Does Consumption Respond to Transitory Shocks?

By Jeanne Commault*

Studies based on natural experiments find that consumption responds strongly and significantly to a transitory variation in income, while semi-structural estimations find no pass-through of transitory shocks to consumption. I develop a more robust semi-structural estimator that relaxes the assumption that log-consumption is a random walk. The robust pass-through estimate is significant and large, implying a yearly MPC of 0.32, close to the natural experiment findings. The robust estimator performs well in numerical simulations of a life-cycle model while non-robust estimators do not. The difference between the two in the simulations is similar to their difference in the survey data.
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How does individual consumption respond to transitory income shocks? The answer has implications for a number of economic questions, including the effect of fiscal policies, the relation between income and consumption inequalities, and the dynamics of business cycles. One obstacle in the way of measuring this response, however, is that transitory shocks are not usually observed directly. Instead, in longitudinal survey data, households report their total income change, without distinguishing between transitory and permanent changes.

To overcome this issue, two main solutions exist in the literature, but they yield opposite conclusions. A first approach consists in exploiting specific episodes of observed transitory income variations, such as a tax rebate or a lottery win, and pairing them with consumption data to directly measure the response of expenditures to an income shock that the researcher observes and knows to be transitory. The great majority of these studies find that transitory income changes have a statistically significant and economically large effect on consumption (see e.g. Parker et al. (2013) or Misra and Surico (2014) for the response to a tax rebate and Fagereng, Holm and Natvik (2018) for the response to a lottery win).[1] A common estimate is that the MPC of nondurable consumption is significant and around 0.25 over the three months following the transitory shock.

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[1]Section A1 of the Online Appendix provides a detailed review of this literature.

A second approach identifies the response of consumption to transitory shocks by putting more structure on the longitudinal survey data. Making assumptions about the specification of income and the way households take their consumption decisions, in particular assuming that log-income is a transitory-permanent process and log-consumption a random walk, the seminal paper of Blundell, Pistaferri and Preston (2008) (hereafter BPP) derives restrictions that can separately identify the pass-through of transitory and permanent shocks to consumption. Yet, contrary to the natural experiment findings, BPP and the subsequent studies that rely on this estimation method find that the pass-through of transitory shocks to consumption is not statistically significant, although it is precisely estimated. This influential result lead some of the later studies to directly set the pass-through of transitory shocks to zero (e.g. Blundell, Pistaferri and Saporta-Eksten (2016) and Blundell, Pistaferri and Saporta-Eksten (2018), which assume away any direct effect of a change in wealth or of a transitory income shock on consumption), or to focus only on the pass-through of permanent shocks.[2]

In this paper, I implement a semi-structural estimation method in a more robust way, that lets log-consumption depart from a random walk. I obtain an estimate that implies a significant and substantially larger average MPC of consumption to transitory shocks, above 0.32 over the year following the transitory shock, a magnitude that is consistent with the natural experiment findings.

First, I discuss how I identify the pass-through of transitory shocks when letting log-consumption depart from a random walk. As in BPP, the identification strategy relies on instrumenting the effect of current log-income growth on current log-consumption growth with future log-income growth, to filter out the contribution of the permanent shocks (which raise log-income once and for all and are thus independent of all future values of log-income growth). The difference is that I select the only value of future log-income growth that also filters out the contribution of the past transitory shocks. This relaxes the need to assume that past shocks have no effect on current log-consumption growth, that is, the need for the random walk assumption.

Contrary to this, the original BPP estimator is not robust to a departure from the random walk assumption because it does not disentangle the effect of current and past transitory shocks on log-consumption growth. More precisely, when transitory shocks have some persistence and affect log-income for more than one period, there exist several values of future log-income growth that correlate with the current transitory shocks (and are independent of the current permanent shocks). One of them is the one used by the robust estimator, but the others are affected by both the current and past transitory shocks. Because the original BPP method uses all these values as instruments, assuming away any effect of past transitory shocks on log-consumption growth, it is biased when past shocks do affect log-consumption growth. Note that, if transitory shocks were not persistent,

[2]Section A2 of the Online Appendix provides a detailed review of the literature that uses, adapts, or extends the BPP estimation method.

there would only be one value of future log-income growth that could be used as instrument and it would be the same as in the robust estimator. In that particular case, an estimator à la BPP would thus be robust to a departure from the random walk assumption. This is in fact the case considered in Kaplan and Violante (2010), and this is why the estimator à la BPP that the authors consider is robust to a departure from the random walk assumption. In the data used by BPP, however, transitory shocks are persistent and alter log-income for two periods so the estimator that BPP implement is biased when log-consumption departs from a random walk.

I also discuss the sign of the bias and note that the BPP estimator would underestimate the true pass-through of transitory shocks to consumption in a standard life-cycle model. Indeed, from the precautionary saving literature, log-consumption departs from a random walk in this standard model, and its growth is negatively affected by past transitory shocks: everything else being equal, having received a good transitory shock in the past reduces the strength of the precautionary motive, thus reduces the need to move resources to the future, and reduces log-consumption growth.[3] Because the original BPP estimator does not disentangle the effect of current and past transitory shocks on log-consumption growth, it underestimates the effect of the current transitory shocks when the effect of the past transitory shocks is negative. Other mechanisms, such as exogenous borrowing constraints or individual-specific interest rates (thus influenced by a household's past shocks), could also generate additional negative sources of correlation between log-consumption growth and past transitory shocks, thus additional sources of downward bias.

Second, I implement the robust version of the BPP estimator, which relaxes the random walk assumption, in data from the Panel Study of Income Dynamics (PSID) between 1978 and 1992, combined with consumption data imputed from the Consumer Expenditure Survey (CEX) over the same period. This data is the same as in the original BPP study, except that I additionally detrend log-income and log-consumption from the effect of past demographic characteristics—rather than detrending only from the effect of current demographic characteristics. I find that the pass-though of transitory shocks to nondurable consumption is 0.60, statistically significant at the 5% level. It implies that a lower bound on the average marginal propensity to consume (MPC) nondurables out of a transitory income shock is 0.32 over the next year, which is consistent with the estimates obtained from natural experiments. In comparison, the original BPP estimator obtains a pass-through of 0.05, not statistically significant.

I also do a step-by-step decomposition of the difference between the original

[3]Carroll (1997) notes early on that log-consumption departs from a random walk in a life-cycle model: he shows that an approximated expression of log-consumption growth includes a term that is proportional to the variance of future log-consumption growth, and this variance depends on the value of the household's level of wealth thus of past variables. Commault (2020) proves analytically that, in a standard life-cycle model, past transitory shocks correlate negatively with current log-consumption growth.

BPP estimate and the robust estimate. First, I apply the original BPP method to data detrended from past demographics, as I do with the robust estimator. The point estimate remains small and not significant though the standard error is small. Second, because the original BPP method measures the pass-through of transitory shocks jointly with other parameters while the robust estimator measures only the pass-through of transitory shocks, I drop from the original BPP method these moments that identify other parameters. There are two remaining moments: the robust estimating moment and an additional moment that does not disentangle the effect of current and past transitory shocks. I implement this simple, non-robust estimator in data detrended from past demographics. The estimate is still non-significant, with a small but precisely measured point estimate. Thus, the simple additional use of a moment that does not disentangle the effect of current and past transitory shocks is sufficient to generate a strong downward bias.

I then apply the robust estimator to different subgroups of the population: I partition the sample by levels of financial income, by levels of annual earnings, by employment status, and by homeownership status. Although the values are not statistically different across subgroups, the point estimates of the MPCs are larger among households with low financial income or low annual earnings, among households with an unemployed or retired head, and among homeowners with a mortgage.

Because the consumption data that I use is imputed, as a check, I implement the robust estimator in the more recent 1999-2017 PSID dataset, which includes direct measures of nondurable consumption so it does not have to be imputed. In this dataset, however, households are only surveyed every other year, which means that I can only estimate a biennial pass-through coefficient. I find that this biennial pass-through coefficient is close to a biennial pass-through measured in the baseline 1978-1992 PSID dataset, although consumption is imputed in one case and not in the other. Importantly, the biennial pass-through coefficients are smaller than the yearly pass-through coefficient. This is consistent with past transitory shocks having a negative impact on subsequent log-consumption growth: in the biennial estimator, a transitory shock that occurs at the beginning of the two year period raises log-consumption growth when it hits but then decreases it afterwards, so the effect over two years is milder than over one year.

