

The main method that I use to impute total consumption in the PSID closely follows the methodology laid out in Blundell et al. (2008). They propose a method to impute expenditures in the PSID using information in the Consumer Expenditure Survey, or CEX.⁵⁶ 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 et al. (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 et al. (2008) analysis along several dimensions. First, I estimate the reverse of the equation (i.e., estimate total consumption as a function of food consumption). Second, I estimate this relationship for both durable and nondurable consumption combined.⁵⁷ Third, I estimate this by OLS, rather than using the instruments as the original paper does. Fourth, I use an updated sample, extending their sample to 2013. Table A6 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

$$\ln C_{it} = Z_{it}\beta + p_t\gamma + g(f_{it}, X_{it}; \theta) + u_{it} \quad (\text{A1})$$

where C_{it} is total household consumption, Z_{it} are household demographics, p_t are relative prices (i.e., Consumer Price Index, or CPI, series), and $X_{i,t}$ 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.⁵⁸

The left panel of Figure A3 shows the time series of actual total consumption in the CEX, which is shown with the red diamonds, and imputed total consumption within the PSID. The blue circles show

⁵⁶ 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.

⁵⁷ 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.

⁵⁸ I follow Blundell et al. (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; and education, year, and children dummies. All of these are interacted with food consumption.

average total consumption in the PSID (which is the baseline used throughout the analysis), and the green squares show total consumption resulting from separately imputing durable and nondurable consumption and then summing them together. The level of total imputed consumption in the PSID is slightly higher, but all three lines show similar levels and time series patterns. In addition to approximating the time series patterns, the imputed consumption in the PSID shows patterns in the cross-section that are similar to those patterns in the CEX. The right panel of Figure A3 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.⁵⁹ This imputation approximates total consumption less food (i.e., net consumption) as a function of demographics and food consumption

$$\ln n_{it} = Z_{it}\beta + p_t\gamma + g(f_{it}; \theta) + u_{it} \quad (\text{A2})$$

where n_{it} is the net consumption of the household, Z are various socioeconomic variables, p are prices, and f 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.⁶⁰ 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

$$\widehat{c}_{it} = f_{it} + e^{Z_{it}\widehat{\beta} + p_t\widehat{\gamma} + g(f_{it}, \widehat{\theta})}$$

Appendix Figure A14 shows that the estimates of the covariance between MPCs and elasticities is similar with this alternate imputation and demonstrates that the paper's main conclusions is unchanged with this alternative measure.

A.3 Additional estimates of marginal propensities to consume

A.3.1 Robustness of baseline MPC estimates

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.⁶¹ 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

⁵⁹ The expanded consumption measure within the PSID includes home insurance, rent, electricity, heating, water and miscellaneous 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.

⁶⁰ I closely follow Attanasio and Pistaferri (2014) in parametrizing 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 .

⁶¹ 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.

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 4.⁶² 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. The right panel of Figure A5 shows that the 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 A7 and Figure A4 display supporting statistics for the baseline estimates discussed in detail in the main text. Specifically, Figure A4 show 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 across households. Table A7 shows the regression estimates for Equation 5 that produce the distribution of MPCs shown in Figure 3 in the main text. 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. Unsurprisingly, these multivariate estimates echo the patterns displayed in Figure 2, in which black, lower-income, and young workers have higher MPCs. Lastly, Figure A7 shows that these baseline estimates are similar, on average, to other similar estimates of average MPCs in the literature.

The following set of tables and figures explores additional patterns for these baseline MPC estimates. The left panel of Figure A5 shows the estimates of MPCs for alternate individual characteristics that are not reported in the LEHD and thus not included in the baseline set of x variables. Less wealthy households and those who do not own homes have higher MPCs. This finding is in line with the extensive theoretical and empirical literature demonstrating that MPCs vary with household wealth, and it bolsters the supposition that patterns across demographic groups likely capture, in part, differences in wealth holdings across these groups.

One key feature of the baseline MPC estimates are that they capture the MPC of household consumption out of *individual* income, rather than household income. Since individual income is what I observe in the LEHD, this is the correct object for exploring the relationship between individual income movements and consumption patterns. However, it is true in the data that household income is less volatile than individual income, suggesting income smoothing through household formation. Indeed, Figure A5 shows that married workers have slightly lower MPCs. To the extent that this degree of household consumption and income smoothing is similar within demographic groups, the baseline estimates of MPCs will account for this. For example, it may be that one reason that black women have higher MPCs is that they are more likely to be married to spouses with volatile incomes. However, if within demographic groups workers with partners with less volatile incomes sort into riskier jobs, I will be overstating the relationship between demographic group MPCs and income sensitivities, since it will be precisely the unobservable high-MPC workers who are in the less risky jobs. Appendix Figure A6 explores the degree to which the MPC out of individual income differs from the MPC out of household income. Since individual unemployment shocks have smaller effects on total household income than individual income, MPCs out of household income are uniformly larger than MPCs out of individual income. However, while the levels are different, the

⁶² 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.

tight linear relationship between the two estimates reveals that they are highly correlated at the individual level. Indeed, the correlation between these two estimates is 0.89. This strongly suggests that assortative matching in the marriage market is not important in driving the MPC patterns across demographic groups. However, I explore the role of household formation further in Appendix A.4.

Lastly, Figure A10 explores the sensitivity of the MPC estimates to using alternate consumption measures. The top panel shows that while the level differs substantially, the individual-level MPC estimates are highly correlated across consumption measures. The blue squares show scatterplots relating the MPCs estimated using food consumption directly reported in the PSID with the baseline MPCs estimated using CEX-based total consumption. The red circles similarly show the relationship of the baseline MPCs with MPCs estimated using an alternate PSID-based imputation of expended consumption. (see Section A.2 for an explanation of this alternate consumption measure) The tight fit of the lines shows that all measures are highly correlated at the individual level. The bottom two panels show the age and income profiles of the MPCs using the alternate consumption measures, respectively. The food-based MPCs demonstrate a slightly different age pattern, with the MPC dropping steadily over the life cycle, while the broader consumption measures feature a U-shape in age. Otherwise, the three outcome measures show similar patterns across demographics.

A.3.2 Stability of MPC estimates

While the above method for estimating MPCs closely follows existing methods in the literature, my subsequent imputation of these MPCs by demographic in the LEHD necessitates several important additional assumptions that warrant further discussion. First, in imposing that MPCs only vary by worker demographic, I assume that individual MPCs are invariant to the sign and magnitude of the income shock. As I discussed above, in a standard model in which agents can borrow and save, an individual's MPC depends on the persistence of the shock, not on the magnitude or sign. However, with liquidity constraints, the marginal propensity to consume may depend on the size of the shock as well as the sign (Kaplan and Violante (2014)). To explore the importance of this assumption, the left panel of Figure A8 shows the overall estimates of the marginal propensity to consume 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 similar. This is true whether I include all workers (as in points 3 and 4) or restrict to those workers who remain employed (as in points 5 and 6). Those who remain employed across years experience a smaller income change yet a similar MPC.⁶³ Lastly, the farthest-right point shows the average MPC estimated using an indicator for whether the worker becomes employed between $t - 2$ and t .⁶⁴ The average MPC is slightly higher with the positive income "shock," but this is an artifact of the different estimation samples – the

⁶³ 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.

⁶⁴ 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 $t - 2$.

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. Lastly, Appendix Figure A9 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. Together, these estimates suggest that, empirically, the MPCs to different business-cycle labor income shocks do not differ substantially depending on the sign or magnitude of the particular shock. The stability of worker MPCs is also something I address within the quantitative exercise in Section 7.

A second key stability assumption embedded in the imputation of MPCs in the LEHD is that for an individual income shock of a given magnitude, the consumption response is constant over the business cycle. I explore this in my setting by adding an interaction of changes in income with the state unemployment rate, thereby allowing the MPC to vary over the business cycle. The right panel of Figure A8 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.

Third, I impose that at the individual level, the marginal propensity to consume is a function only of the characteristics that I include in X (i.e., age, earnings history, gender, and race). While this is obviously an approximation, this assumption would be a problem for my analysis if within each demographic bin there is sorting across jobs such that it was precisely the higher-MPC workers within the group who were at cyclically insensitive jobs. If this were the case, I would be inaccurately capturing the heterogeneity in exposure of workers to business cycles by their MPC. While my data do not allow me to fully address this, I explore the sensitivity of my MPC estimates to including job-level characteristics. If sorting across jobs of different characteristics were important in explaining MPC heterogeneity within demographic group, then these terms should have additional explanatory power. Table A8 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 A8, the resulting MPC heterogeneity change meaningfully when these variables are added.

A.3.3 Alternate MPC estimation methods

In this section, I present an alternative method for estimating MPCs entirely within the Consumer Expenditure Survey (CEX). While the CEX is not a full longitudinal panel like the PSID, it does feature a rolling panel structure in which individuals are interviewed five times, three months apart.⁶⁵ A clear advantage of the CEX over the PSID is that it includes more comprehensive measures of consumption that do not rely on imputation. Indeed, it covers around 95 percent of all expenditures, excluding housekeeping, personal

⁶⁵ The CEX also has a second component in which households are interviewed in two consecutive weeks. This higher-frequency data collection is intended to capture detailed information on the consumption of smaller high-frequency items such as food or household supplies. As the labor market information is not available at such high frequencies, this exercise will focus on the summary measures of these items included in the interview survey.

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.

While the CEX has extensive consumption data, the disadvantage of the CEX is that it includes sparse information on individuals' labor market experiences, making it difficult to identify income shocks. However, while incomplete, the CEX does include enough labor market information to roughly identify periods of nonemployment (Gruber (1998)). In particular, in survey 2 and survey 5 (taken nine months apart), the CEX asks how many weeks in the last year the individual has worked for pay, including vacations and sick leave, as well as how much income the individual and household earned in the preceding 12 months.⁶⁶ I define an individual as employed in survey 2 (what I will refer to as the base period) if they report having worked 52 weeks in the past 12 months. This ensures that the individual is employed both at the time of interview and in the previous three months, when baseline consumption is measured. I define an individual as unemployed in interview 5 if they report having worked fewer than 38 weeks in the previous 12 months.⁶⁷ Importantly, while this definition does capture some labor market disruption, it does not distinguish between voluntary nonemployment, retirement, and unemployment. I restrict the sample to those individuals between ages 25 and 55 to limit the frequency of schooling and retirement decisions, but the concern still remains in this sample.⁶⁸ Additionally, this definition does not guarantee that the individual is unemployed either at the time of the interview or in the three previous months over which consumption is measured.

Restricting to the individuals employed in survey 2, I run the following regression, which is similar to Equation 5 in the main text:

$$\Delta C_{c,i,t} = \beta_0 + \beta_1 \Delta Y_{i,t} + \beta_2 X_{it} + \gamma_{st} + \epsilon_{i,t} \quad (\text{A3})$$

where $C_{c,i,t}$ is consumption in category c of individual i in year t , $Y_{i,t}$ is annual labor income, and $X_{i,t}$ are individual-level controls (the change in the number of individuals in the household). I instrument $\Delta Y_{i,t}$ with an indicator for whether or not the individual is nonemployed in the survey 5.⁶⁹ This should isolate unexpected changes in income. As with the PSID estimates, the coefficient of interest is β_1 , which measures the average MPC for consumption category c . I then explore the heterogeneity by interacting $\Delta Y_{i,t}$ with individual characteristics.

Figure A11 shows the estimates of MPC heterogeneity using Equation A3 for various measures of consumption. First, the left figure shows the estimated MPCs using food consumption, and the right

⁶⁶ Note that because the labor market and earnings information is collected nine months apart but refers to a 12-month lookback period, there is a mechanical overlap in these two variables.

⁶⁷ I explore the robustness of the results to this cutoff. Another obvious possibility would be to use the cutoff of 12 weeks, which essentially ensures that the individual is unemployed at the time of the fifth interview. However, this reduces the sample size substantially, and results are similar to those achieved using less restrictive cutoffs; therefore, I keep 39 weeks as the main specification. An additional possibility is to use an indicator for whether the household received any unemployment insurance compensation in the previous year. This variable is available in the CEX from 1980 to 2013. This does not isolate individuals who are unemployed at the time of the interview, but it does aid in isolating individuals who are unemployed rather than voluntarily nonemployed.

⁶⁸ I can compare the frequency of unemployment in the CEX using this definition and the PSID. The CEX is consistently higher, but the patterns are broadly similar over time.

⁶⁹ I take several additional steps in cleaning the CEX data. First, I drop observations with food or incomes that change by more than 200 percent in the nine months of the sample. I exclude from the analysis any households that have a change in the number of children between survey 2 and survey 5 (approximately 10 percent of the sample). I do this to abstract from nonemployment due to childbirth. Lastly, I further restrict the sample to include workers from age 25 to 55. This is because this is the age range over which the incidence of nonemployment is relatively stable. Above age 55, the probability of nonemployment rises, suggesting that there is the possibility of early retirement in this age range.

figure shows the MPC estimates using total consumption.⁷⁰ A couple of patterns emerge. First, the overall magnitude of the MPCs for food consumption are very similar in the PSID and the CEX. Some of the descriptive patterns are also similar – for example, black men have the highest MPCs. These CEX-based estimates are noisier than those in the PSID, and the patterns from the PSID in age and income are less apparent here. The estimate MPC for total consumption, however, is lower in the CEX than in the PSID. While the estimates are noisier, the qualitative patterns across demographic groups are similar – young, less educated, and poorer households have higher MPCs.

A.4 Additional discussion of heterogeneity in worker exposure to business cycles

A.4.1 Robustness of relationship between worker MPCs and earnings sensitivity to GDP

Figure 1 clearly demonstrates that there is a positive relationship between the average earnings cyclicity of a demographic group and the average marginal propensity to consume of that group. The additional results presented in this section support the robustness of this pattern. First, Figure A12 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 A10 and A9 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 A10 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. Indeed, across all specifications, a 1 standard deviation increase in the MPC of the individual is associated with an increase in the elasticity of earnings with respect to GDP of between 0.33 and 0.39, or between 50 percent and 80 percent.