Finally, to understand whether a life-cycle model—the workhorse model of consumption—could generate results that match the empirical estimates, I run numerical simulations. Until recently, life-cycle models had notorious difficulties to produce quantitatively large consumption responses to transitory shocks when the distribution of assets in the model matches the data. Investigating this, Kaplan and Violante (2014) stress the importance of distinguishing between illiquid assets, that households rarely use to smooth consumption, and liquid assets, that households do use to smooth consumption. They also show that a two-asset framework can generate large MPCs. Here, I encapsulate this insight but rely on a simplification: I build a one-asset framework that models only the liquid part of total assets. For the rest, the calibration mimics the PSID data between 1978 and 1992. Importantly, I set the persistence and variance of the transitory shocks to match what I robustly estimate in the data, and I include a decrease in consumption needs at the end of the working life (documented by e.g. Attanasio et al. (1999) and Attanasio (1999), with the particular shift around retirement documented by Aguiar and Hurst (2005), Aguiar and Hurst (2007), Hurd and Rohwedder (2013)). The model is able to produce a large pass through of transitory shocks to consumption of 0.52.

I implement different semi-structural estimators in these simulated data. The robust estimator gets close to the true value, while the original BPP estimator is strongly downward biased, with a gap between the two that is similar to the gap between the robust and non-robust survey estimates.

I. Robust estimation method

A. *Statistical model*

Log-income growth The log-income of household i at period t, detrended, that is, net of the effect of demographic characteristics, denoted $ln(y_{i,t})$, is a transitory-permanent process:

$$ln(y_{i,t}) = p_{i,t} + \mu_{i,t} + \zeta^y_{i,t} \tag{1}$$

$$\text{with } p_{i,t} = p_{i,t-1} + \eta_{i,t} \tag{2}$$

$$\mu_{i,t} = \varepsilon_{i,t} + \theta_1 \varepsilon_{i,t-1} + ... + \theta_k \varepsilon_{i,t-k}. \tag{3}$$

It is the sum of a permanent income component $p_{i,t}$ that is a random walk process, and of a transitory income component $\mu_{i,t}$ that is an MA(k) process. I additionally incorporate a shock $\zeta^y_{i,t}$, which can capture measurement error. The term $\eta_{i,t}$ is the innovation to the permanent component, and it affects log-income at all subsequent periods. The term $\varepsilon_{i,t}$ is the innovation to the transitory component, and it only affects log-income for $k + 1$ periods. Taking a first difference, the growth of detrended log-income is:

$$\Delta ln(y_{i,t}) = \eta_{i,t} + \varepsilon_{i,t} - (1 - \theta_1)\varepsilon_{i,t-1} - ... - \theta_k \varepsilon_{i,t-k-1} + \zeta^y_{i,t} - \zeta^y_{i,t-1}. \tag{4}$$

Log-consumption growth The log-consumption of household i at period t, detrended, denoted $ln(c_{i,t})$, is a flexible function of the current and past realizations of the transitory and permanent shocks. Thus, the growth in detrended log-consumption is itself a flexible function of the current and past realizations of the transitory and permanent shocks, and of $\zeta^c_{i,t}$, a shock that can be interpreted either as measurement error or as a consumption-specific shifter:

$$\Delta ln(c_{i,t}) = f_t(\varepsilon_{i,t}, ..., \varepsilon_{i,1}, \eta_{i,t}, ..., \eta_{i,1}, \zeta^c_{i,t}, ..., \zeta^c_{i,t-1}), \tag{5}$$

This specification encompasses the standard life-cycle model as a special case. Indeed, Arellano, Blundell and Bonhomme (2017) (for instance) note that the consumption rule in the standard model is a function of current assets, current permanent income, and the current transitory shock (plus past transitory shocks depending on how persistent they are). Iterating backwards, because assets is a function of past consumption, past assets, past permanent income, and past transitory shocks, and because permanent income is a function of the current permanent shock and past permanent income, consumption eventually writes as a function of all the current and past permanent and transitory shocks experienced by the household, as in (5). However, (5) is consistent with a wider range of models than the life-cycle framework, and does not even require households to solve a maximization problem.

Distributional assumptions I make the following assumptions about the distributions of the shocks in the economy:

i the shocks $\varepsilon, \eta, \zeta^y, \zeta^c$, are drawn independently from one another

ii they are drawn independently over time

iii they are drawn independently across households

However, the shocks are not necessarily drawn from the same distributions at each period, nor from the same distributions across households, since the estimation is robust to heteroskedasticity. Also, because I remove the effect of demographic characteristics with a linear regression, this means I assume that demographic characteristics are independent of the shocks that a household experiences (since these shocks are in the residual of such a regression).

Household information The model does not impose that households know about their income process, nor that they can distinguish between the transitory and permanent shocks they receive. If they do not, they will simply respond to a transitory shock in a more similar way as they would to a permanent shock.[4]

Pass-through coefficient The outcome that is measured by the BPP method, denoted ϕ^ε, is the ratio of the covariance between log-consumption growth and the contemporaneous transitory shock over the variance of the shock. Because past log-consumption $ln(c_{i,t-1})$ is orthogonal to the value of the transitory shock

[4]Although such a mistake is allowed for, the study of Druedahl and Jørgensen (2020) suggests that households have almost perfect information about the nature of the shocks they receive, and that this type of mistake is unlikely.

at t, it also coincides with the covariance between log-consumption and the contemporaneous transitory shock, over the variance of the shock:

$$\phi^{\varepsilon} = \frac{cov(\Delta ln(c_{i,t}), \varepsilon_{i,t})}{var(\varepsilon_{i,t})} = \frac{cov(ln(c_{i,t}), \varepsilon_{i,t})}{var(\varepsilon_{i,t})}. \tag{6}$$

An interpretation popularized by Kaplan and Violante (2010) is that it represents the share of the variance of the transitory shocks that is passed on to log-consumption. Note that when the shocks are drawn from different distributions, with different variances—which I allow for and which is present in the simulations of Kaplan and Violante (2010)—, the pass-through coefficient still corresponds to a weighted sum of the shares of the variance that are passed on to log-consumption in each subgroup facing the same distribution.[5]

Interpretation of the coefficient as an average elasticity Under the additional assumption either that log-consumption growth is linear in the current transitory shock (which is what BPP assumes), that log-consumption growth is quadratic in the current transitory shock and that the skewness of the shocks, $E[\varepsilon^3_{i,t}]$, is negligible, or that the transitory shocks are normally distributed, the pass-through coefficient coincides with the average elasticity of consumption to a transitory shock:

$$\frac{cov(\Delta ln(c_{i,t}), \varepsilon_{i,t})}{var(\varepsilon_{i,t})} = E\left[\frac{dln(c_{i,t})}{d\varepsilon_{i,t}}\right]. \tag{7}$$

I prove the last two result in Section B of the Online Appendix. I also present estimates of the moments of the transitory shocks distribution, which show that the skewness, $E[\varepsilon^3_{i,t}]$, is non-significant and small, although precisely estimated. This means that assuming that log-consumption is quadratic in the current transitory shock is sufficient to interpret the pass-through coefficient as an elasticity. I also find that the distribution is significantly more leptokurtic than a normal, so the normality assumption does not seem to hold.

B. *Identification: instrumenting with future income growth*

When the realizations of the shocks ε are observed, typically in the context of natural experiments, it is straightforward to measure the covariance $cov(\Delta ln(c_{i,t}), \varepsilon_{i,t})$

[5]If shocks are heteroskedastic or non-stationary so that households do not all draw their shocks from the same distributions but from J different distributions with variance ${\sigma_{j,t}}^2$ for each $j \in J$ at each period t (with enough observations in each so the empirical moments converge to their theoretical values), the variance in the sample is: $var(\varepsilon_{i,t}) = \frac{1}{N_{(i,t)}} \sum_{(i,t)} \varepsilon^2_{i,t} = \sum_{j=1}^{J} \frac{1}{N_{(i,t)\in J_j}} \sum_{(i,t)\in J_j} \varepsilon^2_{i,t} = \sum_{j=1}^{J} {\sigma_{j,t}}^2$. Eventually, the pass-through coefficient in the whole sample is a weighted sum of the pass-through coefficients within each subsample, with the weights being the share of the total variance explained by each subsample.

and variance $var(\varepsilon_{i,t})$, and to estimate the pass-through of transitory shocks. In survey data, however, the realizations of the shocks ε are not directly accessible. Only the whole income y is reported, and, from equation (4), a change in $ln(y)$ can be driven by the realizations of several different shocks: the current transitory shock, but also the current permanent shock, and the past transitory shocks (plus the change in measurement error).

Robust estimator: using only $\Delta ln(y_{i,t+k+1})$ as an instrument The solution, to isolate the effect of the current transitory shock in current log-income growth, is to use future log-income growth at $t+k+1$ as an instrument. Indeed, it correlates with the realization of the transitory shock at t but not with any of the other current or past shocks that affect log-consumption growth: the permanent shock at t is independent of all future values of log-income growth, and none of the past transitory shocks that occur before period t are still affecting $\Delta ln(y_{i,t+k+1})$. Thus, log-income growth at $t+1+k$ covaries with log-consumption growth at t only through the realization of the transitory shock at t:[6]

$$cov(\Delta ln(c_{i,t}), -\Delta ln(y_{i,t+k+1})) = \theta_k cov(\Delta ln(c_{i,t}), \varepsilon_{i,t}). \tag{8}$$

Similarly, log-income growth at t covaries with log-income growth at $t+k+1$ only through the realization of the transitory shock at t (for $k \geq 1$):

$$cov(\Delta ln(y_{i,t}), -\Delta ln(y_{i,t+k+1})) = \theta_k var(\varepsilon_{i,t}). \tag{9}$$

Therefore, an estimator of the pass-through coefficient that is robust to whether past shocks affect log-consumption growth or not is:

$$\widehat{\phi^{\varepsilon}} = \frac{cov(\Delta ln(c_{i,t}), -\Delta ln(y_{i,t+k+1}))}{cov(\Delta ln(y_{i,t}), -\Delta ln(y_{i,t+k+1}))} = \phi^{\varepsilon}. \tag{10}$$

Provided that $k \geq 1$, this robust estimator is also immune to two effects that are mentioned in the semi-structural literature as potential sources of bias: (i) measurement error, as noted by BPP themselves, and (ii) permanent and transitory shocks being uniformly distributed over the period rather than occurring discretely once at the beginning of each period, as noted by Crawley (2020). First, the presence of classical income measurement error, acknowledged in the expressions of log-income (1) and log-income growth (4) does not appear in the expression of the estimator because classical (thus non-serially correlated) measurement error only affects the covariance between log-income growth at t and at $t+1$, and not the covariance between log-income growth at t and at $t+k+1$ for $k \geq 1$. Second, when assuming that permanent and transitory shocks are

[6] The moment (8) in this paper corresponds to moment (9) in the original BPP paper, taken at their $s = k+1$ and rearranged.

uniformly distributed over the period, neither moment (8) nor moment (9) are affected. Indeed, the main problem with shocks being uniformly distributed over the period is that, because the shocks hit at some point in the middle of the period, they generate additional covariance between growth at t and at $t+1$ (the effect of the shock is partial at t and only complete at $t+1$). Using only covariance between growth at t and at $t+k+1$ for $k \geq 1$, the robust estimator is immune to this.[7]

Original BPP estimator: bias from using also $\Delta ln(y_{i,t+s}), 1 \leq s \leq k$ as instruments The original BPP estimator does not select only the value of future log-income growth that is independent of the realizations of past shocks. It uses the covariance between current log-consumption growth and all the values of future log-income growth that covary with the current transitory shock to identify the effect of this shock: $\forall\ 1 \leq s \leq k$

$$(11) \quad cov(\Delta ln(c_{i,t}), -\Delta ln(y_{i,t+s})) = (\theta_{s-1} - \theta_s) cov(\Delta ln(c_{i,t}), \varepsilon_{i,t}), \\ \underbrace{+(\theta_s - \theta_{s+1}) cov(\Delta ln(c_{i,t}), \varepsilon_{i,t-1}) + ... + \theta_k cov(\Delta ln(c_{i,t}), \varepsilon_{i,t-(k-s)-1})}_{= 0 \text{ under random walk assumption but } < 0 \text{ in life-cycle}}$$

$$(8) \quad cov(\Delta ln(c_{i,t}), -\Delta ln(y_{i,t+k+1})) = \theta_k cov(\Delta ln(c_{i,t}), \varepsilon_{i,t}),$$

with $\theta_0 = 1$. When log-consumption departs from a random walk, the terms under brace are not zero. Erroneously assuming a random walk and using the random walk versions of (11) then means neglecting this effect of past shocks on current log-consumption growth and biasing the measure of $cov(\Delta ln(c_{i,t}), \varepsilon_{i,t})$. Intuitively, the original BPP method relies on $\Delta ln(y_{i,t+s})$ as additional instruments to identify $cov(\Delta ln(c_{i,t}), \varepsilon_{i,t})$ but these instruments are endogenous when log-consumption departs from a random walk because they covary with $\Delta ln(c_{i,t})$ not only through the current transitory shock $\varepsilon_{i,t}$ but also through the past transitory shocks $\varepsilon_{i,t-1}$, ..., $\varepsilon_{i,t-k}$. I prove in Commault (2020) that, in a simple life-cycle model similar to the one presented in the BPP paper, the covariance between log-consumption growth and past transitory shocks is negative.[8] This expression would then identify the covariance with the current transitory shocks with a downward bias: the negative effect of $cov(\Delta ln(c_{i,t}), \varepsilon_{i,t-s})$ on $cov(\Delta ln(c_{i,t}), -\Delta ln(y_{i,t+s}))$ would erroneously be attributed to the fact that $cov(\Delta ln(c_{i,t}), \varepsilon_{i,t})$ is smaller than it really is.

Note that, when transitory shocks are not persistent, then $k = 0$. In that case, there are no moments (11), and the identification of $cov(\Delta ln(c_{i,t}), \varepsilon_{i,t})$ relies only

[7]This holds provided that the persistence of the transitory shock is a discrete process, and is modeled as the existence of second, third,..., $k+1^{th}$ shocks that reoccur one, two,..., k periods after the first one. Otherwise, the equation (8) and (9) are partly modified as well.

[8]Although BPP present their random walk expression of log-consumption as a second order approximation of the solution of this simple life-cycle model, I also show in Commault (2020) that their derivation implicitly assumes away precautionary terms that would not disappear around neither a second order nor a first order approximation around small shocks.

on (8), as in the robust estimator. This is the particular case studied in Kaplan and Violante (2010).

Also, in the original BPP estimator, $var(\varepsilon_{i,t})$ and the θ_s are identified from:

(12)
$$\begin{aligned} cov(\Delta ln(y_{i,t}), -\Delta ln(y_{i,t+1})) &= (1-\theta_1)var(\varepsilon_{i,t}) \\ &- (1-\theta_1)(\theta_1-\theta_2)var(\varepsilon_{i,t-1}) - ... - (\theta_{k-1}-\theta_k)\theta_k var(\varepsilon_{i,t-k}) + \underbrace{var(\zeta^y_{i,t})}_{\substack{=0 \text{ without} \\ \text{meas. error}}} \end{aligned}$$

$\forall\ 2 \leq s \leq k$

(13)
$$\begin{aligned} cov(\Delta ln(y_{i,t}), -\Delta ln(y_{i,t+s})) &= (\theta_{s-1}-\theta_s)var(\varepsilon_{i,t}) \\ &- (\theta_{s-1}-\theta_s)(\theta_s-\theta_{s+1})var(\varepsilon_{i,t-1}) - ... - (\theta_{k-1}-\theta_k)\theta_k var(\varepsilon_{i,t-(k-s)-1}) \end{aligned}$$

(9)
$$cov(\Delta ln(y_{i,t}), -\Delta ln(y_{i,t+k+1})) = \theta_k var(\varepsilon_{i,t}).$$

Thus, misspecifications in these moments can also affect the pass-through estimate from the BPP estimator. Note that the BPP paper also relies on $cov(\Delta ln(c_{i,t}), \Delta ln(y_{i,t}))$ and $cov(\Delta ln(y_{i,t}), \Delta ln(y_{i,t}))$ but they are the only moments in which $cov(\Delta ln(c_{i,t}), \eta_{i,t})$ and $var(\eta_{i,t})$ appear so they uniquely identify these values and play no role in the identification of $cov(\Delta ln(c_{i,t}), \varepsilon_{i,t})$ and $var(\varepsilon_{i,t})$.

Simple non-robust estimator To disentangle the effect of mismeasuring $cov(\Delta ln(c_{i,t}), \varepsilon_{i,t})$ because of neglecting the effect of past shocks on log-consumption growth and the effect of mismeasuring $var(\varepsilon_{i,t})$ because of neglecting measurement error (and possibly because of a uniform distribution of shocks over the period) on the pass-through estimate, I build a simple non-robust estimator that drops (12) and (13), and relies only on (8), on the random walk version (11) (conditional on the values of θ_s measured with the original BPP), and on (9).

II. Results

A. Data and estimator

Data I implement the robust estimator, based only on (8) and (9), in data from the Panel Study of Income Dynamics (PSID) between 1978 and 1992, which contains longitudinal information on income and food consumption for a representative sample of US households surveyed every year. This PSID data is combined with consumption data imputed from the Consumer Expenditure Survey (CEX) over the same period, to obtain a measure of nondurable consumption that is broader than food consumption. The main dataset is obtained from Blundell, Pistaferri and Preston (2008 dataset). To examine heterogeneity, I supplement their files with additional variables from the original files of the Panel Study of Income Dynamics (1978-1992). The sample selection and the definition of the variables are the same as in BPP, and I detail them in Section C of the Online Appendix.