Columns 2 and 3 of Table A9 show that the overall sign of the relationship is insensitive to the functional form imposed on the dependent variable. 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. Column 2 shows that the patterns are similar when using a log transformation (i.e. $\Delta E_{i,t} = \log(E_{i,t} + 100) - \log(E_{i,t-1} + 100)$), and Column 3 shows similar patterns when using a level transformation, in which the level change in earnings is normalized by the average level of earnings in that worker's MPC bin. Both of these are alternate functional forms that combine the intensive and extensive margins of earnings, with the baseline transformation producing the most conservative estimate.

The following columns of Table A9 show that the estimated relationship is robust to various other modifications. Baseline estimates consider movements in fourth-quarter earnings, but Column 5 shows that patterns are similar when considering annual incomes. Column 6 restricts to a balanced panel from 1995 to 2011 and finds that in this subset, the estimate is similar but slightly larger. Column 7 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.

⁷⁰ Total consumption is defined to include nondurable consumption, education, health care, insurance, and other housing expenditures.

Lastly, Column 8 of Table A9 shows adjusted standard errors for the baseline estimate. Individually clustered standard errors 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 500 draws in which I randomly sample with replacement both the CEX and the PSID. This produces 500 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):

$$\bar{\alpha}_2 = \sum_{i=1}^{500} \frac{\hat{\alpha}_{2,i}}{500}$$

$$var(\alpha) = \sum_{i=1}^{500} \frac{var(\hat{\alpha}_{2,i})}{500} + \sum_{i=1}^{500} \frac{(\hat{\alpha}_{2,i} - \bar{\alpha}_2)^2}{499} + \sum_{i=1}^{500} \frac{(\hat{\alpha}_{2,i} - \bar{\alpha}_2)^2}{499 * 500}$$

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. Column 8 of Table A9 shows that while the standard error is larger, as should be expected, the coefficient is still tightly estimated. This methodology is very computationally intensive due to the large sample size, and therefore, given the small qualitative difference, I proceed with the simple clustered standard errors and leave the estimation of adjusted standard errors to future drafts.

Table A11 explores the robustness of the results using the expanded information available in the ACS subsample. This expanded information helps me test for the possibility of additional sorting patterns within demographic group that could potentially bias the estimated relationship between worker MPCs and earnings elasticities. For a direct comparison, Column 1 of Table A11 first shows the baseline estimate in the LEHD for only 2001 to 2011, the years of the ACS subsample. The overall relationship is smaller in the later part of the sample, and Column 2 shows that the estimate is nearly identical in the much smaller ACS subsample in those same years. More interestingly, Column 3 of Table A11 shows the robustness to an estimate using an individual-level MPC that varies along additional demographic characteristics – namely, the number of children in the household and an individual’s marital status. One possibility is that workers of the same demographic group but with different household structures sort into jobs with different sensitivity to aggregate movements. The results in Column 3 show that this is not the case. While the magnitude of the coefficient changes slightly, there is still a strong positive relationship between an individual’s MPC and the sensitivity of their earnings to GDP.

The MPC used above is the household consumption response to changes in individual-level earnings, but it’s possible that high-MPC individuals are actually in low-MPC and low-sensitivity households if their partners have lower MPCs and earnings that are less sensitive to the aggregate shock. The individual MPCs that I estimate and use as the baseline already include the average effect of this by demographic group, but the concern is that workers within these demographic groups sort across jobs of different riskiness based on household MPC, which is an omitted variable in the baseline analysis. Moving explicitly to the household level is the cleanest way to address these concerns. In Columns 4 and 5 of Table A11, the unit of observation is the household and the dependent variable is the change in income of the household, rather than of the individual. In Column 4, the household MPC is calculated as the earnings-weighted average individual MPCs of the members of the household, while in Column 5, I specifically construct

the MPC at the household level.⁷¹ In both columns, I find that the earnings of higher-MPC households are more exposed to movements in aggregate GDP. Column 4 provides the most direct comparison to the baseline results and shows that the coefficient is invariant to aggregating to the household level.

A.4.2 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 A13, 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.⁷² The LEHD misses the income of the top earnings along two dimensions. First, it is top-coded, 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 benchmarking the amount of potential missing income and reestimating Equation 6 assigning 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 A13 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.4.3 Additional heterogeneity patterns

While the overall estimates of the differential earnings elasticities by MPC are the key inputs to the calculation of the matching multiplier, or MM, in this section, I decompose this overall relationship to explore possible reasons that high-MPC workers are more exposed to aggregate fluctuations. One key factor that could underlie the positive relationship between worker MPCs and the sensitivity of earnings to the aggregate could be the sorting of workers across industries, firms, and jobs according to their characteristics and skills. Firms differ substantially in their exposure to recessions; industries such as manufacturing or construction are more cyclically sensitive than other industries, such as health care or education, and even within an industry, firms differ in their exposure to business cycles, with young and small firms being

⁷¹ I construct a household MPC using household-level data in the PSID and using only household, rather than individual, characteristics. Specifically, I allow the household MPC to vary by the lagged earnings of the household, grouped into five earnings bins, a quadratic in the age of the oldest member of the household, an indicator for whether one or both members of the household are black, and the number of people in the household.

⁷² The magnitude of the relationship documented in the left panel of Figure A13 is somewhat smaller than that documented in Guvenen et al. (2017), who show that workers in the 80th percentile have an earnings elasticity that is a full 2 points lower than the bottom decile. Since the LEHD does not include the uncensored earnings of the very high earners, the movement among the highest earners in Figure A13 is also smaller.

particularly cyclically sensitive (Fort et al. (2013), Crouzet and Mehrotra (2017).) In addition, a large and growing literature has documented substantial and increasing sorting of workers across firms along several dimensions. For example, young firms are more likely to hire young workers (Ouimet and Zarutskie (2014)), women have a higher willingness to trade higher pay for job security (Wiswall and Zafar (2018)), and high-wage workers congregate together in high-paying firms (Barth et al. (2016), Song et al. (2015)).⁷³ Together, the sorting of workers across firms could mean that high-MPC workers are more exposed to business cycles if the skills of high-MPC workers are utilized by more cyclically sensitive firms.

I explore the role that this sorting of workers plays in explaining the aggregate relationship displayed in Figure 1 by adding various fixed effects to Equation 6. Adding a full set of four-digit industry-by-year fixed effects will sweep out any earnings sensitivities that are common within an industry; thus, the remaining relationship is identified using purely within-industry differences in the exposure of workers to shocks. The top row of Column 1 in Table A12 reproduces the overall heterogeneity estimate from main-text Table 1. The top row of the second column in Table A12 shows that while the estimated slope drops when industry fixed effects are added, the sorting of workers of different MPCs across industries explains only about 12 percent of the differential exposure of high-MPC workers to recessions. Column 3 in Table A12 shows the estimated slope after adding a full set of firm-by-year fixed effects, which isolates the within-firm heterogeneity in worker exposure to recessions.⁷⁴ These fixed effects have very little further effect on the estimates, suggesting that the sorting across firms within industries explains very little of the total relationship.

Together, the previous two results suggest that the large majority of heterogeneity in business cycle exposure by MPC occurs within the firm rather than between firms. Within the firm, occupation is a key dimension along which workers of different MPCs may sort and along which earnings sensitivities may differ. While the LEHD does not include worker occupation, the ACS does. Therefore, for the subset of individuals whom I observe in both the ACS and the LEHD, I estimate a specification where I include a full set of industry-by-year-by-occupation fixed effects.⁷⁵ Column 4 of Table A12 reproduces the results using only year fixed effects on this modified subsample of people matched to the ACS and shows that the estimates of the overall heterogeneity are somewhat smaller in this subsample.⁷⁶ More importantly, Column 5 shows that this coefficient drops by about 40 percent when restricting the variation to within-industry occupation pairs.

If the sorting of workers across occupations, industries, or firms only explains up to 40 percent of the heterogeneity in exposure, what economic forces are driving this systematic positive relationship between a worker's MPC and their earnings cyclicity? The lower rows of Table A12 explore this by decomposing the MPC into two components – the component that comes from differences in the worker demographics (age, race, and gender) and the component that comes from differences in earnings histories. The final four rows of Table A12 go even further and explicitly break down the patterns by the four worker characteristics that enter the MPC calculation – age, gender, race, and earnings histories. Several important patterns appear. First, comparing across rows, all components of the worker MPC contribute to the overall positive

⁷³ Several of these sorting patterns are present in this sample as well. Specifically, I find that workers at firms fewer than five years old are younger, have lower earnings histories, and have higher average MPCs. Similarly, I find that small firms employ, on average, a workforce that has higher MPCs and is more male, white, and low-income.

⁷⁴ I define the firm as the combination of the firm and state, which is defined by the State Employer Identification Number. I define both the firm and the industry for the job held in $t - 1$.

⁷⁵ Because of the diminished sample size, I do not fully restrict to within the firm and include firm-by-year-by-occupation fixed effects. However, since cross-industry sorting is almost as important as cross-firm sorting, this specification should mostly capture the within-firm heterogeneity.

⁷⁶ Estimates on the full LEHD sample restricting to 2001 to 2011, which is the time period covered by the ACS subsample, are very similar to those in Column 4 of Table A12, confirming that the difference in the overall estimate is driven not by the different subsampling but by the different estimation period.

relationship between MPCs and earnings sensitivities to GDP. The earnings of women, black workers, lower-income workers, and younger workers, all of whom have higher MPCs on average, are all more exposed to GDP. However, comparing the importance of the various fixed effects across columns reveals that while demographic differences become less important within industries and occupations, differences in lagged incomes actually become *more* important within the firm and further within occupations.

Indeed, the importance of lagged income in explaining within-firm patterns suggests that workers could actually be high MPC *because* they are exposed to aggregate shocks. Workers who experience unemployment during recessions are likely to have lower lifetime earnings and fewer assets, thereby raising their MPC. This pattern, wherein heterogeneity in earnings volatility across workers within the firm is largely explained by variation in their earnings history, is consistent empirically with a large literature showing that an unemployment spell increases the risk of future unemployment spells (Stevens (1997)), as well as consistent theoretically with a job ladder model as in Jarosch (2014), wherein workers search for both more productive and more secure jobs, and thus, as they climb the job ladder they sort into higher-paying and more secure jobs.

To summarize, while what will matter for the overall consumption response will be the total relationship between earnings sensitivities and GDP and MPCs, the patterns in Table A12 highlight that the substantial positive relationship is largely a within-firm phenomena that is only partially explained by the sorting of workers across occupations within the firm. Instead, the within-firm patterns are explained largely by a worker's past earnings.

A.4.4 MPCs and hiring over the business cycle

Since the baseline analysis is restricted to the set of incumbent workers, the differential exposure of workers to recessions is the combination of differential separation probabilities or wage growth across worker MPCs. However, it does not include differences in exposure to recessions through the hiring margin, which is an equally if not more important margin of adjustment for firms during recessions. For example, while the construction and manufacturing sectors experienced spikes in their separation rates during the Great Recession, most other industries adjusted their employment levels with large swings in their hiring rates. If high-MPC workers are less likely to be hired during recessions, there will be an additional contribution to the matching multiplier coming from the unemployed.

In order to explore the heterogeneous exposure to recessions among the unemployed, I combine information in the LEHD and the ACS. The LEHD is a data set of employment, not of the labor force as a whole. The ACS is a sample of the entire population, but it does not include the within-person time series variation that is necessary to identify hiring patterns over the business cycles. Thus, I explore the differential sensitivity of hiring by worker MPC using the overlap between the ACS and the LEHD. Specifically, I identify an individual as unemployed in year t in sample state s using their reported unemployment status and residence in the ACS. I then match that set of unemployed workers to the LEHD in the following year $t + 1$ to determine whether they are employed a year later and if so, what their earnings are.⁷⁷ I then explore how this re-employment probability varies over the business cycle by estimating Equation 6 on this set of unemployed workers. I explore the extensive margin of hires using an indicator for whether the individual transitions to employment between t and $t + 1$ as the outcome variable, and I explore the intensive margin of earnings using the earnings conditional on re-employment. For worker MPCs, I deviate from the baseline analysis and use the MPC estimated using an instrument for being hired, rather than an

⁷⁷ Worker MPCs are a function of an individual's earning history, but the ACS does not include the earnings history for an individual. Therefore, I calculate a worker's lagged earnings using the LEHD. For each unemployed individual, I match them to the LEHD in years $t - 1$ and $t - 2$ and assume that if they do not appear anywhere in the sample in those years, they did not earn any labor market earnings over that period.

instrument for becoming unemployed. This estimate may better capture the variation that is most relevant for the unemployed. However, since this MPC estimate and the baseline MPC is very close, the results are similar when using the baseline MPC instead.

Column 1 of Table A13 shows that re-employment probabilities over the business cycle are similar for high- and low-MPC workers. Similarly, Column 3 shows that the earnings of the re-employed are also not more sensitive to GDP. This finding is possibly driven by changes in the composition of the unemployed over the business cycle. In recessions, the unemployed are higher quality workers on average, and thus, the re-employment wages conditional on worker quality could fall in recessions while the overall re-employment wage goes up. If the magnitude of the selection on worker quality over the business cycle is smaller for higher-MPC workers, you would observe this pattern wherein the re-employment wages of high-MPC workers are, on average, less sensitive to the business cycle.

An alternate method for defining the unemployed is to roughly define the set of unemployed within the LEHD. While this has the disadvantage of relying on a cruder definition of the unemployed, it has the advantage of including a much larger sample. Within the LEHD, I define the unemployed as the set of individuals who were employed in year t in a sample state in some previous year $t - k$ but who do not have any earnings in the LEHD at time t . This definition of the unemployed makes three potential errors. First, it excludes the unemployed who are actively searching for employment in those states but who have never been employed in those states. Aside from new market entrants, this group is likely unimportant for aggregate earnings dynamics, as it is very unattached from the labor market. Second, it includes as unemployed those who actually found jobs in states or sectors outside of the LEHD sample (e.g., transitioned to federal employment or moved to a state outside the 23-state sample). Third, it includes as unemployed those who in fact left the labor market and are not actively searching. While I can further restrict the sample to prime-age workers between ages 25 and 50 to mitigate this concern, this is still a possible source of misallocation.

Despite the crudeness of the definition, Columns 2 and 4 of Table A13 show that the estimated heterogeneity in earnings elasticities among the unemployed are similar to those resulting from the ACS-based identification. These two methods are likely similar because, as was discussed in Section A.2, individuals of different MPCs do not show different propensities to move either across sectors or across states over the business cycle. Thus, while the pool of unemployed differs across the two pools, the earnings variation from which the estimates in the LEHD are identified are similar.