Detrending from past demographic characteristics Following BPP, I detrend log-income and log-consumption from the impact of demographic characteristics by regressing them on dummies for year, year-of-birth, family size, number of children, existence of outside dependent children, education, race, employment status, presence of an additional income recipient that is not the head or spouse, region, residence in a large city, interacting most of these demographic characteristics with year dummies to allow their effect to shift with calendar time.[9] The only difference between the way I proceed and the way BPP do is that I additionally include the value of the demographic characteristics at $t-1$ in the set of regressors, to allow for some persistence in the way these characteristics affect log-income and log-consumption.

Indeed, the general rationale for using detrended values of log-consumption and log-income is to avoid capturing as shocks or as responses to shocks the covariances between the changes in demographic characteristics (e.g. the presence of new household member for a period can affect both the income and the consumption of the household, but the change in consumption might result more from the change in the composition of the household than from the pass-through of the change in income). Thus, if past demographic characteristics also influence current log-income and log-consumption, not detrending log-income and log-consumption from their effect causes the same issue.[10] When I additionally include the demographic characteristics at $t-1$ in the set of detrending variables, I find that it makes a difference in the value and in the precision of the estimate. That is why this is the specification that I use. Including the past characteristics at $t-2$ and before no longer changes the estimate (see second column of Table G1 in Section G of the Online Appendix), so I only use past values up to $t-1$.

Estimator I implement the robust estimator, based on (8) and (9), and the simple non-robust estimator, based on (8), (9) and the random walk version of

[9]The subset of characteristics that are interacted is made of education dummies, race dummies, employment status dummies, region dummies, and a dummy for residence in a large city.

[10]Formally, denoting $\kappa_t z_{i,t}$ and $\delta_t z_{i,t}$ the linear effect of demographic characteristics $z_{i,t}$ on log-income and log-consumption, the difference between using detrended and non-detrended variables is the additional presence of the term $cov(\Delta(\delta_t z_{i,t}), \Delta(\kappa_{t+2} z_{i,t+2}))$ in (8) and of $cov(\Delta(\kappa_t z_{i,t}), \Delta(\kappa_{t+2} z_{i,t+2}))$ in (9) when variables are not detrended (since by assumption changes in demographics do not covary with the shocks). These terms are non-zero in the presence of serial correlation in Δz, which is likely. When past demographic characteristics $z_{i,t-1}$ influence current log-income and log-consumption, the difference between using variables that are detrended from the effect both current and past demographic characteristics and variables that are detrended only from the effect of current demographic characteristics is the presence of the term $cov(\Delta(\delta_t z_{i,t-1}), \Delta(\kappa_{t+2} z_{i,t+1}))$ in the numerator and of $cov(\Delta(\kappa_t z_{i,t-1}), \Delta(\kappa_{t+2} z_{i,t+1}))$ in the denominator. Again, these terms are non zero in the presence of serial correlation in Δz, which is again likely.

(11), with a generalized method of moment, as detailed in Section D of the Online Appendix. I implement the original BPP estimator in the same way as the authors do in their paper (and thus obtain exactly the same estimates when I use the same data detrended in the same way as they do).

B. *Estimating moments*

TABLE 1—COVARIANCES BETWEEN $\Delta ln(y)$ OR $\Delta ln(c)$ AND PRESENT AND FUTURE $\Delta ln(y)$

Covariances	$\Delta ln(y_{i,t})$	$\Delta ln(y_{i,t+1})$	$\Delta ln(y_{i,t+2})$	$\Delta ln(y_{i,t+3})$
$cov(\Delta ln(y_{i,t}),.)$	0.0657	-0.0184	-0.0066	-0.0000
	(0.0028)	(0.0014)	(0.0012)	(0.0014)
$cov(\Delta ln(c_{i,t}),.)$	0.0093	0.0017	-0.0040	0.0000
	(0.0017)	(0.0016)	(0.0017)	(0.0016)
Obs.	7,600	7,600	7,600	6,285

Note: Consumption is nondurable consumption, detrended. Income is net income including transfers, detrended. Standard errors are in parentheses are clustered at the household level.

Covariances of log-income growth The first line of Table 1 presents the autocovariance of detrended log-income growth. The autocovariance is statistically significant up to $t+2$. At $t+3$ the autocovariance is no longer significant and the point estimate is very small, at -0.0000. This implies that, letting transitory income be an MA(k) of any length, the best fit is an MA(1). If the transitory component was an MA(0), the covariance between log-income growth at t and log-income growth at $t+2$ would not be statistically different from zero, while it is. If the transitory component was an MA(2), the covariance between log-income growth at t and log-income growth at $t+3$ would be non-zero, while it is not statistically significant and small. In the remainder, I thus assume that transitory income is an MA(1) process, $k=1$, and I denote θ the MA(1) coefficient. Note also that, if permanent income was not a random walk but an AR(1) with a coefficient different from one, the autocovariances between log-income growth at t and at all future periods would be non-zero, while they stop being statistically different from zero after two periods. Note that, however, if the AR(1) coefficient was not one but just slightly around one, non-zero covariances between log-income growth at t and at all future periods could be present but too small to be precisely estimated. This is why I still examine the consequence of having an AR(1) permanent income with a coefficient smaller than one in the alternative specifications. I find that, if anything, the pass-through is larger when permanent income is assumed to be AR(1) process (see Table F1 in Section F of the Online Appendix).[11]

[11] Also, the literature on heterogeneous income trends suggests that the true permanent income process

Covariances of log-consumption growth The second line of Table 1 presents the covariances between detrended log-consumption growth and current and future detrended log-income growth. First, it shows that the covariance between log-consumption growth and contemporaneous log-income growth is significant and positive, at 0.0093, which reassuringly suggests that fluctuations in income associate with fluctuations in consumption. Second, the covariance between log-consumption growth at t and future log-income growth at $t+1$ is not statistically significant, with a modestly positive point estimate of 0.0017, while the covariance between log-consumption growth at t and future log-income growth at $t+2$ is statistically significant and negative, at -0.0040. This is consistent with a model in which log-consumption does not evolve as a random walk. Indeed, when log-consumption is a random walk, the covariance between log-consumption growth at t and log-income growth at $t+1$ must be proportional by a factor $(1-\theta)/\theta$ to the covariance between its growth at t and log-income growth at $t+2$. These moments taking opposite signs would thus require extreme values of the persistence θ for $(1-\theta)/\theta$ to be negative: θ should either be larger than one or smaller than zero, in contradiction to the results of Meghir and Pistaferri (2004) who find that θ is between 0 and 1 in the PSID data over a similar period.[12] Relaxing the random walk assumption, however, an additional term $-\theta cov(\Delta ln(c_{i,t}), \varepsilon_{i,t-1})$ is present in $cov(\Delta ln(c_{i,t}), \Delta ln(y_{i,t+1}))$ (as seen in equation (11)), which can overturn the sign of this covariance and explain why its point estimate is slightly positive, while the covariance with log-income growth at $t+2$ is negative.

Why do I find that the covariance between log-consumption and log-income two periods later, $cov(\Delta ln(c_{i,t}), \Delta ln(y_{i,t+2}))$, is statistically different from zero at 2%, while, in BPP, a test that the covariances $cov_t(\Delta ln(c_{i,t}), \Delta ln(y_{i,t+2}))$ at each period are all equal to zero yields a p-value of 27%? There are two main reasons for that: first, what I compute in Table 1 is the covariance obtained when pooling all periods together, while what BPP tests is whether the covariances at each period—which are less precisely measured—, are all statistically different from zero; second, in my estimation, I detrend log-consumption and log-income from the effect of both current and past demographic characteristics rather than only from the effect of current characteristics. To assess the respective importance of these two elements, I compute the covariance obtained when pooling all periods together, but with data only detrended from the effect of current characteristic. It is -0.0025, statistically different from zero at 14.2%. I also implement the original BPP test, taking the covariance at each period separately, in data that have been additionally detrended from the effect of past demographics. The p-value of the

could be an AR(1) with a coefficient below one, and that the empirical autocovariances could miss the serial correlation over time that such a process implies because the data is not precise enough (Guvenen (2009)). In addition to the AR(1) process, the presence of an expected trend to future log-income growth should have the same impact as that of the anticipation of future permanent shocks, and I find that the pass-through would again be even larger under this alternative assumption (see Table F1 in Section F of the Online Appendix).

[12] See their p11 (and the θ in their paper is the opposite of the θ in this paper).

BPP test drops to 4.2%.[13] Thus, the more complete detrending accounts for a large part of the difference in significance although the doing a pooled test also contributes.

C. Pass-through of transitory shocks

Table 2—Pass-through of transitory shocks to consumption ϕ^{ε}

	Robust	BPP	BPP	Simple non-robust
Detrending past demographics	yes	no	yes	yes
Value of θ	Not required	Estimated $\hat{\theta} = 0.113$	Estimated $\hat{\theta} = 0.211$	Imposed $\theta = 0.211$
ϕ^{ε}	0.596	0.053	-0.009	0.017
	(0.273)	(0.044)	(0.047)	(0.054)
$\underline{MPC^{\varepsilon}}$	0.320	0.029	-0.005	0.009
	(0.147)	(0.023)	(0.025)	(0.029)
Obs.	7,600	9,626	9,070	7,600
Estimating moments	(8), (9)	(8), (11), (9), (12), (13)	(8), (11), (9), (12), (13)	(8), (11), (9)

Note: Consumption is nondurable consumption, detrended. Income is net income including transfers, detrended. Standard errors in parentheses are are clustered at the household level. For columns 2 and 3, I report as number of observations the number of household-year observations for which at least $\Delta ln(c_{i,t})$ and $\Delta ln(y_{i,t+1})$ or $\Delta ln(c_{i,t})$ and $\Delta ln(y_{i,t+2})$—which are required to observe (1.10) or (1.12)—are jointly observed, although some parameters that enter these moments are measured over a different and larger sample.

Robust estimator The first column of Table 2 reports the results that I obtain with the robust estimator, based on (8) and (9) only, which remains unbiased when log-consumption departs from a random walk. The pass-through of transitory shocks to nondurable consumption is large, with a point estimate of 0.596, statistically significant at 2.9%. Under the additional assumptions discussed at the end of I.A., this coefficient also corresponds to the average elasticity, so it means that, on average in the sample, a transitory shock that raises current income by 10% and next period income by $\theta \times 10\%$ is associated with a 5.96%

[13]Finally, when I compute the covariance obtained when pooling all periods together and using data that have been additionally detrended from the effect of past demographics, the covariance is -0.0039, statistically significant at 2.1%. The last difference between this covariance and the covariance of -0.0040 in Table 1 comes from the fact that, in Table 1, I compute the covariance over the set of 7,600 household-year observations that I use for estimation rather than over all the households for which this covariance is observed, as in BPP.

increase in current nondurable consumption.

Non-robust estimators The next three columns present the results obtained with non-robust estimators, which are biased when log-consumption does not evolve as a random walk, because they rely on at least one moment that assumes log-consumption growth to be independent of past shocks. Table 2 shows that these non-robust estimators yield considerably smaller estimates of the pass through coefficient.

The second column features the estimate from the original BPP estimator, applied to variables that are detrended using the same set of demographic characteristics as BPP. The estimate is therefore the same as in their paper, 0.053, not statistically significant. It is more than ten times smaller than the robust estimate.

In the third column, I apply this original BPP estimator to variables that are additionally detrended from the effect of past demographic characteristics, as I do in the baseline estimation. The point estimate remains small, at -0.009, and not statistically significant. Thus, the additionally detrending from the effect of past characteristics is not what drives the large pass-through that I obtain with the robust estimator.

With the fourth column, I further decompose the gap between the robust estimate and the original estimate, by running the simple non-robust estimator, which is similar to the robust method except for additionally using the random walk version of (11). The pass-through estimate is 0.017, not statistically significant. Thus, the simple additional use of the non-robust moment (11) is able to explain most of the drop between the robust estimate and the original BPP estimate. Note that using (11) requires knowing the value of θ, and that, for this decomposition exercise, I plug in the same value as the one estimated with the BPP method, which is possible biased. I can decompose the gap further by computing the simple non-robust estimate with a value of θ that is likely to be closer to its true value, that is $\theta = 0.5$—because this value is in the range of the estimates of θ I obtain in Section D. The estimate of the pass-through of transitory shocks remains non-significant and modest, at 0.159.[14]

Marginal Propensity to Consume (MPC^{ε}) In order to compare the robust pass-through estimate with the findings from natural experiments, I compute the MPC that the pass-through implies, as it is the MPC that natural experiments typically measure: $MPC_{i,t}^{\varepsilon} = \left(\partial c_{i,t}^{not.det.} / \partial \varepsilon_{i,t}\right) / \left(\partial y_{i,t}^{not.det.} / \partial \varepsilon_{i,t}\right)$. I compute the

[14]In fact, the estimate obtained with the random walk version of (11) and (9) alone is negative regardless of the value of θ that is used, and it decreases as θ increases. On the contrary, the estimate of the simple non-robust estimator, which uses the three moments (8), the random walk version of (11), and (9), increases as θ increases. This is because, in the simple non-robust estimator, as θ increases, the variance of the estimate associated with (11) also increases, and less weight is put on the identification from (11) relative to the identification from (8) so the estimate gets closer to the larger value obtained with the robust estimator.

MPC of nondetrended consumption, denoted with a superscript *not.det.*, because most natural experiments measure the response of non-detrended consumption (or detrend only from year effects and changes in the size of the households).[15] The relation between the MPC and the elasticity of consumption $\partial ln(c_{i,t})/\partial\varepsilon_{i,t}$ is:

$$MPC^{\varepsilon}_{i,t} = \frac{\partial c^{not.det.}_{i,t}/\partial\varepsilon_{i,t}}{\partial y^{not.det.}_{i,t}/\partial\varepsilon_{i,t}} = \frac{1}{y^{not.det.}_{i,t}}\frac{\partial c^{nd}_{i,t}}{\partial\varepsilon_{i,t}} = \frac{c^{not.det.}_{i,t}}{y^{not.det.}_{i,t}}\frac{\partial ln(c_{i,t})}{\partial\varepsilon_{i,t}}, \tag{14}$$

A difficulty is that I do not measure the individual elasticities, $\partial ln(c_{i,t})/\partial\varepsilon_{i,t}$, but only the pass-through coefficient, which is a proxy of the average elasticity, $\phi^{\varepsilon} \approx E[\partial ln(c_{i,t})/\partial\varepsilon_{i,t}]$. Under the assumption that all households have the same elasticity, the average and individual elasticities coincide. Under the assumption that the households with the highest elasticity (who respond most) are on average those with the highest ratios of consumption over income (who consume the largest share of their income),[16] a lower bound of the average MPC is:

$$\underline{MPC}^{\varepsilon} = E[\frac{c_{i,t}}{y_{i,t}}]\phi^{\varepsilon} \approx E[\frac{c_{i,t}}{y_{i,t}}]E[\frac{\partial ln(c_{i,t})}{\partial\varepsilon_{i,t}}] \leq E[\frac{c_{i,t}}{y_{i,t}}\frac{\partial ln(c_{i,t})}{\partial\varepsilon_{i,t}}] = E[MPC^{\varepsilon}_{i,t}]. \tag{15}$$

Because the average ratio of nondurable consumption over income is roughly one-half, the lower bound for the average MPC is roughly one-half of the average pass-through coefficient: households consume on average at least 32% of the change in current income caused by a current transitory shock.

MPC out of a hypothetical non-persistent shock A difference between the shocks observed in natural experiments and the transitory shocks identified in survey data is that the latter are more persistent, they correspond to the innovations of an MA(1) process, while the former are non-persistent shocks, the innovations of an MA(0) process. To get a sense of what would be the response of consumption to a hypothetical non-persistent shock, I consider two extreme cases. First, assuming that current consumption does not respond at all to an increase in future income (e.g. because households are constrained and cannot borrow against future income), the MA(1) structure makes no difference, and a household responds to the innovation of an MA(1) process as it would to the innovation of an MA(0) process. Thus the lower bound MPC out of a hypothet-

[15]The MPCs of non-detrended and detrended consumption are different, because the effect of demographic characteristics is multiplicative on the level of consumption. Thus, whether or not demographic characteristics respond, the MPC of non-detrended consumption is proportional to the effect of demographics while the MPC of detrended consumption is not. Contrary to that, the elasticities of detrended and non-detrended consumption are the same (when, as assumed, demographics affect log-consumption linearly and are independent of the income shocks)

[16]I examine this assumption and find that, for instance, among the households with a ratio of consumption over income below 30% , the pass-through is 0.542, while among the households with a ratio of consumption over income above 30%, the pass-through is 0.605.

ical MA(0) process is $\underline{MPC}_{i,t}^{MA(0)\,\varepsilon} = \underline{MPC}_{i,t}^{\varepsilon} = 0.320$. Second, assuming that current consumption responds to an increase in the net present value of future income exactly in the same way as it does to an increase in current income, the MPC out of an MA(1) innovation is $1 + \theta(1+r)^{-1}y_{i,t+1})/y_{i,t}$ larger than the MPC out of an MA(0) innovation. Assuming that the persistence of a transitory shock is $\theta = 0.50$ and the interest rate on the risk-free assets is $r = 0.02$, the lower bound MPC is $\underline{MPC}^{MA(0)\,\varepsilon} = 0.211$. Thus, the MPC out of a hypothetical MA(0) innovation is at least 0.211 in the sample.