Lastly, Table A14 shows that these unemployment estimates have a very minor effect on the overall estimates of the matching multiplier. This is a direct consequence of the small amounts of heterogeneity in Table A13 and the very small share of the overall dollars in the economy earned by the unemployed.

A.5 Details of commuting zone analysis

A.5.1 Additional data definitions

Local control variables: I closely follow Kaplan et al. (2016) 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, multiplied by the Zillow Home Value Index for All Homes.⁷⁸ 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

⁷⁸ 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.

each county from 1999 to 2011. 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.⁷⁹

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 $t_0 = 1999$ and $\Delta \log E_{i,t,-c}$ is the change 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 the own commuting zone, 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 cyclicalities using this Bartik shock, I *both* re-estimate MM_c using this shock and then re-estimate Equation 7 replacing aggregate GDP with this shock.

A.5.2 Robustness of results at the commuting zone level

The following section includes several results supporting the robustness of the findings presented in Table 3 and Table 4 in the main text. Before revisiting the full estimates of Equation 7, Figure A16 first shows year-by-year estimates of the relationship between \widehat{MM}_c and the change in local employment. Specifically, the coefficients plotted in Figure A16 are the coefficients on \widehat{MM}_c from the following regression, estimated separately in each year t

$$\Delta \log L_{c,t} = \kappa_1 \widehat{MM}_c + \kappa_2 \widehat{B}_c + \sum_x \kappa_x x_{c,t-1} + \epsilon_{c,t}$$

where $x_{c,t-1}$ includes controls for fraction of the commuting zone in each two-digit industry; the average age, race, gender, and lagged earnings of the area; and the fraction of the population that is employed. If a higher matching multiplier makes areas more sensitive to shocks, then we should see that during the years of the great recession, areas with a higher matching multiplier had a bigger fall in their employment (i.e., κ_1 is negative). The left panel of Figure A16 shows this is indeed the case. The value of κ_1 in 2008 is negative, meaning that between the fourth quarter of 2007 and the fourth quarter of 2008, areas that had a

⁷⁹ 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.

larger matching multiplier saw a greater fall in their employment than areas with a smaller matching multiplier. Indeed, in that time period, employment in areas with a matching multiplier 1 standard deviation above the mean fell by about 1 percentage point more than areas with a matching multiplier at the mean. However, the other points in the figure show that the opposite relationship holds in boom years. Indeed, in the boom years from 2002 to 2005, employed areas with a matching multiplier 1 standard deviation above the mean grew by about 0.7 percentage points more per year. In other words, exactly as I found in Table 3, the relationship between local earnings growth and the matching multiplier is cyclical – during the years of the Great Recession, areas with a higher matching multiplier experienced larger employment losses, but during the boom of the early 2000s, those areas were also experiencing faster employment growth. Furthermore, the differential sensitivities to GDP reported in Table 3 are not simply driven by different experiences in only recessions or only in booms; rather, they experience the entire business cycle differently.

To show this more clearly, the right panel of Figure A16 plots the annual coefficients not against years as in the left panel but against the change in GDP in those years. The point in the bottom left is 2008, when there was both a negative movement in aggregate GDP and a negative relationship between the matching multiplier and employment. The boom years of the mid 2000s are in the top right, where GDP was booming and so were areas with a higher matching multiplier. As was expected given the time series pattern, there is a clear positive relationship between the effect of the matching multiplier on employment and the movement of aggregate GDP. The slope of the relationship in the right panel is in essence a more nonparametric estimate of ϕ_1 , the coefficient on the interaction between \widehat{MM}_c and GDP in Equation 7; when there is a positive aggregate shock, a higher matching multiplier is associated with more employment growth, but when the shock is negative, a higher matching multiplier is associated with lower employment growth.

Table A15 explores the robustness of the overall cross-commuting zone patterns presented in main-text Table 3. Column 1 simply replicates the baseline estimates for comparison. Column 2 shows the estimates of the relationship replacing aggregate GDP with a Bartik shock. The coefficient on \widehat{MM}_c interacted with GDP is still positive and statistically and economically significant – a commuting zone with the average matching multiplier has an employment response to the shock that is 0.2 percentage points higher than an area with a matching multiplier of 0, representing a 42 percent increase above the average response. Column 3 presents the estimates using an alternate imputation of MPC, which is based on the positive income shock from hires rather than the negative income shock of unemployment. While the magnitudes adjust, the sign of the coefficients remains the same. Column 4 shows the estimates replacing \widehat{MM}_c with simply the difference between the actual and benchmark MPC, which is the numerator of \widehat{MM}_c . This alternate functional form reveals similar patterns and magnitudes. Lastly, Column 5 includes the baseline commuting zone demographic controls interacted with a full set of time dummies, controlling nonparametrically for differences across commuting zones along these dimensions. The results are very similar, suggesting that allowing for a different trend and cycle closely captures the heterogeneity along these dimensions.

Figure A15 zooms in on a case study of the Great Recession. The left panel shows the relationship between the employment change in the Great Recession and the matching multiplier, estimated over the full sample. The right panel plots the same y-axis but instead shows the relationship with the matching multiplier estimated on the full sample instrumented with the matching multiplier estimated pre-2007. While the estimates of pre-recession \widehat{MM}_c are noisier, the correlation with full-sample \widehat{MM}_c is high at 0.55 and the first stage relationship is strong. Both figures demonstrate a strong negative relationship, with the slope on the right being slightly steeper than the slope on the left.

Lastly, Table A16 explores the sensitivity of the relative patterns for employment in tradable and non-tradable industries presented in main-text Table 4. Column 1 reproduces the baseline estimates from Column 3 of Table 4. Column 2 shows that the estimates are similar when moving to more disaggregated

four-digit NAICS codes. Column 3 shows that the coefficient on the triple interaction between the matching multiplier and tradables is robust to including financial controls. Finally, Column 4 shows estimates using only the numerator of \widehat{MM}_c , which measures the difference between the actual and benchmark MPCs. While the magnitudes of the coefficients naturally rescale with the change in the function, the relative patterns across tradable and nontradable industries remain similar.

B Theory appendix

B.1 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 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:

$$MPC = \frac{dC}{dY} = \frac{dC}{dE} \frac{dE}{dY} + \frac{dC}{dK} \frac{dK}{dY}$$

or, defining the average earnings elasticity as $\gamma = \frac{dE}{dY} \frac{Y}{E}$, this becomes

$$MPC = \frac{dC}{dY} = \frac{E}{Y} \frac{dC}{dE} \gamma + \frac{dC}{dK} \frac{dK}{dY}$$

This simple total derivative highlights the importance of two terms that were not in the simple framework – the consumption response from changes in nonlabor income ($\frac{dC}{dK} \frac{dK}{dY} = MPC_{nl}(1 - \alpha_l)$) and the labor share $\alpha_l = \left(\frac{E\gamma}{Y}\right)$. 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 MPC, where all workers have the same earnings elasticity, is given by

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

The actual MPC is instead given by

$$MPC^a = \frac{E}{Y} \sum_i MPC_i \gamma_i \frac{E_i}{E} + MPC_{nl}(1 - \alpha_l)$$

Using the definition of MM in Equation 4 and these expanded expressions for MPC^a and MPC^b , I arrive at Equation for the adjusted multiplier in the main text.

B.2 Details for model in Section 7

B.2.1 Proof of Proposition 1

Proposition 1: *Under the assumption that wages are sticky for $k + 1$ periods, for any shock to parameters (θ, τ, θ_G) , the total change in output from an initial flexible price allocation is given to first order by*

$$dY = (I - C_Y J_k - (C_r + G_r) J_{T-k} (L_r)^{-1})^{-1} \partial Y \quad (B1)$$

where subscripts denote partial derivatives (i.e., C_r is the partial derivative of consumption with respect to r) and J_k and J_{T-k} are diagonal matrices with 1s in the first k or the last $T - k$ entries, respectively.

Proof. Begin by totally differentiating the good market clearing condition (Equation 16) in each period t :

$$dY^t = \sum_{j=1}^k C_{t,y_j} dy_j + \sum_{j=1}^T (C_{r_j} + G_{r_j}) dr_j + \sum_{j=1}^T C_{t,\tau} d\tau_t + C_{t,\theta} d\theta + \sum_{j=1}^T G_{t,\tau_t} d\tau_t + G_{t,\theta_G} d\theta_G \quad (\text{B2})$$

where $C_{t,x}$ is an I -length vector across individuals where each entry is the partial derivative of the individual consumption function $c_i(\{y_{i,t}\}_{t \leq k}, \{\tau_{i,t}\}_{t \in T}, \{r_t\}_{t \in T}, \beta_i, b)$ with respect to the variable x . Recall that in the rationed equilibrium, income is exogenous in all rationed periods, and thus enters the consumption function. Note that the first sum is only across periods 1 through k , the periods in which there is labor market rationing. Beyond that, the workers are back on their labor supply curves and their income is endogenously given by their decisions and prices. By the definition of the income process imposed by the rationing function in Equation 19,

$$dy_{i,t} = n_{i,t} - l_{i,t-1} = \gamma_i \frac{l_{i,t-1}}{L_t} dY_t$$

Denote N_y as the I vector where the i entry is $dy_{i,t} = \gamma_i \frac{l_{i,t-1}}{Y_t}$. Plugging this in, we get:

$$dY^t = \sum_{j=1}^k \left(C'_{t,y_j} N_y dY_j \right) + \sum_{j=1}^T (C_{r_j} + G_{r_j}) dr_j + \sum_{j=1}^T C_{t,\tau} d\tau_t + C_{t,\theta} d\theta + \sum_{j=1}^T G_{t,\tau_t} d\tau_t + G_{t,\theta_G} d\theta_G \quad (\text{B3})$$

Note that $C'_{t,y_j} N_y = \frac{dc_t}{dy_j} = C_{t,j}$, which is the aggregate response in time t to a change in income at time j . Equation B3 holds for all periods t , and stacking equations, this becomes

$$dY = C_Y J_k dY + (C_r + G_r) dr + C_\tau d\tau + C_\theta d\theta + G_\tau d\tau + G_{\theta_G} d\theta_G \quad (\text{B4})$$

where C_Y is a matrix where the i, j entry is the aggregate consumption response at time i to an income shock in time j and J_k is a diagonal matrix with 1s only for the first k periods. For the first k periods, the interest rate is pinned down by the monetary policy rule (rather than by labor market clearing). Given the rule specified,

$$dr_t = 0 \quad \forall t \leq k$$

After k periods, the interest rate goes back to the flexible price scenario and the change in the interest rate is pinned down by the labor market clearing condition. The total derivative of the labor market clearing condition is given by:

$$dY_t = \sum_{j=0}^T L_{t,r_j} dr_j + \sum_{j=1}^T L_{t,\tau} d\tau_t + L_{t,\theta} d\theta \quad \forall t > k$$

Stacking across periods and solving for dr , we get the expression for the change in the interest rate at time $t > k$:

$$dr = (L_r)^{-1} (dY - L_\tau d\tau - L_\theta d\theta)$$

Stacking these equations over time and defining

$$\partial Y = C_\tau d\tau + C_\theta d\theta + G_\tau d\tau + G_{\theta_G} d\theta_G + (C_r + G_r) J_{T-k} (L_r)^{-1} (L_\tau d\tau - L_\theta d\theta)$$

we can rewrite Equation B4 as

$$dY = C_Y J_k dY + (C_r + G_r) J_{T-k} (L_r)^{-1} dY + \partial Y \quad (\text{B5})$$

where dY and ∂Y are $T \times 1$ matrices and C_Y is a $T \times T$. J_k is just a diagonal matrix with ones along the diagonal for the first k entries, and J_{T-k} is a diagonal matrix with 1s for the last $T - k$ entries. C_r, G_r are $T \times T$ matrices.

□

B.2.2 Comparing flexible and sticky price multipliers

Since this paper empirically explores the role that the distribution of income shocks across worker MPCs plays in affecting the economy's response to shocks, I focus on the case where labor is rationed and thus workers are off their labor supply curve. However, it is illustrative to consider the multiplier when prices are flexible and the interest rate adjusts such that workers remain on their labor supply curves.

Proposition 2. *Under the assumption that all prices are flexible, for any shock to parameters (θ, τ, θ_G) , given initial conditions, the total change in output is given to first order by*

$$dY = (I - (C_r + G_r)(L_r)^{-1})^{-1} \partial Y \quad (\text{B6})$$

where subscripts denote partial derivatives (i.e., C_y is the partial derivative of consumption with respect to y).

Proof. As in the proof for Proposition 1, begin by taking the total derivative of the goods market clearing condition, noting that the consumption function for the individual is only a function of exogenous variables and prices as given by Equation 14:

$$dY_t = \sum_{j=0}^t (C_{r_j} + G_{r_j}) dr_j + \sum_{j=1}^T (C_{r_j} + G_{r_j}) dr_j + \sum_{j=1}^T C_{t,\tau} d\tau_t + C_{t,\theta} d\theta + \sum_{j=1}^T G_{t,\tau} d\tau_t + G_{t,\theta_G} d\theta_G \quad (\text{B7})$$

The labor market clearing condition implies $dY_t = \sum_{j=0}^T L_{t,r_j} dr_j + \sum_{j=1}^T L_{t,\tau} d\tau_t + L_{t,\theta} d\theta$. Stacking these across years, you get:

$$dY = L_r dr + L_\tau d\tau - L_\theta d\theta \quad (\text{B8})$$

where L_r is also a $T \times T$ matrix. Assuming it is invertible, we can write $dr = (L_r)^{-1} (dY - L_\tau d\tau - L_\theta d\theta)$.

Define the partial equilibrium response as the movement in aggregate output *before* there are any movements of endogenous variables (e.g., r and w),

$$\partial Y = C_\tau d\tau + C_\theta d\theta + G_\tau d\tau + G_{\theta_G} d\theta_G + (C_r + G_r)(L_r)^{-1} (L_\tau d\tau - L_\theta d\theta) \quad (\text{B9})$$

Plugging Equation B9 and Equation B8 into Equation B7, we get:

$$dY = (C_r + G_r)(L_r)^{-1} dY + \partial Y$$

□

What is this multiplier in the flexible price case? It only captures the response of consumption and labor to changes in the interest rate, which adjusts endogenously to clear the labor and output markets. When prices are flexible, workers are always on their labor supply curves, meaning that when their taxes go up, they will want to work more and consume less. However, since consumption demand fell, firms will want

to hire fewer workers, and the wage will fall (or since the wage is normalized, the interest rate will fall to encourage people to work less today (and consume more today)). Changes in income are determined by changes in labor supply; thus, the change in the interest rate (and the change in the labor supply that it induces) are sufficient for understanding the response to shocks.

Indeed, in this standard RBC model with flexible prices, this multiplier is always weakly less than 1 (i.e., there is no amplification of the initial shock). Consider the case with two time periods. In this case, Equation B6 becomes

$$\begin{bmatrix} dY_1 \\ dY_2 \end{bmatrix} = \begin{bmatrix} C_{1,r} + G_{1,r} & 0 \\ 0 & C_{2,r} + G_{2,r} \end{bmatrix} \begin{bmatrix} L_{1,r}^{-1} & 0 \\ 0 & L_{2,r}^{-1} \end{bmatrix} \begin{bmatrix} dY_1 \\ dY_2 \end{bmatrix} + \begin{bmatrix} \partial Y_1 \\ \partial Y_2 \end{bmatrix}$$

or

$$\begin{bmatrix} dY_1 \\ dY_2 \end{bmatrix} = \begin{bmatrix} (C_{1,r} + G_{1,r})L_{1,r}^{-1} & 0 \\ 0 & (C_{2,r} + G_{2,r})L_{2,r}^{-1} \end{bmatrix} \begin{bmatrix} dY_1 \\ dY_2 \end{bmatrix} + \begin{bmatrix} \partial Y_1 \\ \partial Y_2 \end{bmatrix}$$

This matrix is block-diagonal, so we can write the first period responses independently of the second period as

$$dY_1 = (1 - (C_{1,r} + G_{1,r})L_{1,r}^{-1})^{-1} \partial Y_1$$

For each entry i , C_r is weakly negative. The Euler equation implies that a higher interest rate will cause consumption today to fall, unless the individual is constrained, in which case they will not behave according to the Euler equation and will not respond to changes in r . $L_{1,r}$ is weakly positive – when the interest rate goes up, today is a better time to work (since the future payoff from working today is higher). Thus, $(C_{1,r} + G_{1,r})(L_{1,r})^{-1}$ is weakly negative, meaning that the multiplier is weakly less than 1.

B.3 Quantitative details

B.3.1 Calibration of Unemployment Process

I assume that the unemployment process follows a 2-state markov process. The two possible states are $e_{it} = 1$, which means that they are unemployed for the year, and $e_{it} = X$, where X is the average earnings loss as a percent of total employment earnings for someone who is observed to be unemployed for at least 1 month in a given year.

The transition probabilities between these two states is given by the Markov transition matrix $P(m)$, which is determined by the job-finding and job-separation rates.

$$P(m) = \begin{bmatrix} (1-s) & s \\ f & 1-f \end{bmatrix}$$

The combination of X and $P(m)$ capture the persistence of unemployment for each demographic group. I calculate the values of $P(m)$ using the monthly job flows in the Current Population Survey as I describe in more detail below. I use as the value of X the replacement rate that is implied by the job finding rates, job separation rates, and an underlying monthly income process in which you earn nothing in the months in which you are unemployed and earn the employed wage process in the months in which you are employed. With this model of unemployment, the combination of job-finding and job-separation rates yield an average number of months that an individual is working in each year for individuals who are observed to be employed in a given month and those who are observed to be unemployed in a given month. Therefore, estimates of the job-finding and job-separation rates will pin down the value of X as

well as $P(m)$.

I calculate monthly labor market flows using the matched monthly basic CPS. I restrict the sample to only include 1994-2018, those who report being either unemployed or employed, and those between the ages of 25 and 62. From that sample, I calculate the probability that across two consecutive months, someone transitions from unemployment to employment and from employment to unemployment. I then average these monthly rates across the entire sample period.

Panel A of Table A17 reproduces the values of the job-finding rate (f) and the job-separation rate (s) that I calculate for each of the 8 demographic groups and report in Table 5 in the main text. The combination of the job-finding and job-separation rate induce an expected unemployment rate and unemployment duration for each group.⁸⁰ Columns 3 and 4 of Table A17 show the unemployment rate that is implied by these labor market flows and the empirical average unemployment rate reported in the CPS, respectively. While the steady-state unemployment rate is on average a little below the empirical unemployment rate, the model-implied rates are highly correlated with measures unemployment rates. Columns 5 through 7 show the average duration of unemployment that is implied by the job-finding rate relative to the average duration of unemployment that is reported in the CPS or PSID. While the level of unemployment duration is higher in the CPS than the job-finding rate implies, the cross-demographic group correlation is very high.⁸¹ The unemployment duration variable in the PSID is defined slightly differently and therefore the level is not directly comparable, but still the cross-sectional variation is similar to both the model and the CPS. This suggests that these job-finding rates are accurately capturing key features of unemployment for each demographic group.

Lastly, as discussed above, the job-market flows imply an annual replacement rate for unemployment (X) for each demographic group. If each individual earns nothing in the months in which she is unemployed, longer unemployment durations will imply bigger differences in annual earnings for those who are observed to be unemployed in a given month. In the Panel C of Table A17, I report the replacement rate implied by the estimated job market flow rates. I compare this to the the replacement rates that I estimate separately within the PSID, which actually correspond to the first stage of the MPC estimation regression. These PSID estimates reflect not only differences in the unemployment duration but also reflect differences in the re-employment wage, something that is outside of the earnings process in the model. Despite this difference, the level for these replacement rates are broadly similar in the model and in the data. Additionally, some of the broad patterns are similar (i.e. more educated groups have higher replacement rates). However, the cross-demographic group correlation is low, and the PSID estimates are relatively noisy.

B.3.2 Estimation of the income process

I loosely follow Heathcote et al. (2010) in estimating the wage process . I begin with the assumption that earnings are generated by the following model:

$$\log(y_{ia}) = \mu + z_{ia} + \epsilon_{ia}$$

$$z_{ia} = \rho z_{i,a-1} + u_{ia}$$

$$u_{ia} \sim (0, \sigma_u)$$

$$z_{i,0} \sim (0, \sigma_{z_0})$$

⁸⁰The expected steady-state unemployment rate is given by $\frac{s}{s+f}$, which is the invariant distribution of the markov chain. Additionally, the expected duration of unemployment is given by $\frac{1}{f}$.

⁸¹It is well-documented in the literature that there is a long right-tail in the unemployment duration distribution and that the mean duration is higher than the median. This increases the average duration in the CPS relative to the model.

$$\epsilon_{ia} \sim (0, \sigma_\epsilon)$$

where i is the individual, a is the age, and μ is the average level shift common to all individuals and ages. Assume that the shocks are all i.i.d and thus uncorrelated with each other. The set of parameters that characterizes this income process is: $\theta = \rho, \sigma_u, \sigma_{z0}, \sigma_\epsilon$. I identify these parameters using within-person variances and covariances in income over time. Specifically,

$$\text{var}(y_{i0}) = \sigma_{z0} + \sigma_\epsilon \quad (\text{B10})$$

$$\text{var}(y_{ia}) = \text{var}(z_{ia}) + \sigma_\epsilon \quad (\text{B11})$$

$$\text{var}(z_{ia}) = \rho^2 \text{var}(z_{i,a-1}) + \sigma_u \quad (\text{B12})$$

$$\text{Cov}(y_{ia}, y_{i,a-j}) = \text{cov}(z_{ia}, z_{i,a-j}) \quad \forall j > 0 \quad (\text{B13})$$

$$\text{Cov}(z_{ia}, z_{i,a-j}) = \rho^j \text{var}(z_{i,a-j}) \quad \forall j > 0 \quad (\text{B14})$$

$$\frac{\text{cov}(y_{ia}, y_{i,a-2})}{\text{cov}(y_{i,a-1}, y_{i,a-2})} = \frac{\rho^2 \text{var}(z_{i,a-2})}{\rho \text{var}(z_{i,a-2})} = \rho \quad (\text{B15})$$

The identification of σ_ϵ (the variance of the transitory component) comes from the difference between the variance and the covariance:

$$\text{var}(y_{i,a-1}) - \frac{1}{\rho} \text{cov}(y_{ia}, y_{i,a-1}) = \text{var}(z_{i,a-1}) + \sigma_\epsilon - \text{var}(z_{i,a-1}) = \sigma_\epsilon \quad (\text{B16})$$

Once you know ρ and σ_ϵ , the identification of $\text{var}(z_{i0})$ comes immediately from Equation B10. Lastly, the identification of σ_u (the variance of the persistent component) comes from

$$\text{var}(y_{i,a-1}) - \text{cov}(y_{ia}, y_{i,a-2}) - \sigma_\epsilon = \sigma_u \quad (\text{B17})$$

I implement this estimation using a minimum distance estimator constructed using the following steps:

1. Construct a matrix of the covariances of earning across ages in the data.
2. Vectorize the matrix to include the set of unique covariances (i.e., take the upper triangular portion of C and turn it into a vector).
3. Define $f(\theta)$ as the corresponding vector based on the model covariance matrix.
4. The estimator solves the minimization problem:

$$\min_{\theta} [m - f(\theta)]' \Omega [m - f(\theta)]$$

where Ω is the identity matrix (Altonji and Segal (1996)).

In selecting the sample on which to estimate the income process, I restrict to those who report being employed the the time of the PSID survey, are between the ages of 30 and 40, and for whom I can impute an MPC (i.e., observations with at least two lags of earnings). I include both the nationally representative

sample and SEO subsample of the PSID. I match the analysis in the LEHD and use individual labor rather than household earnings or total post-tax-and-transfer earnings. Table A18 shows the parameter estimates that result from the analysis by demographic group. These parameter estimates are similar to, although slightly higher than, comparable estimates in the literature. For example, Heathcote et al. (2010) estimate an average permanent component of around 0.015 and a transitory component of around 0.1. Carroll et al. (2015) review the literature and show that estimates in the literature for the variance of the permanent component range from 0.01 to 0.054 and that estimates of the transitory variance range from 0.01 to 0.2.

B.3.3 Additional quantitative results

Additional Results: Table A19 summarizes the strength of the matching multiplier in the model. All estimates summarize the mechanism in period 1. The first row shows the model estimates of the empirical statistic. The second row shows statistics for a 1-period negative 1 percent shock. The third row shows the effect for a persistent 1 percent shock, where the persistence is equal to the average persistence of an unemployment shock in the model. The estimates in the table correspond directly to those plotted in Figure 4. Lastly, the fourth row explores the stability of MPC estimates across the benchmark and actual scenarios, as is described below.

While main-text Figure 4 and Table A19 focus on the matching multiplier in period 1, Figure A18 shows the dynamics of the consumption response. The left panel shows the aggregate marginal propensity to consume in the actual and the benchmark scenarios, while the right panel shows just the difference between those MPCs. As in Table A19, in the period of the shock, the consumption response is larger in the actual scenario than in the benchmark scenario. However, in the following years, this pattern reverses, and consumption in the benchmark scenario is actually higher than in the empirical case. This overshooting pattern is intuitive; since, on aggregate, in the benchmark scenario, less was consumed and more was saved in the first period, there is more to spend in future periods. This pattern persists until both scenarios eventually converge back to the steady-state level of consumption.

Figure A19 explores the importance of the rationing function for the strength of the matching multiplier mechanism. When labor is rationed for only one period, agents only respond directly to changes in their income in the first period, and thus, the only non-0 column of the intertemporal MPC matrix (C_Y in Proposition 1) is the first column. However, if wages are sticky for three periods, labor will be rationed for two periods, and the intertemporal MPC matrix will have non-0 entries in the first two columns. More generally, as the length of the rationing period grows, the columns of the intertemporal MPC matrix fill in. In Figure A19, I plot the matching multiplier as a percentage of the overall multiplier for different lengths of the rationing period. I assume that the interest rate is fixed and use Proposition 1 to calculate MM as I increase the length of the rationing period. As shown in Auclert et al. (2018), I find that the level of the multiplier increases as intertemporal MPCs are taken into account, and Figure A19 shows that the relative importance of the matching multiplier in period 1 also increases.

Income Volatility in the Benchmark Scenario: While the empirical measure of the matching multiplier treats the MPCs of different demographic groups as fixed, in practice, consumption behavior will be determined as a function of current and future income shocks, and thus, will change as a function of the shock and its incidence. In the last row of Table A19, I explore the importance of the assumption that the shock is completely unanticipated, meaning that as the incidence of the shock changes, workers MPCs in the initial period remain the same. However, if workers know they are in the benchmark scenario in which aggregate shocks are more evenly distributed, they are likely *also* facing a different overall income process, and thus when the aggregate shock eventually hits, they will have accumulated different assets and may have different MPCs. Therefore, the assumption that I can change the incidence of the shock without changing the distribution of MPCs may be incorrect. There is no formal relationship between

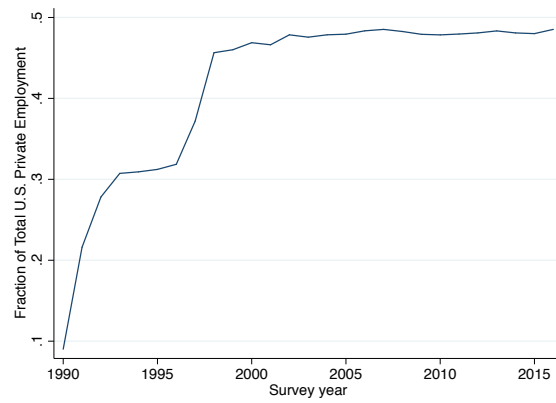
the shape of the rationing function and income volatilities in the model, so I explore the importance of this assumption in a reduced form way. Specifically, I re-estimate the steady state of the model in a case where all demographic groups face the same transitory *and* persistent variance of income, which is given by the earnings-weighted average in the population. I then define the benchmark consumption change as the percent drop in consumption in response to the evenly distributed shock but beginning from this new steady state. I call this benchmark consumption response the “endogenous benchmark” to refer to the endogenous response of initial MPCs to the incidence of the aggregate shock. The actual case stays the same and continues to be calculated beginning at the original steady state. Row 4 of Table A19 show that this endogenous MPC response makes little difference for the strength of this mechanism. Furthermore, since equating the sensitivity of earnings to the aggregate across individuals does not fully equate the overall volatility of the income process across groups, this exercise likely provides an upper bound for the response of MPCs to this change.