Comparison with the literature on natural experiments How do the pass-through coefficient and the MPC that I estimate compare with the results derived from natural experiments? Although different studies consider different types of shocks, positive (e.g. tax rebate) and negative (e.g. government shutdown), most of them finds that the MPC associated with nondurables out of a transitory income shock is statistically significant. The point estimates vary from a MPC of 0.09 over the next three months (Souleles (1999) who consider only a narrower category of nondurables than other papers) to a MPC of 0.37 over the next three months (Johnson, Parker and Souleles (2006)). Section A1 in the Online Appendix details this literature. These findings are broadly consistent with the result that the MPC out of an MA(1) shock is statistically significant and above 0.32 over the next year (and the MPC out of an MA(0) innovation above 0.21 over the next year).

Dynamics Making additional assumptions about the variance of measurement error (and about whether the income shocks are discreetly or continuously distributed), I use a version of (11) that does not assume a random walk and a version of (12) that allows for measurement error (and possibly for continuous shocks), to estimate the dynamics of the response: the pass-through of past transitory shocks to current log-consumption growth. Consistent with the direction of the bias that I observe in the BPP method, I find that past transitory shocks affect negatively current log-consumption growth, which implies that a transitory shock raises contemporaneous log-consumption more than it raises log-consumption after one year, therefore, that the response to a transitory shock is short-lived. However, the estimates are not very precise, and the pass-through to contemporaneous consumption is statistically different from the pass-through to later consumption in only one of the five specifications that I consider. Incidentally, I find that, in some specifications, a transitory shock at t raises log-consumption at t but actually reduces log-consumption at $t+1$. I present the assumptions, the estimating restrictions, and the detailed results in Section E of the Online Appendix.

Alternative specifications I consider a number of variations from the baseline specification: making the permanent income process an AR(1) rather than a random walk, allowing for the anticipation of the shocks, and allowing for serial correlation in measurement error (and not only for classical measurement error). The pass-through of transitory shocks remains significant and large under these three sets of alternative assumptions. I present the specifications and results in Section F of the Online Appendix.

Variations in demographic characteristics, interactions, clusters, and measures of consumption and income I check the sensitivity of the results to variations in the set of demographic characteristics that I use for detrending, and to variations in the set of variables by which I interact the effect of the demographic characteristics. I find that the results are robust to such variations. I also present the results that I obtain with other measures of consumption (food and total consumption, including durables), and with other measures of income (gross income and gross income before transfers). These alternative measures of consumption and income still suggest a large pass-through of transitory shocks to consumption, although they are consistent with taxes and transfers providing some insurance against transitory fluctuations. I present these results in Section G of the Online Appendix.

D. Heterogeneity

Table 3 shows the estimates that I obtain when I partition the sample and run the robust estimator separately on different subgroups. The partitions are by levels of financial income from liquid assets,[17] by levels of annual earnings, by employment status, and by homeownership status. The way these variables are constructed is described in section C of the Online Appendix. The cut-off points for the subgroups of financial income from liquid assets are 'no income from liquid asset', 'income from liquid asset below \$1,500', and 'income from liquid asset strictly above \$1,500' (in 1982-84 \$). The cut-off points for the subgroups of annual earnings are 'below \$15,000', 'strictly above \$15,000 and below \$35,000', and 'strictly above \$35,000' (in 1982-84 \$). The lines titled 'p-values of equality test' present the p-values of testing the equality of the pass-though coefficients between two subgroups, and indicate that the point estimates are not statistically different across subgroups for any of the partitions considered: none of the p-values are below 0.10. Although they are not statistically different, Table 3 still shows that the point estimates are quite different across subgroups, so the lack of statistical differences is likely to stem from the imprecision of the estimation on these subsamples rather than from the fact that the pass-though coefficients are the same. In terms of ranking, the point estimates of the MPCs are larger among households with low financial income from liquid assets, with low annual earnings,

[17] There are no direct measures of liquid assets in pre-1999 PSID data, which is why I use financial income from liquid assets as a proxy.

Table 3—Estimates in different subgroups

	Robust estimator					
	Financial income from liquid assets			Annual earnings		
	Low	Middle	High	Low	Middle	High
ϕ^{ε}	0.710	0.612	0.374	0.584	0.638	0.524
	(0.327)	(2.162)	(0.358)	(0.571)	(0.297)	(0.544)
p-values of equality test	Low-Middle: 96% Low-High: 49% Middle-High: 91%			Low-Middle: 93% Low-High: 94% Middle-High: 85%		
$\underline{MPC^{\varepsilon}}$	0.409	0.304	0.198	0.504	0.361	0.215
	(0.188)	(1.076)	(0.189)	(0.494)	(0.169)	(0.223)
Obs.	3,044	2,431	2,125	1,039	3,180	3,381

	Employment status			Homeownership status	
	Employed	Unemployed	Retired	Owner with mortgage	No mortgage or renter
ϕ^{ε}	0.432	1.213	0.760	0.796	0.322
	(0.292)	(0.466)	(1.581)	(0.389)	(0.450)
p-values of equality test	Employed-Unemployed: 14% Employed-Retired: 84% Unemployed-Retired: 79%			With mortgage- No mortgage: 43%	
$\underline{MPC^{\varepsilon}}$	0.226	0.679	0.540	0.400	0.193
	(0.153)	(0.266)	(1.127)	(0.195)	(0.269)
Obs.	6,871	176	553	4,543	2,063

Note: Consumption is nondurable consumption, detrended. Income is net income including transfers, detrended. Standard errors in parentheses are are clustered at the household level. The assignation of an observation to a subgroup is based on the characteristics of the household at the observation year (i.e. at the year when log-consumption growth is observed).

whose head is either unemployed or retired, and with a mortgage on their home. I present additional partitions by age, female and male earnings, education level, and year of birth in Section H of the Online Appendix. The differences across subgroups are not significant in these additional partitions either.

Comparison with the literature on natural experiments Natural experiment studies commonly find that households with more liquid wealth respond more, consistent with the finding that the categories of 'low financial income from liquid assets' and 'owner with a mortgage' have a higher point estimate. These studies also find that even the categories that respond the least still respond quite substantially.[18] This is consistent with the results presented here, as Table

[18]For instance, Parker (1999) finds that households with a younger male head have a higher quarterly

3 shows that the point estimates of the MPCs are above 0.193 in all the subgroups.

Specification check Under the assumptions that I make, the point estimate of the pass-through corresponds to the average pass-through in the population. This implies that, when partitioning the sample into subgroups, the (weighted) average of the subgroup point estimates should broadly coincide with the estimate over the full sample (0.596). This is close to what I find, confirming that the specification seems to fit.

E. *Biennial pass-through and 1999-2017 PSID data*

TABLE 4—ESTIMATES FOR DIFFERENT OBSERVATION PERIODS

	Robust estimator		
Period	One year	Two years	Two years
Dataset	1978-1992	1978-1992	1999-2017
ϕ^{ε}	0.512	0.254	0.125
	(0.236)	(0.123)	(0.062)
$\underline{MPC}^{\varepsilon}$	0.275	0.141	0.040
	(0.127)	(0.068)	(0.019)
Obs.	7,600	5,322	11,954

Note: Consumption is nondurable consumption, detrended. Income is net income including transfers, detrended. Standard errors in parentheses are are clustered at the household level.