The patterns displayed in the Figure A17 illuminate why the endogenous response of worker MPCs to the change in their income processes does not matter for the magnitude of the matching multiplier. The blue circles in Figure A17, on the y-axis, show the endogenous benchmark MPCs of each group, which characterize the steady state when the stochastic income process is equalized across groups. On the x-axis are the calibrated transitory MPCs. Even though everyone faces the same income risk, the dispersion across demographic groups remains in the equal income process case because of remaining differences in discount factors across groups. While these baseline and endogenous MPCs are highly correlated, there are substantial within-group responses of consumption behavior to the income process. For example, the average MPC of black women with at least some college increases by 13 percent, as their asset accumulation falls in response to the drop in their income volatility in the endogenous scenario. However, in bringing the income volatilities to the average, other groups experience an increase in their income volatility, meaning that the increase in the MPC of black women is offset by a fall in income in other demographic groups. Since all workers in the benchmark scenario face the same earnings cyclicity, the benchmark MPC reduces to the average elasticity of earnings to the shock times the earnings-weighted average MPC. Therefore, the endogenous response of MPCs to the changing income process only matters insofar as they affect aggregate earnings-weighted MPC. The green “x” in Figure A17 shows that the new average MPC lies very close to the 45-degree line – it is virtually unchanged across the scenarios.

The conclusion of this exercise is that while the endogeneity of MPCs may matter in some counterfactuals, it does not affect the magnitude of the aggregate MPC in the benchmark scenario that I consider in this paper in which all workers face the *average* income elasticity to GDP.

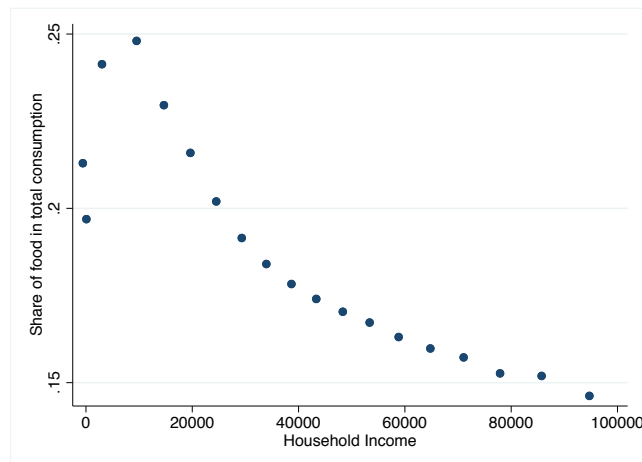
A.4 Appendix figures

Figure A1: Fraction of U.S. Employment in LEHD Sample



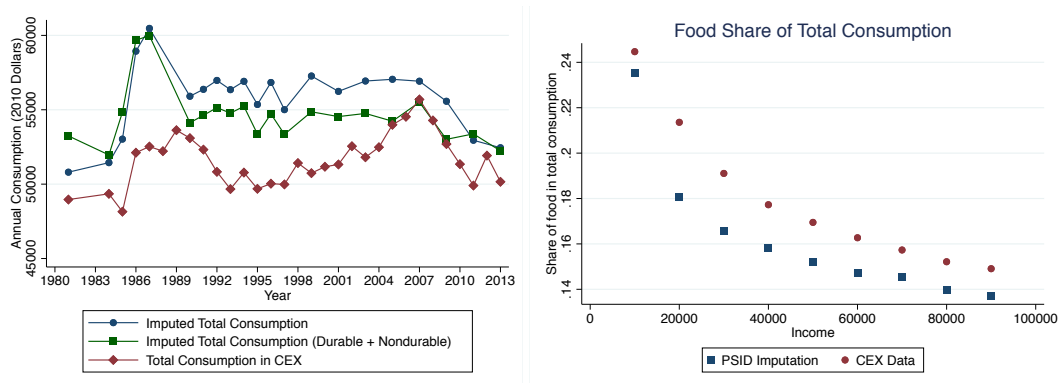
Notes: Figure is constructed using data from the Current Population Survey Annual Social and Economic Supplement. States included in the LEHD sample are Arkansas; Arizona; California; Colorado; Washington D.C.; Delaware; Florida; Iowa; Illinois; Indiana; Kansas; Maryland; Maine; Montana; New Mexico; Nevada; Oklahoma; Oregon; Pennsylvania; Tennessee; Washington; and West Virginia. See Table A2 for the sample years for each state.

Figure A2: The Fraction of Food in Total Spending



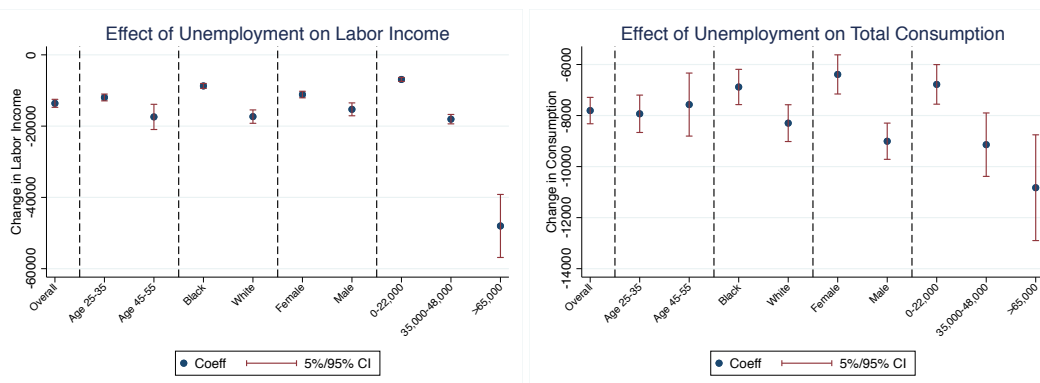
Notes: Data are from the Consumer Expenditure Survey and are pooled across 1984 to 2014 for all households with a head between the ages of 25 and 62. Household income is adjusted to 2010 dollars.

Figure A3: Imputed Total Consumption Using CEX-Based Imputation



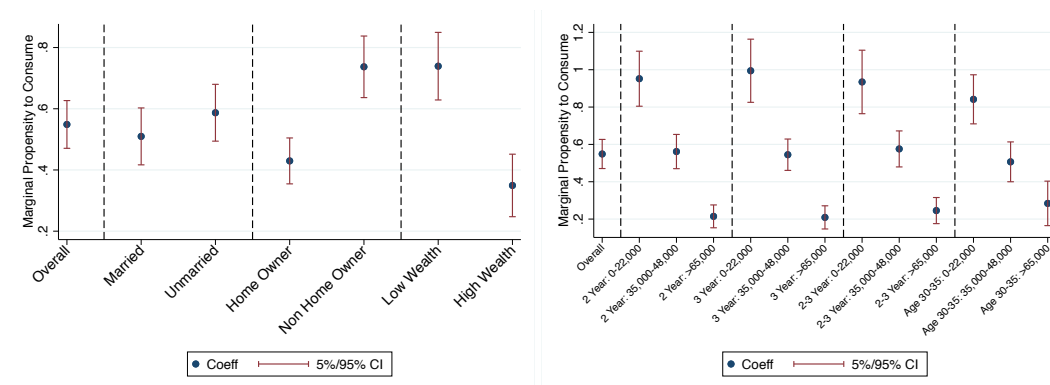
Notes: Average total consumption in the PSID is imputed using Equation A1. Averages are calculated using sample weights in the CEX and based on the nationally representative subsample in the PSID. Income refers to household income, adjusted to 2010 dollars.

Figure A4: Heterogeneity in the Marginal Propensity to Consume: First Stage and Reduced Form



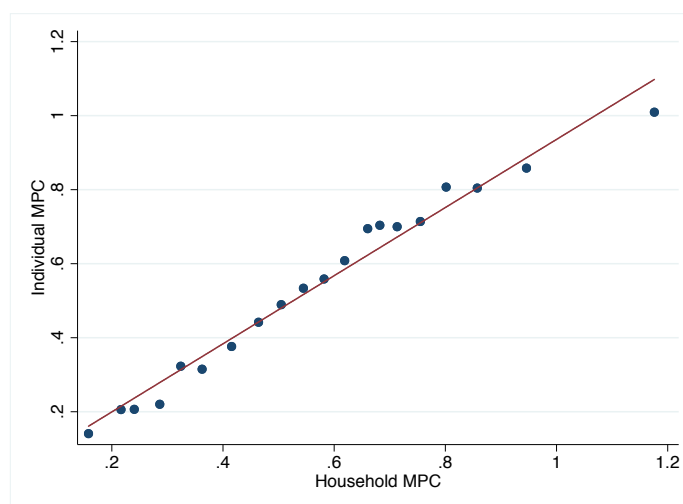
Notes: The left panel shows the first stage of unemployment on the level of labor earnings and the right panel shows the reduced form of unemployment on the level of consumption. These correspond to the instrumented regressions in Figure 2. Consumption is measured using total consumption, imputed using the method in Blundell et al. (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.

Figure A5: Sensitivity of Baseline MPC Estimates to Specification of Demographic Variables



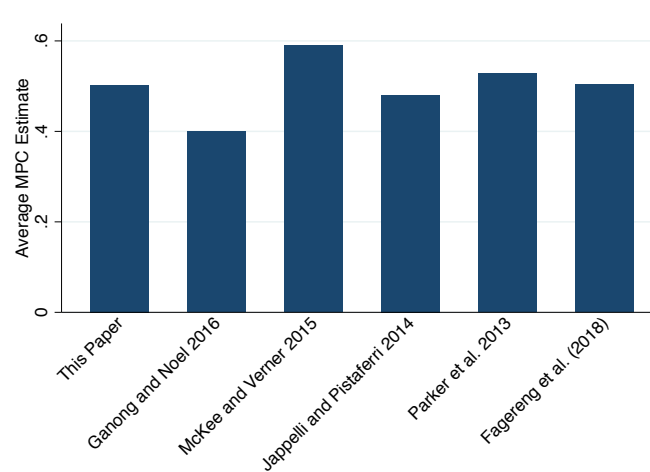
Notes: In the left panel, wealth is defined as the sum of assets less the value of debt plus the value of home equity. Assets include farm or business worth, checking or savings accounts, real estate assets, stocks, vehicles, and individual retirement accounts. Debts include business debt, real estate debt, credit cards, student loans, medical debt, legal debt, and family loans. Wealth is defined in 1984, 1989, and every year from 1999 to 2015. The right panel shows MPC estimates for different definitions of lagged earnings. “2 Year” defines income bins using the average earned in $t - 1$ and $t - 2$ (this is the baseline). “3 Year” defines income bins using the average earned in $t - 1$, $t - 2$, and $t - 3$. “2-3 year” defines income bins using the average earned in $t - 2$ and $t - 3$. “Age 30-35” defines income bins using the income earned from ages 30 to 35, no matter what the current age of the worker. All regressions are otherwise as in Figure 2.

Figure A6: MPCs out of Individual and Household Incomes



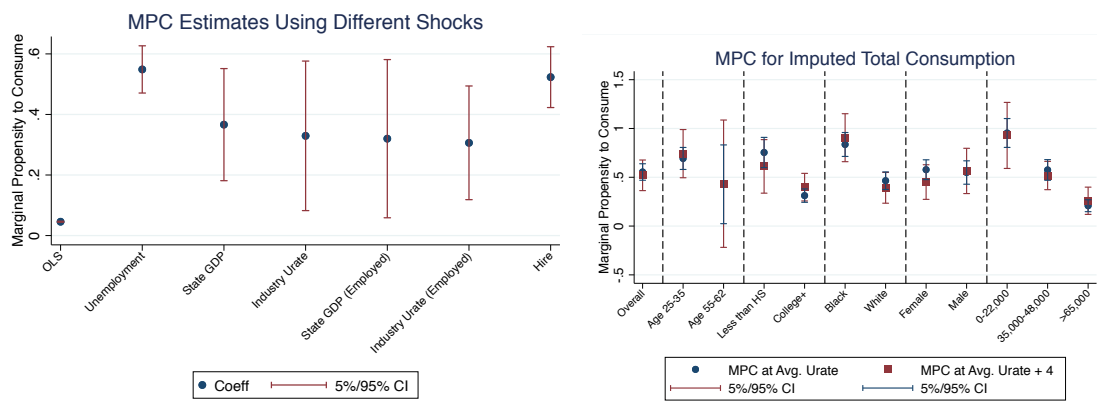
Notes: Individual MPCs on the y-axis are the baseline estimates plotted in Figure 3. Household MPCs on the x-axis replace individual labor income with total household income, but otherwise, the specification is exactly as for the baseline MPC estimates. Each point represents an equal number of individuals. The sample includes all workers in the PSID estimation sample.

Figure A7: Estimates of the Average Marginal Propensity to Consume in the Literature



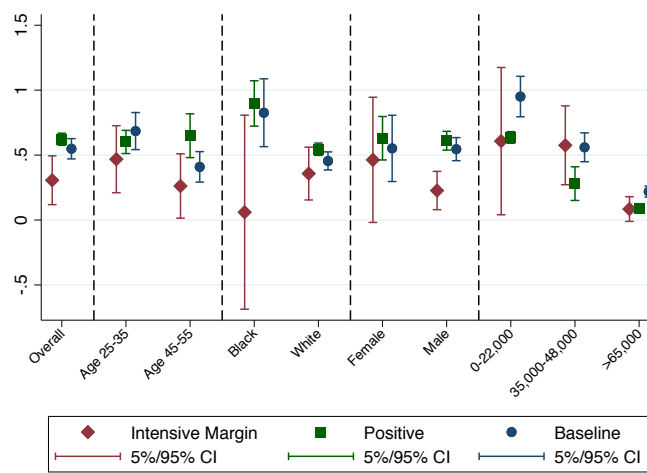
Notes: The estimates for this paper, labeled “baseline,” are those plotted Figure 2. Ganong and Noel (2019) estimate the MPC at the onset of unemployment using balance sheet data from JPMorgan Chase & Co.. See Appendix Table 5 in their paper. Jappelli and Pistaferri (2014) use survey data in Italy to illicit MPCs out of transitory income shocks. Parker et al. (2013) identify the consumption response to the 2008 tax rebates. See Table 2 in their paper. McKee and Verner (2015) use Nielsen panel data to estimate the MPC out of unemployment insurance benefits.

Figure A8: The Stability of Marginal Propensity to Consume Estimates



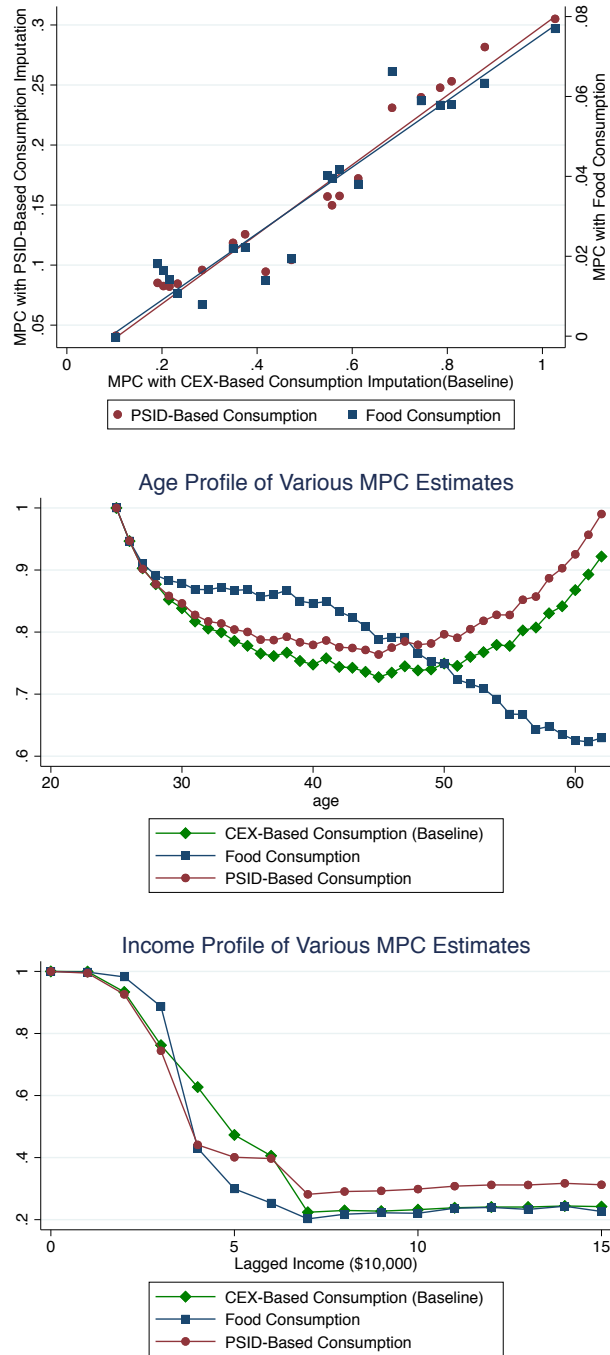
Notes: The instrument labeled “State GDP” in the left panel is defined as the percentage change in state GDP, defined by the Bureau of Economic Analysis. The industry unemployment rate is calculated from the Basic Monthly Current Population Survey, pooled over months within the year, and defined using 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 $t - 2$. The unemployment rate in the right panel 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. In both panels, regressions are based on two-year periods.

Figure A9: The Correlation of MPCs Using Different Identifying Income Shocks



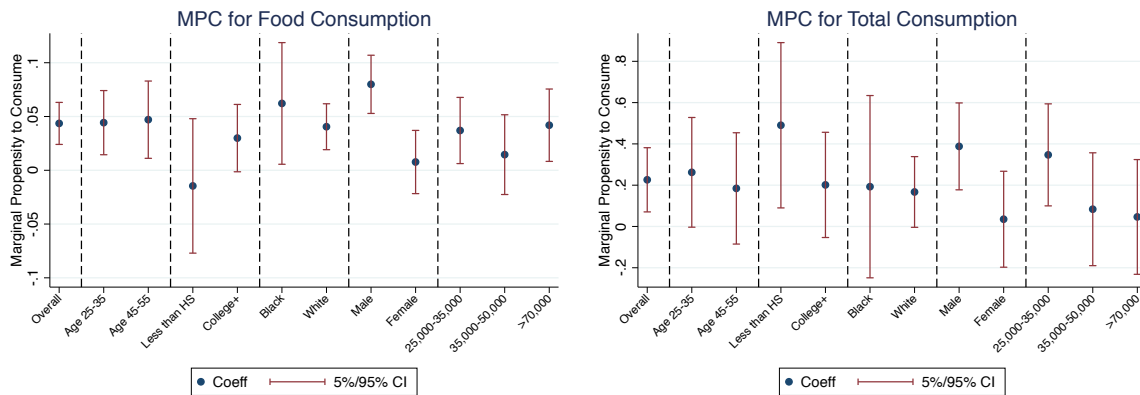
Notes: Each series presents an MPC estimate using a different shock as an instrument for the change in earnings. The baseline shock is unemployment, the “intensive” series instruments the change in earnings with the unemployment rate in the industry in which the individual worked in $t - 2$, and the “positive” series instruments earnings being hired 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 employed in $t - 2$. MPCs estimated using the industry unemployment rate are estimated without a restriction on employment status in $t - 2$. While the estimation sample differs across estimation methods, the MPCs are then imputed for the entire sample and the correlations are reported across the entire nationally representative subsample of the PSID.

Figure A10: Marginal Propensities to Consume: Alternate Consumption Variables



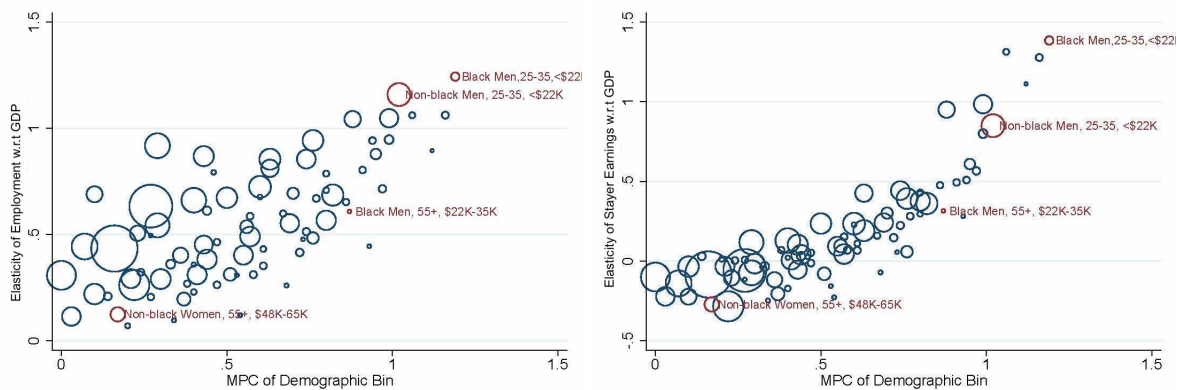
Notes: Each point in the top panel represents an equally sized data bin. Across all specifications, MPCs are estimated as in main-text Equation 5 with the baseline demographics. Income is measured using individual labor income. Food expenditure is measured using total food expenditure inclusive of food stamps. In all estimates, the instrument for income changes is unemployment and the sample includes the set of workers who were employed in $t - 2$ and 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. Regressions are estimated on the full sample, but the above figures are calculated on the nationally representative subsample of the PSID.

Figure A11: Marginal Propensities to Consume Estimated in the CEX



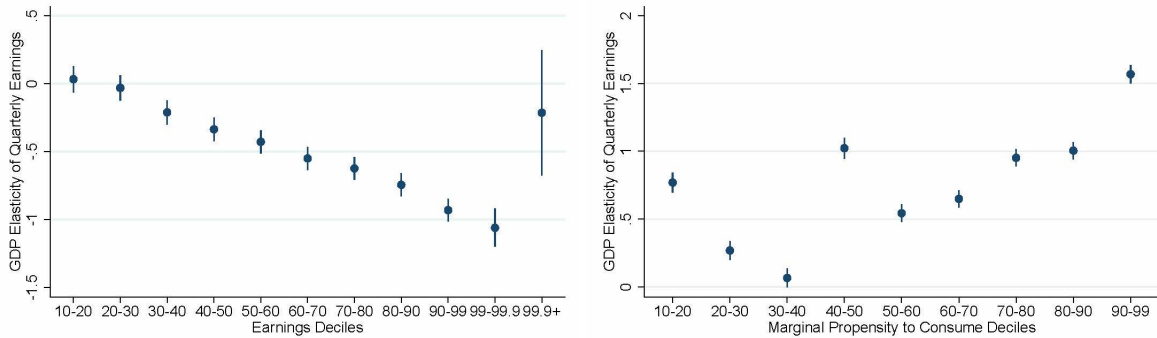
Notes: Income is measured using individual wage and salary earnings. Food expenditure is measured as the sum of food consumed at home and food eaten out. The instrument for income changes is reporting fewer than 38 weeks of employment in the previous year. The sample includes the set of workers who worked the prior 52 weeks in the second interview. Each regression excludes outlier observations, which are defined as observations with a change in income or relevant consumption of more than 200 percent. All regressions include year-by-quarter fixed effects, as well as month dummies.

Figure A12: Earnings Sensitivity to GDP and MPCs: Intensive and Extensive Earnings Margins



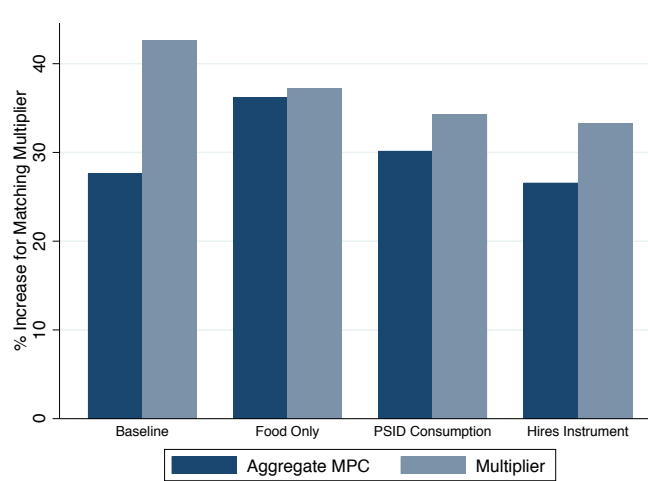
Notes: Sample includes the set of all workers employed in a sample state in year $t - 1$ between 1995 and 2011. The dependent variable in the regression producing the y-axis estimates on the left graph is $\log(E_{i,t}) - \log(E_{i,t-1})$. The dependent variable in the regression producing the y-axis 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.

Figure A13: Earnings Sensitivity to GDP, by Decile of the MPC and Income Distribution



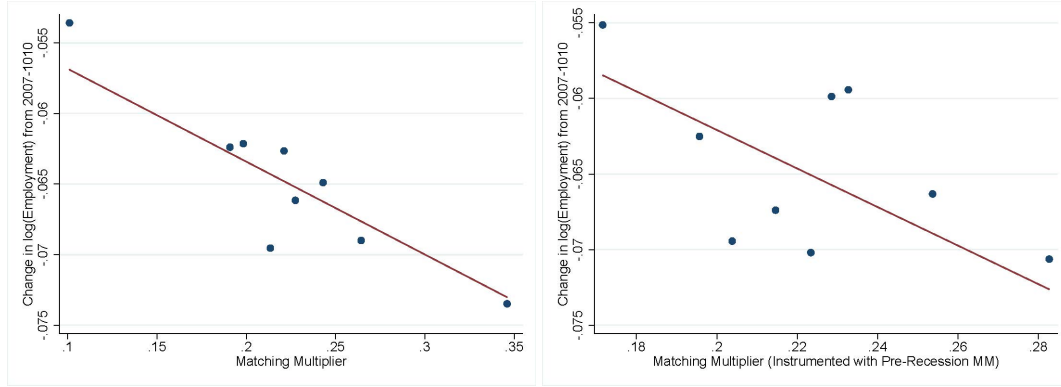
Notes: Sample includes a 5 percent random subset of all workers employed in a sample state in year $t - 1$ between 1995 and 2011. The dependent variable in the regression is $\frac{E_{i,t} - E_{i,t-1}}{.5 * E_{i,t} + .5 * E_{i,t-1}}$. MPC decile bin cutoffs are defined on a sample pooled across all years and each bin represent 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 percent confidence intervals.

Figure A14: Robustness of Matching Multiplier Estimates: Alternate specifications



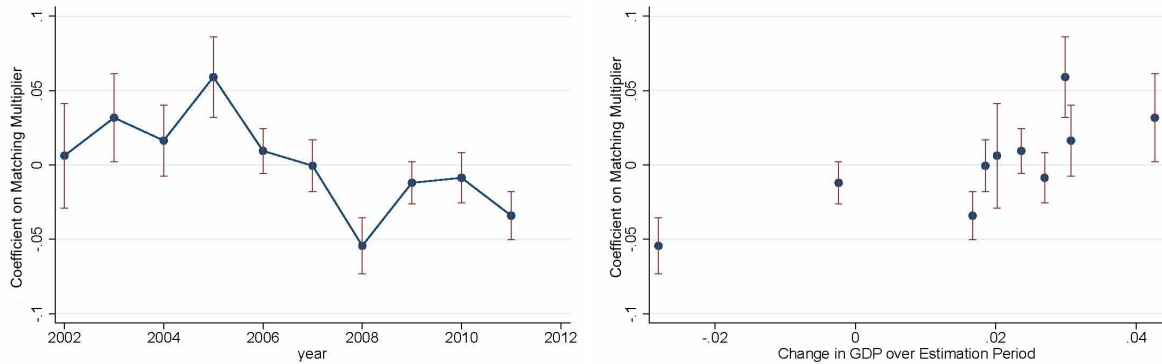
Notes: The dark blue bars show the percent increase in the aggregate MPC between the actual and benchmark scenarios and light blue bars show the percent increase in the multiplier between the actual and benchmark scenarios. The “Baseline” case defines consumption using total consumption imputed from the CEX, “Food Only” uses only food consumption reported in the PSID, “PSID Consumption” imputes consumption within the PSID using the methodology in ?, and “Hires Instrument” defines consumption using total consumption imputed from the CEX but identify the MPC using the positive shock of becoming hired. All other estimates use the unemployment shock to identify the MPC.