Biennial pass-through A number of studies apply the method developed by BPP to data that is recorded biennially instead of yearly, which has become more widely available—the PSID itself became biennial in 1999. These studies change the duration of the period from one year to two years and adapt to transitory income being an MA(0) process over the period. Yet, I note that the pass-through coefficient is not the same in biennial data as in yearly data. With the same

elasticity to a change in take-home pay, but the elasticity among the older group is still 0.466 (his Table 5). Fagereng, Holm and Natvik (2018) compute the effect of a lottery win by quartiles of households' level of liquid assets, and by quartiles of age. They find that, for each partition, most of the differences across quartiles are significant, so variations in level of liquid assets and age make a difference. Yet, despite these differences, households in the highest quartile of liquid assets still have an average yearly elasticity of total consumption of 0.459, statistically significant (their Table 8), and households in the highest quartile of age still have an average yearly elasticity of total consumption of 0.436, statistically significant (their Table 9).

income process, the two are:[19]

$$\phi_2^{\varepsilon} = \frac{cov(\Delta ln(c_{i,t}) + \Delta ln(c_{i,t-1}), \varepsilon_{i,t} + \theta\varepsilon_{i,t-1})}{var(\varepsilon_{i,t} + \theta\varepsilon_{i,t-1})} \quad vs \quad \phi^{\varepsilon} = \frac{cov(\Delta ln(c_{i,t}), \varepsilon_{i,t})}{var(\varepsilon_{i,t})},$$

with ϕ_2^{ε} the biennial pass-through and ϕ^{ε} the yearly pass-through. If log-consumption evolves as a random walk, the biennial pass though should approximately be larger by a coefficient $(1+\theta)/(1+\theta^2) > 1$ when $\theta < 1$—approximately, that is, assuming the sample is long enough so that the pooled covariances and variances are approximately equal, $cov(\Delta ln(c_{i,t}), \varepsilon_{i,t}) \approx cov(\Delta ln(c_{i,t-1}), \varepsilon_{i,t-1})$ and $var(\varepsilon_{i,t}) \approx var(\varepsilon_{i,t-1})$. However, if log-consumption departs from a random walk, a negative covariance between its growth at t and the transitory shocks that occur in the middle of the two-year period, $\varepsilon_{i,t-1}$, reduces the value of the biennial pass-through coefficient. Intuitively, when the period is short, the pass-through coefficient only captures the positive effect of the transitory shock on contemporaneous log-consumption growth. Over a longer period of time, shocks occur several times over the period. The transitory shocks that occur at the beginning of the period have a positive effect on log-consumption growth at the beginning of the period, but also a negative effect on log-consumption growth at the end of the period, which pushes down the value of the pass-through coefficient.

To quantify the difference empirically, I estimate both coefficients in the same data, that is, in the baseline, yearly 1978-1992 PSID dataset. The estimator of the biennial pass-through is:

$$\hat{\phi}_2^{\varepsilon} = \frac{cov(\Delta_2 ln(\tilde{c}_{i,t}), -\Delta_2 ln(\tilde{y}_{i,t+2}))}{cov(\Delta_2 ln(\tilde{y}_{i,t}), -\Delta_2 ln(\tilde{y}_{i,t+2})) - var(\zeta_{2_{i,t}})}, \tag{16}$$

with Δ_2 the growth of a variable over two years,[20] and $var(\zeta_{2_{i,t}})$ the variance of measurement error over two years. To be conservative, I set $var(\zeta_{2_{i,t}})$ to be as large as the variance of the transitory income shocks over two years (and a large variance of measurement error raises the estimated value of the biennial pass-through coefficient). I consider gross income rather than net income, because it reduces the possibilities of discrepancies between the 1978-1992 and the 1999-2017 dataset when I later compare them. From the first two columns of Table 4, the yearly pass-through of transitory shocks to gross income in the 1978-1992 PSID dataset is 0.512, statistically significant at 5%, while the biennial pass-through is substantially smaller, at 0.254, statistically significant at 5%. This is consistent with the presence of a strong, negative correlation between log-consumption growth at t and past transitory shocks at $t-1$. It also means that one should be

[19] I detail the computation of this expression of the biennial pass-through coefficient in Section I of the Online Appendix.

[20] Although I build growth over two years, I observe it every year, since the sample is yearly. I could have arbitrarily dropped observations every other year, but I would have lost observations and the sample would have been even more different from the one on which I measure the yearly pass-through.

careful when comparing biennial and yearly pass-through estimates, as they do not capture the same thing.

Comparison with non-imputed data (1999-2017) This exercise also makes it possible to check the quality of the consumption data that I use: I estimate the biennial pass-through in the more recent waves of the Panel Study of Income Dynamics (1999-2017), which are biennial but in which consumption is observed directly and does not have to be imputed. This data is detailed in Section C of the Online Appendix. The definition of consumption includes almost the same goods as in the baseline definition except for personal care and clothing. I compare this estimate with the biennial pass-through measured in the baseline dataset, in which consumption is imputed. Given the difference in period (thus probably type and variance of shocks) and the slight difference in the consumption goods included, the two point estimates are not too different: it is 0.125 in the 1999-2017 dataset without imputation, and 0.254 in the baseline dataset.

III. Comparison with simulations from a life-cycle model

A. Model and calibration

Household's maximization problem To understand whether these empirical estimates are consistent with a life-cycle model, the workhorse model of consumption studies, I calibrate and simulate such a model. Households i choose their consumption at period t, $c_{i,t}$, in order to maximize their expected intertemporal utility, which the sum of their utility at each period: $\sum_{s=0}^{T-t} \beta^{t+s} e^{\delta_{t+s} z_{i,t+s}} E_t \left[u(c_{i,t+s})\right]$. A period is a year. The period utility $u(.)$ is a log-utility function. The discount factor is $\beta = 0.97$. The demographic characteristics z are constant up to age 53, and after that, the change in demographics is such that $e^{\Delta \delta_{t+s} z_{i,t+s}} = 0.965$. This is to match the hump-shaped pattern of consumption over the life-cycle, which is typically attributed to a life-cycle shift in consumption needs (see e.g. Attanasio et al. (1999) and Attanasio (1999)), including a drop around retirement documented in Aguiar and Hurst (2005), Aguiar and Hurst (2007), and Hurd and Rohwedder (2013)). I choose age 53 because it is the year after which I observe a steady decrease in consumption in the baseline PSID dataset, and choose the 0.965 coefficient to match a ratio of consumption at age 53 over consumption at age 65 of 1.5, close to what I observe in the baseline PSID dataset. Note that, although I detrend log-consumption and log-income from deterministic demographic shifters, it matters whether or not such shifters are present, because they interact with the strength of the precautionary motive: households' need for precautionary saving is not the same when they do not put a large weight on the value of future consumption and when they do.

Budget and borrowing constraints Households only have access to a risk-free and perfectly liquid asset a to store their wealth, which means that at each period

$t + s$ they face the following budget constraint: $a_{i,t+s+1} = (1 + r)a_{i,t+s} - c_{i,t+s} + y_{i,t+s}$, with $y_{i,t}$ the income earned by household i at period t. The yearly interest rate on the risk-free asset is $r = 0.02$. I set the initial wealth to replicate the empirical distribution of wealth for young households (I use the data from Kaplan and Violante (2010 dataset) whose calibration is based on young households in the Survey of Consumer Finances (SCF)).[21]

In addition to the period budget constraints, households face a borrowing limit at \$15,000, an amount that is little more than the average value of one year of nondurable consumption (cf Table 5). This limit is not supposed to represent the maximum amount of debt that households could hold, but the maximum amount they could hold to finance consumption (thus excluding the financing of a house or of a business investment), since the framework only models these expenses. Indeed, as Kaplan and Violante (2014) note the importance of the distinction between liquid assets, which are used to smooth nondurable consumption, and illiquid assets, which are rarely used to smooth nondurable consumption, I abstract from illiquid wealth and choose a borrowing constraint that is consistent with the holdings of liquid wealth.

Life-cycle Households are modeled from age 30 on, an age at which they are all assumed to be in the workforce. They all retire at age 65. After retirement, they have a non-zero probability to die at each period from age 65 to age 80. The probabilities are obtained from the National Center for Health Statistics (I use the data from Kaplan and Violante (2010 dataset)). If still alive, a household dies with certainty at age 80.

Income The income that households earn at each period is stochastic when they are working, and is a deterministic function of their past income when they retire. The modeling of income follows that of Kaplan and Violante (2010), except for the transitory income process, which they set to be an MA(0) with a variance taken from the (potentially biased) estimate in BPP. Instead, I let transitory income be an MA(1) process, as it is in the PSID dataset. I set the persistence at $\theta = 0.50$, to be withing the range of estimates I obtain when looking into the dynamics of the response of consumption.[22] I also calibrate the variance of the transitory shocks from my estimation (based on expression (9) and expression (E3) in Section E of the Online Appendix), at ${\sigma_\varepsilon}^2 = 0.007$, which is lower than the BPP estimate. Apart from these adjustments, I take the variance of the permanent shocks and the same deterministic age profile for log-income Γ from Kaplan and Violante (2010 dataset). I also use the same initial variance of the permanent shocks, at ${\sigma_{\eta_0}}^2 = 0.15$, which they set to match the dispersion in household earnings at the

[21] Kaplan and Violante (2010) additionally tie initial wealth to initial income, which I do not: instead of multiplying Kaplan and Violante's distribution of initial wealth with the household's initial income draw, I multiply it by the average income draw.

[22] Table E1 in Section E of the Online Appendix shows that robust estimates of θ range from 0.385 to 0.857.

beginning of working age observed in the PSID. The modeling of social benefits is also identical to the one implemented by Kaplan and Violante (2010), which mimics the US legislation.