Figure A15: Employment in the Great Recession and the Local Matching Multiplier



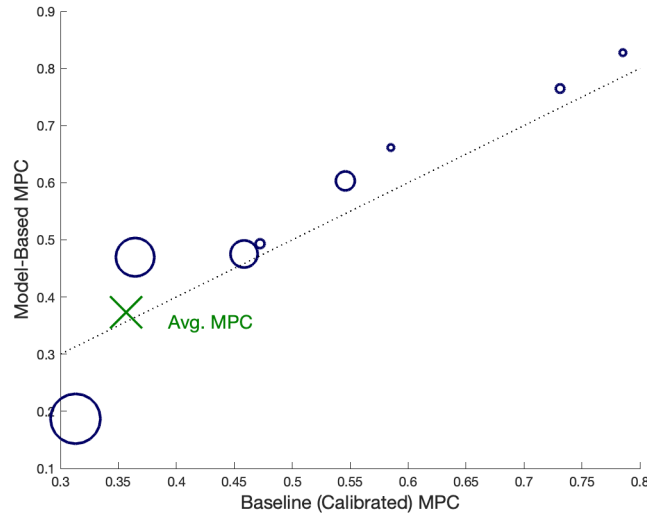
Notes: Each point represents a decile of the distribution of commuting-zones, which includes 270 commuting zones. Each commuting zone is weighted by its share of labor market earnings in 2007. Each plot includes controls for the share of employment in the 2-digit industry; the average age and lagged earnings of the area; as well as the fraction of the commuting-zone that is female, black, and in the labor force.

Figure A16: Employment Changes and the Local Matching Multiplier Over Time



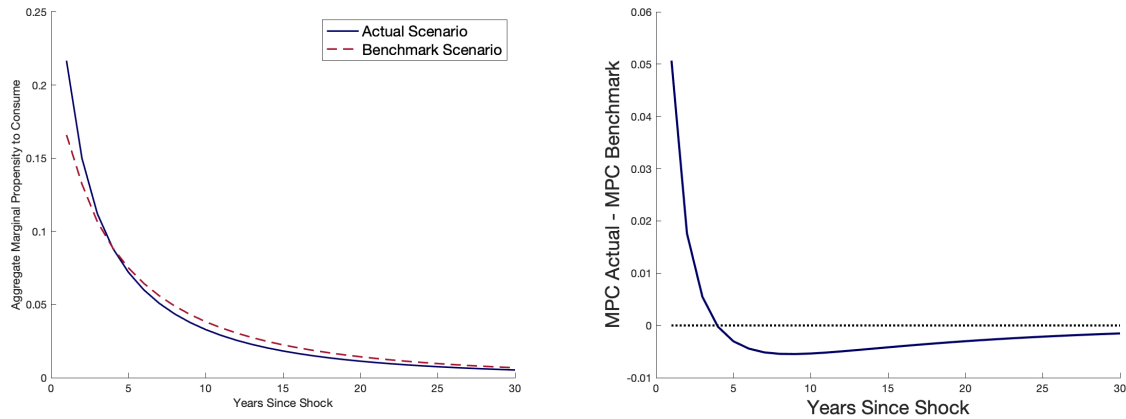
Notes: The left panel shows coefficients on \widehat{MM}_c from estimates of $\Delta \log E_{c,t}$ on \widehat{MM}_c in each year. The right panel shows the same annual estimates plotted against the change in GDP over that period. All regressions include controls for the share of employment in two-digit industries; the average lagged income and age; as well as the average fraction of the area that is black, female, and in the labor force. Red bars show the 90/10 confidence intervals.

Figure A17: The Sensitivity of MPCs to the Income Processes



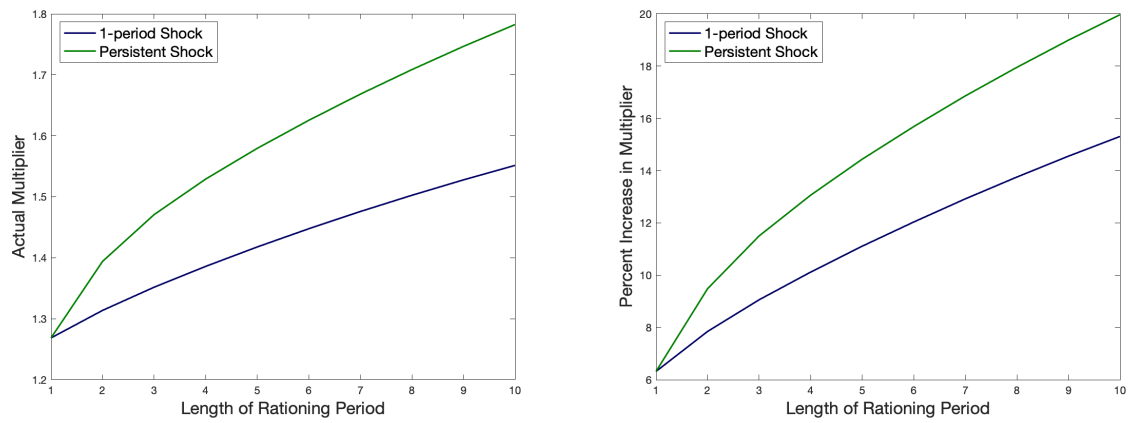
Notes: The y-axis plots the average group-level MPC in the case where the variance of earnings is equated across groups. The x-axis plots the steady state transitory MPC of each group. The 45-degree line is marked by the black dashed line. Each bubble represents one of the eight demographic groups, and the size of the bubble reflects that group's share of total earnings.

Figure A18: Consumption Response to Aggregate Shock in Benchmark and Actual Scenarios



Notes: The left panel shows the aggregate change in consumption divided by the aggregate change in income in the actual and benchmark scenarios. The right panel shows the difference between the aggregate MPC across these scenarios. In both figures, the interest rate is fixed at its steady-state value and the income shock is unanticipated and lasts for only one period.

Figure A19: The Matching Multiplier and the Length of the Rationing Period



Notes: The y-axis plots the percent difference between the actual multiplier and the benchmark multiplier, showing the percentage increase in the overall multiplier coming from heterogeneity in the shock incidence. The x-axis shows the length of the rationing period. The matching multiplier and the overall multiplier are calculated using the sufficient statistic in Proposition 1, with the assumption that the interest rate is fixed in the future.

A.5 Appendix tables

Table A1: Summary Statistics for 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
<i>Worker Characteristics</i>			
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
<i>Job Characteristics</i>			
Average Total Quarterly Earnings	10,650	11,920	11,794
Average Annual Earnings	40,140	45,430	44,119
Average No. Jobs per quarter per worker	1.16	1.14	1.15
Fraction with multiple jobs	0.13	0.11	0.12

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: Mobility Patterns: Cross-State

Characteristic (X)	Worker Age		Past Earnings		Marginal Propensity to Consume	
X_{t-1}	-0.002** (0.001)	0.004 (0.001)	-0.045 (0.044)	-0.095 (0.054)	0.177 (0.064)	0.284 (0.084)
$X_{t-1} * \Delta \log GDP_t$		-0.376 (0.055)		0.000 (0.000)		-6.098 (3.179)
No. Observations	333	333	446	446	144	144
R-Squared	0.064	0.179	0.014	0.019	0.052	0.077

Notes: The dependent variable in each regression is the fraction of the workers in demographic bin x who are employed at time t and $t - 1$ who change state of employment between $t - 1$ and t . Worker age is binned into years, past earnings are binned into \$1,000 bins, and MPCs are rounded to the nearest 0.01. The number of observations records the number of demographic bin years. All regressions include year fixed effects. Standard errors are clustered at the individual level.

Table A4: Mobility Patterns: Cross-Sector

Marginal Propensity to Consume (MPC)	-0.0036*** (0.0002)		-0.0032*** (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 employment in self-employment, 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 A5: Summary Statistics for the Panel Study of Income Dynamics

	LEHD Comparison Sample	National Sample of Employed	MPC Estimation Sample
<i>Worker Characteristics</i>			
Fraction Male	0.548	0.54	0.514
Average Worker Age	42.7	42.3	41.3
Average 2-year Lagged Income	57,295	57,458	51,153
Fraction College Educated	0.365	0.373	0.308
Fraction Black	0.0469	0.053	0.265
Average Income	60,692	60,312	52,683
Change in Income	3,013	2,734	1,552
<i>Household Characteristics</i>			
Household Size	2.995	3.06	3.134
Food Consumption	9,033	9,163	8,795
Total Consumption	63,052	63,266	58,431
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	77,876

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 used in the estimation of MPCs and thus restricts to the set of workers employed in $t - 2$. 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 A6: Summary Statistics for the Consumer Expenditure Survey

	CEX Sample	PSID Sample
<i>Worker Characteristics</i>		
Fraction Male	0.47	0.48
Average Worker Age	43.31	42.30
Fraction College Educated	0.34	0.37
Fraction Black	0.10	0.06
Average Income	45,620	50,775
<i>Household Characteristics</i>		
Household Size	3.16	3.03
Food Consumption	8,366	8,884
Total Consumption	41,725	43,181
Number of Individuals	127,165	97,204

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 A7: Coefficient Estimates for Individual Marginal Propensities to Consume

Dep. Var.	Food Consumption	PSID Imputation	CEX Imputation
< 22000*Labor Income	0.0273 (0.1173)	0.2223 (0.2125)	0.9171 (0.7844)
(22,000-35,000)*Labor Income	0.0148 (0.1166)	0.1235 (0.2117)	0.6824 (0.7858)
(35,000-48,000) *Labor Income	-0.0157 (0.1173)	0.0635 (0.2127)	0.5572 (0.7901)
(48,000-65,000) *Labor Income	-0.0309 (0.1191)	0.0047 (0.2155)	0.3471 (0.7878)
> 65,000 *Labor Income	-0.0348 (0.1187)	-0.0305 (0.2143)	0.1887 (0.7936)
Age*Labor Income	0.0027 (0.0059)	0.0045 (0.0106)	-0.0013 (0.0381)
Age ² *Labor Income	-0.0334 (0.0701)	-0.0223 (0.1264)	0.0415 (0.4464)
Female*Labor Income	-0.0224 (0.0139)	-0.0873 (0.0234)	-0.1347 (0.0706)
Black*Labor Income	0.0417 (0.0589)	0.2073 (0.1036)	1.2314 (0.4141)
Black*Age*Labor Income	-0.0008 (0.0014)	-0.0042 (0.0025)	-0.0237 (0.0095)
Black*Female*Labor Income	-0.0052 (0.0296)	0.0128 (0.0515)	-0.2532 (0.1717)
No. Observations	123439	110403	69788
Year FEs	X	X	X

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 last column is total consumption imputed using the CEX data. The fitted values of the regression in Column 3 are plotted in Figure 3. 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. All regressions include state-by-year fixed effects. Columns 1 and 2 include years from 1971 to 2013 while Column 3 includes data from 1992 to 2013.

Table A8: 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	0.995	0.971	0.968	1.000		
w/ Occ. Variance	0.972	0.953	0.955	0.968	1.000	
w/ Region	0.999	0.977	0.974	0.994	0.972	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 A9: Robustness of Relationship Between MPCs and Earnings Elasticities: Alternate Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		<i>Alt. Outcome</i>						
	Baseline Estimate	log(Eit +100)	Levels	Aggregated Sample	Annual Income	1993 State Subsample	State GDP	Multiple Imputation
$MPC_{i,t-1}$	-0.245*** (0.001)	-0.378*** (0.002)	-0.258*** (0.002)	-0.058*** (0.002)	-0.077*** (0.001)	-0.262*** (0.001)	-0.237*** (0.001)	-0.2261*** (0.054)
$MPC_{i,t-1} * \Delta GDP_t$	1.300*** (0.028)	2.681*** (0.068)	2.073*** (0.080)	1.144*** (0.083)	0.732*** (0.018)	1.619*** (0.033)	0.888*** (0.017)	1.204*** (0.214)
No. Observations	29,204,700	29,204,700	29,204,700	2,496	29,204,700	20,859,200	29,204,700	29,204,700
R-Squared	0.009	0.004	0.007	0.532	0.003	0.010	0.012	0.009
Avg. MPC	.431	.431	.431	.429	.42	.423	.431	.431

Notes: Column 1 shows regression estimates from Table 1, estimated on a 5 percent subsample of the data set. Columns 2 and 3 show different specifications of the earnings variable, both of which combine the intensive margin of earnings and the extensive margin of employment. Column 4 aggregates from the individual level to MPC bins (MPC rounded to the nearest 0.01) and runs a regression on the full aggregated sample. Column 5 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 6 restricts to the subsample of states that are present in 1993, meaning that there is a balanced panel of states over time. Column 7 replaces aggregate GDP with state-level GDP. This specification includes state-by-year fixed effects, rather than simply year fixed effects. Lastly, Column 8 shows the estimates using multiple imputation, as described in the text. Across all columns, the number of observations is rounded to the nearest 100 to comply with U.S. Census Bureau disclosure requirements. Standard errors are clustered at the individual level in all columns except for Column 8.

Table A10: Robustness of Relationship Between MPCs and Earnings Elasticities: Alternate MPC Imputations

<i>MPC Definition:</i>	Baseline Estimate	Food	Age Bins	PSID-Based Consumption	Hires Instrument
$MPC_{i,t-1}$	-0.245 (0.001)	-2.151 (0.009)	-0.229 (0.001)	-0.863 (0.002)	-0.400 (0.004)
$MPC_{i,t-1} * \Delta \log GDP_t$	1.300 (0.028)	14.328 (0.310)	1.312 (0.027)	4.183 (0.082)	2.087 (0.113)
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	0.431	.029	.421	.169	.246

Notes: Each column defines the marginal propensity to consume in a different way. Column 1 is the baseline MPC estimate; Column 2 is the same as in Column 1 but includes age bins rather than a quadratic in age. Column 3 uses the MPC defined only using food 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 standard errors are clustered at the individual level. Across all columns, the number of observations is rounded to the nearest 100 to comply with U.S. Census Bureau disclosure requirements.

Table A11: Heterogeneity in Worker Exposure to Recessions: ACS Subsample With Household Characteristics

	(1) LEHD 2001-2001	(2) ACS Sample	(3) Extended MPC	(4) Household Avg. MPC	(5) Household MPC
$MPC_{i,t-1}$	-0.25 (0.001)	-0.22 (0.002)	-0.177 (0.001)	-0.187 (0.002)	-0.077 (0.001)
$MPC_{i,t-1} * \Delta \log GDP_t$	0.952 (0.033)	0.926 (0.059)	0.802 (0.057)	0.896 (0.066)	0.447 (0.049)
Year FE	X	X	X	X	X
ACS Sample?		X	X	X	X
No. Observations	20,729,800	4,011,100	3,997,800	2,922,700	2,922,700
R-Squared	0.010	0.009	0.007	0.007	0.003
Avg. MPC	.421	.408	.422	.392	0.530

Notes: Column 1 restricts the baseline 5 percent LEHD subsample to 2001 to 2011, the years of the ACS sample. The dependent variable in Columns 1 through 3 is $\Delta E_{i,t} = \frac{E_{i,t} - E_{i,t-1}}{.5 * E_{i,t} + .5 * E_{i,t-1}}$ at the individual i level, and the dependent variable in Columns 4 and 5 is $\Delta E_{h,t} = \frac{E_{h,t} - E_{h,t-1}}{.5 * E_{h,t} + .5 * E_{h,t-1}}$ at the household h level. Observations using the ACS subsample are weighted by the multiple of the ACS person survey weight, and their earnings share in $t - 1$ and observations in the LEHD are weighted by their earnings share. The MPC in Columns 1 through 3 is the baseline individual-level estimate used throughout the analysis. The household MPC in Column 4 is the earnings-weighted average individual MPC within the household. The MPC in Column 5 is constructed at the household level, allowing for heterogeneity by the following variables: the lagged earnings of the household, grouped into five earnings bins; a quadratic in the age of the oldest member of the household; an indicator for whether one or both members of the household are black; and the number of people in the household. Standard errors are clustered at the individual level in Columns 1 through 3 and at the household level in Columns 4 and 5.

Table A12: Decomposing the Relationship Between Worker MPCs and GDP Cyclicalty

	Baseline LEHD Sample			ACS Sample	
	Overall	Industry	Firm	Overall	Industry *Occupation
<i>Marginal Propensity to Consume</i>	1.300 (0.028)	1.151 (0.030)	1.142 (0.035)	0.926 (0.059)	0.548 (0.073)
<i>Age</i>	-0.001 (0.001)	0.003 (0.001)	0.007 (0.001)	-0.011 (0.002)	-0.003 (0.002)
<i>Female</i>	-0.491 (0.015)	-0.120 (0.016)	-0.081 (0.018)	-0.505 (0.032)	-0.112 (0.041)
<i>Black</i>	0.042 (0.026)	0.177 (0.026)	0.314 (0.029)	-0.093 (0.060)	0.028 (0.064)
<i>Lagged Earnings</i>	-0.238 (0.010)	-0.249 (0.010)	-0.275 (0.012)	-0.176 (0.018)	-0.121 (0.024)
<i>MPC with Demographics Only</i>	2.087 (0.113)	1.435 (0.112)	1.721 (0.117)	1.767 (0.153)	0.270 (0.176)
<i>MPC with Lagged Earnings Only</i>	1.093 (0.029)	1.125 (0.031)	1.090 (0.037)	0.721 (0.060)	0.565 (0.077)

Notes: Each entry reports an estimate of $\hat{\alpha}_2$ from a separate estimation of Equation 6, where $MPC_{i,t-1}$ is replaced by the specified variable in the row (i.e., MPC, worker age, etc.). Each column refers to the set of fixed effects included in the regression. Columns 1 and 4 include year fixed effects. Column 2 includes industry-year fixed effects, Column 3 includes firm-year fixed effects, and Column 5 includes industry-year-occupation fixed effects. In Columns 1 through 3, the regression sample is a 5 percent subsample of the LEHD. In Columns 4 and 5, the regression sample includes the set of individuals in both the LEHD sample and ACS. The dependent variable in all regressions is $\Delta E_{i,t} = \frac{E_{i,t} - E_{i,t-1}}{.5 * E_{i,t} + .5 E_{i,t-1}}$. All standard errors are clustered at the individual level. Observations in Columns 1 through 3 are weighted by the earnings share in $t - 1$, and observations in Columns 4 and 5 are weighted by the product of the ACS individual weight and the earnings share in $t - 1$. The standard deviation of the baseline MPC is 0.257, and the standard deviation of the demographics and lagged-earnings-only MPCs are 0.06 and 0.249, respectively.

Table A13: Heterogeneity in Earnings Elasticity Among the Unemployed

	Hires		Conditional Earnings	
	ACS	LEHD	ACS	LEHD
$MPC_{i,t-1}$	-0.430 (0.006)	-0.266 (0.001)	-1.824 (0.022)	-2.065 (0.008)
$MPC_{i,t-1} * \Delta \log GDP_t$	0.309 (0.244)	0.527 (0.048)	-0.284 (0.826)	-1.958 (0.275)
No. Observations	322,200	7,341,400	139,100	1,465,500
R-Squared	0.057	0.055	0.113	0.117

Notes: In Columns 1 and 3, the unemployed are identified using the ACS. In Columns 2 and 4, the unemployed are defined within the LEHD as the set of individuals who were employed in a sample state but are no longer employed. In Columns 1 and 2, the dependent variable is an indicator for becoming employed in $t + 1$. In Columns 3 and 4, the dependent variable is log earnings conditional on hire. In all columns, MPC is defined using hiring as the instrument for income changes. All regressions include year fixed effects.

Table A14: National Estimates of the Matching Multiplier: Including the Unemployed

	<i>Employed</i>		<i>Unemployed</i>		Unemp.	Total	% Increase
	<i>MPC^b</i>	<i>MPC^a</i>	<i>MPC^b</i>	<i>MPC^a</i>	share	MM	
ACS Sample	0.23	0.29	0.79	0.79	0.04	0.19	56.93%
LEHD Sample	0.23	0.29	0.83	0.81	0.04	0.19	55.80%

Notes: Columns 1 and 2 are taken from Row 1 of main-text Table 2. Columns 3 and 4 show the actual and the benchmark MPCs only among the unemployed, estimated using a linear specification, as in Table A13. Column 5 gives the share of the total wage bill going to new hires from unemployment. Columns 6 and 7 give the overall estimates of the matching multiplier incorporating both the employed and the unemployed. The assumed labor share is two-thirds, and I assume that the overall MPC out of non-labor income is $\overline{MPC}\beta$.

Table A15: Employment Cyclicalilty and the Local Matching Multiplier: Robustness

	Baseline	Bartik Shock	Hires-Based MPC	MPC Level	Saturated Demographics
$MM_c * Shock_t$	0.853 (0.303)	0.572 (0.203)	1.657 (0.857)	1.767 (0.776)	0.905 (0.299)
$B_c * Shock_t$	-1.748 (1.223)	-0.103 (0.075)	1.522 (1.227)	1.765 (1.092)	-0.057 (0.407)
Year FE	X	X	X	X	X
Demographic Controls	X	X	X	X	X
No. Observations	2245	1545	2028	2245	2245
R-Squared	0.751	0.776	0.812	0.749	0.799
Avg. MM_c	.199	0.123	0.076	.089	.0199

Notes: Regression includes an unbalanced panel of 270 commuting zones from 2001 to 2011. All regressions include controls for the share of employment in the two-digit industry; the average age and lagged earnings of the area; and the fraction of the commuting zone that is female, black, and in the labor force. Each control is included independently and interacted with GDP. Column 2 shows results using the Bartik shock rather than GDP. See Appendix A.5 for details on the construction of the shock. Column 3 shows estimates using hires as the identifying instrument for MPCs. Column 4 replaces \widehat{MM} and \widehat{B} with the level differences between MPC_c^a and MPC_c^b and the level of MPC_c^b , respectively. Column 5 includes demographic controls each interacted with a full set of year dummies. All regressions include year and commuting zone fixed effects. Observations are weighted by the share of employment in $t - 1$, and standard errors are clustered at the commuting zone level.

Table A16: Tradable and Nontradable Employment and the Local Matching Multiplier: Robustness

	Baseline	4-digit NAICS	Additional Controls	MPC Level
$MM_c * \Delta \log GDP_t$	1.113 (0.294)	1.116 (0.260)	0.878 (0.324)	2.949 (0.693)
$MM_c * \Delta \log GDP_t * Tradable_i$	-1.475 (0.658)	-1.034 (0.567)	-1.354 (0.714)	-5.319 (1.953)
$B_c * \Delta \log GDP_t$	-0.824 (0.479)	-0.817 (0.361)	-0.795 (0.507)	2.103 (1.095)
$B_c * \Delta \log GDP_t * Tradable_i$	1.327 (0.452)	0.777 (0.372)	1.536 (0.491)	1.129 (0.446)
Industry*Year FE	X	X	X	X
CZ*Industry FE	X	X	X	X
Demographic Controls	X	X	X	X
Financial Controls			X	
No. Observations	50269	125308	41173	50269
R-Squared	0.394	0.329	0.401	0.394

Notes: Column 1 restates the baseline estimates from Column 3 in main-text Table 4. Column 2 shows results estimated on data disaggregated to four-digit NAICS codes. Column 3 shows estimates including additional commuting zone level controls, both interacted with GDP and with a tradable indicator. Column 4 shows results using the level differences in the MPC^a and MPC^b , thus eliminating the rescaling in the calculation of \widehat{MM}_c . The dependent variable in each regression is winsorized at the 5th and 95th percentiles, as are the estimates of \widehat{MM}_c . Observations are weighted by the share of employment in $t - 1$, and standard errors are clustered at the commuting zone level.

Table A17: Robustness of Unemployment Process

			Unemployment Rate		Unemployment Duration			Replacement Rate	
	f	s	Model	CPS	Model	CPS	PSID	Model	PSID
<i>High School or Less</i>									
Non-Black Men	0.35	0.35	0.05	0.05	2.85	5.16	3.32	0.68	0.66
Black Men	0.26	0.26	0.09	0.09	3.78	6.66	3.84	0.60	0.80
Non-Black Women	0.31	0.31	0.04	0.04	3.19	5.19	2.44	0.65	0.57
Black Women	0.23	0.23	0.08	0.08	4.42	6.51	3.37	0.55	0.55
<i>Some College or More</i>									
Non-Black Men	0.32	0.32	0.02	0.03	3.16	5.55	2.36	0.65	0.63
Black Men	0.29	0.29	0.05	0.05	3.44	6.30	2.61	0.62	0.64
Non-Black Women	0.34	0.34	0.02	0.03	2.92	4.93	2.15	0.67	0.49
Black Women	0.27	0.27	0.04	0.05	3.72	6.19	2.80	0.60	0.63

Notes: Columns 1 and 2 report the average monthly job finding (f) and job separation (s) rates, respectively, calculated from the matched monthly basic CPS. Column 3 reports the unemployment rate implied by the job-finding and job separation rate ($u = \frac{s}{s+f}$) while Column 4 reports the average monthly unemployment rate in the CPS. Column 5 reports the average unemployment duration implied by the job-finding rate ($\frac{1}{f}$) while column 6 reports the average unemployment duration (in months) in the CPS. Column 8 reports the average number of months in a year that someone who is unemployed at the time of the survey will be unemployed for in the PSID. Unlike the estimate in Column 7, this measure is not restricted to a continuous unemployment spell and is truncated at 52 weeks. Lastly, Column 8 reports the model-based fraction of earnings captured by those in the unemployment state, which is the result of a simulated earnings process with 10,000 individuals and 30 years of earnings. Column 9 reports the percent difference in annual earnings for the unemployed and employed in the PSID. This is estimated on the sample used for the MPC estimation and described in detail in Section 4.1.

Table A18: Estimated Parameters for Income Process

	ρ	$\sigma_{persistent}^2$	$\sigma_{transitory}^2$	μ
<i>High School or Less</i>				
Non-Black Men	0.96	0.03	0.22	10.77
Black Men	0.94	0.04	0.31	10.45
Non-Black Women	0.95	0.05	0.30	10.13
Black Women	0.93	0.04	0.43	10.07
<i>Some College or More</i>				
Non-Black Men	0.98	0.03	0.16	11.18
Black Men	0.94	0.03	0.25	10.78
Non-Black Women	0.95	0.06	0.29	10.60
Black Women	0.95	0.04	0.30	10.43

Notes: Table reports the estimated parameters of the income process as described in Appendix Section B.3. The sample includes those who report being employed the the time of the PSID survey, are between the ages of 30 and 40, and for whom I can impute an MPC (i.e., observations with at least two lags of earnings). I include both the nationally representative sample and SEO subsample of the PSID.

Table A19: Model-Based Estimates of the Matching Multiplier

	MPC^b	MPC^a	Pct. Increase in MPC	Benchmark Multiplier	Multiplier Multiplier	Matching Multiplier	Pct. Increase in Amplification
Empirical Benchmark	0.374	0.464	24.07%	1.60	1.87	0.27	0.17
Transitory 1 % Shock	0.166	0.216	30.39%	1.35	1.55	0.21	0.15
Persistent 1 % Shock	0.394	0.518	31.35%	1.49	1.78	0.30	0.20
Anticipated Benchmark	0.165	0.216	30.82%	–	–	–	–

Notes: Column 1 shows the level decline in consumption relative to steady state in the first period in the benchmark case in which everyone gets a 1 percent income shock. Column 2 shows the level decline in consumption relative to steady state in the first period in the actual case in which everyone gets a γ_i percent income shock. Column 3 shows the aggregate MPC in the benchmark case, and Column 4 shows the aggregate MPC in the actual case, both in the first period. Column 5 shows the differences between those two MPC (i.e. Column 5 less Column 4). Column 6 shows the percentage increase in the consumption response in the actual vs. benchmark case (i.e., $\frac{\Delta C^a - \Delta C^b}{\Delta C^b}$). All rows except for the one labeled “Endogenous Interest Rate” assume that the interest rate is fixed at the steady-state level.