Measurement error To be closer to what a survey dataset would resemble, I introduce classical measurement error in the simulations. More precisely, I add to the true values of log-consumption and log-income a noise variable, drawn from a normal distribution with mean zero and variance 0.01.[23]

Tax rebate shock I also simulate the effect of a shock that resembles the ones used in natural experiments. For each household, I compute an additional trajectory of consumption, the one that would take place if they received at age 40 a tax rebate of \$600—a value chosen because in the 2008 tax rebate in the US, single individuals received \$300–\$600 and couples received \$600–\$1,200. I compute the MPC as the difference between the consumption observed when the households received the tax rebate and the consumption observed when they do not receive it, everything else being equal (that is, all shocks being exactly the same for each individuals), divided by the size of the shock, \$600.

B. *Simulation and model fit*

Simulation I simulate an artificial panel of 2,000 households, and I solve the model using the method of endogenous grid points developed by Carroll (2006).[24] I then select households age 30-65. For estimation, I detrend log-income and log-consumption from life-cycle effects by regressing them on year dummies.

Table 5—Goodness of fit statistics

	Mean cons.	Std. dev. cons.	Mean inc.	Std. dev. inc.	Corr(cons.,inc.)
PSID data	14,430	8,104	32,661	22,534	0.365
Simulations	13,891	8,575	36,534	24,672	0.940

Note: The values from the PSID data are in 1982-1984 \$. There is no inflation in the numerical simulations.

Model fit Table 5 presents some moments of nondurable consumption and income both in the PSID data and in the simulated data (before detrending). Al-

[23] I calibrate this from Meghir and Pistaferri (2004) who estimate the variance of measurement error to be 0.0138 in the PSID, for the pooled sample (the first column of their Table III).

[24] The number of gridpoints is as follows: the grid for assets has 150 exponentially spaced grid points; the grid for lifetime average earnings has 11 equally spaced points; the grid for the permanent component of income is age-varying and at each age has 25 equally spaced points; the grid for the transitory shock has 15 equally spaced points.

though there is no distinction between durable and nondurable consumption in the model, with only one consumption good, such distinction exists in the data, so I set nondurable consumption in the model to be 40% of total consumption. This 40% is the ratio that I observe in the PSID data.[25] The moments in Table 5 are not directly targeted by my calibration—nor by the calibration of Kaplan and Violante (2010) that I broadly follow. It shows that the model is able to replicate quite closely the level and variance of nondurable consumption and income: the level of nondurable consumption is \$13,891, only 4% smaller than in the PSID data; the variance of nondurable consumption is \$8,575, which is 6% larger than in the PSID data; the level of income is \$36,534, which is 12% larger than in the PSID data; the variance of income is \$24,672, which is 9% larger than in the PSID data. However, the correlation between consumption and income is not fitted as well by the model: it is two times and a half larger in the simulations than in the PSID data. One explanation could be that the variance of the permanent shocks (which I simply take from Kaplan and Violante (2010)) is smaller than what I calibrate, while the variance of individual-specific income and consumption shocks as well as the variance of measurement error is larger.

C. *Estimation results*

Table 6—Pass-through of transitory shocks to consumption ϕ^{ε}

	True values	Estimators		
		Robust	BPP	Simple non-robust
$cov(\Delta ln(c_t), \varepsilon_{t-1})$	$cov = -0.176$			
Value of θ	$\theta = 0.500$	Not required	Estimated $\hat{\theta} = 0.186$	Imposed $\theta = 0.186$
ϕ^{ε}	0.547	0.532	0.085	0.148
		(0.041)	(0.009)	(0.009)
MPC out of tax rebate and $\underline{MPC}^{\varepsilon}$	0.255	0.210	0.034	0.058
		(0.016)	(0.004)	(0.004)
Obs.	68,000	68,000	68,000	68,000

True values Because the data is simulated, the shocks are directly observed, and the first column of Table 6 presents the true relation between consumption and the transitory shocks in the model. First, the line '$cov(\Delta ln(c_{i,t}), \varepsilon_{i,t-1})$' shows

[25]In the PSID sample, the ratio of nondurable consumption over total consumption is 43%.

that log-consumption substantially departs from a random walk, as the true covariance between log-consumption growth and past transitory shocks is large and negative, at -0.176. Second, the pass-through of transitory shocks to consumption is $\phi^{\varepsilon} = 0.547$, which is large, and only a little below the empirical PSID estimate of $\phi^{\varepsilon} = 0.596$. Third, the MPC of nondurable consumption out of a transitory \$600 tax rebate is 0.255 over the next year—whether or not this is close to the natural experiment findings that the MPC is around 0.25 over the next three months depends on how consumption responds over the following nine months, which is usually imprecisely measured in natural experiments.

Performance of the different estimators The robust estimator, which allows for a departure from the random walk assumption, yields a measure that is close to the true value, with a point estimate of 0.532, close to the true value of 0.547. This confirms the robustness of this estimator, which performs well even in a model in which log-consumption departs from a random walk. On the contrary, the two other estimators, which are not robust to a departure from the random walk assumption, strongly underestimate the pass-through of a transitory shock to consumption. The original BPP estimator obtains a point estimate of 0.085, largely below the true value. Also, consistent with the results I obtain when I make additional assumptions to estimate θ and find it to be larger than the original BPP estimate,[26] I find that the original BPP method underestimates the persistence of the transitory shocks in these simulations: its point estimate of θ is only 0.186 when the true value is 0.5. Finally, the simple non-robust estimator also underestimates the pass-through coefficient, with a point estimate of 0.148. Thus, in this life-cycle model as in the PSID data, the simple use of an additional non-robust moment drives a large downward bias in the estimation.

MPC out of a tax rebate Having simulated a tax rebate shock, I can examine how the true MPC out of this MA(0) shock compares with the estimate of the lower bound on the MPC out an MA(1) shock. The second column shows that this lower bound is 0.210. This is not too different from the MPC out of the tax rebate, despite the fact that the two shocks do not have the same statistical properties. It means that, if a life-cycle model is the true generating process behind the PSID data, the lower bound estimate is below but close to the true MPC out of a non-persistent shock.[27]

Sensitivity analysis I conduct a number of variations in the calibration of all the main parameters to examine how sensitive the results are to my choices. These

[26] When I estimate θ to examine the dynamics of the response, I find it to be between 0.385 and 0.857 (Table E1 in the Online Appendix), while the original BPP estimator applied to the same fully detrended data yield an estimate of $\theta = 0.211$.

[27] Note that the estimate of the lower bound on the MPC out of a hypothetical non-persistent shock under the limit assumption that households treat future income in the same way as current income—which does not hold exactly in the life-cycle model—, is 0.140.

include variations in the persistence θ of the transitory shocks, in the variances of the transitory and permanent shocks, in the discount factor and interest rate, in the value of the borrowing limit, in the initial distributions of permanent income and assets, in the length of the retirement period, and in the value of the demographic shifter after age 53. The detailed results are presented in Tables J1 and J2, in Section J of the Online Appendix. The true pass-through coefficient appears most sensitive to the calibration of the variance of the shocks, and to that of the deterministic determinants of log-consumption growth—the discount factor, the interest rate, and the demographic shifter.[28] However, the pass-through generated by the model remains above $\phi^{\varepsilon} = 0.33$ in all the variations I consider, thus even under conservative assumptions about these deterministic determinants of log-consumption growth. The estimates from the robust version of the BPP estimator are close to the true values in all these variations, except when transitory income is an MA(0)—in which case the robust estimator is no longer valid. The non-robust estimators, which are biased when log-consumption is not a random walk, underestimate the true coefficients in all these variations as well.

Random walk model I verify in Section K of the Online Appendix that when data is simulated from a model in which log-consumption is a random walk, all three types of estimators are close to the true value.

IV. Conclusion

In this paper, I clarify that the BPP semi-structural estimation method, commonly used in several literatures to measure the pass-through of shocks to consumption, is biased when log-consumption is not a random walk. Indeed, it does not disentangle the effect of current and past transitory shocks. This leads to a downward bias when past transitory shocks have a negative effect of subsequent log-consumption growth, as is the case in a standard life-cycle model because of precautionary motives.

I develop a more robust estimator that remains unbiased when log-consumption departs from a random walk, and implement it in the same data as the original BPP estimator. The pass-through of transitory shocks to consumption becomes statistically significant and large, with a point estimate of 0.596, which is more than ten times larger than the point estimate obtained with the original BPP method. This robust pass-through estimate implies that the average marginal propensity to consume nondurables out of a change in transitory income is at least 0.320 over the next year, which is consistent with the results obtained in natural experiments of transitory income changes.

These findings have two consequences. First, the similarity in estimates between the robust semi-structural method and the natural experiment studies sug-

[28]Note also that, even with an MA(0) process, the true value remains quite large, at 0.465, consistent with the finding of Druedahl and Jørgensen (2020) that shifting from an MA(0) to an MA(1) transitory process only changes modestly the pass-through coefficient.

gests that the strong response of consumption to a transitory income shock is a widespread phenomena, and not a finding limited to fiscal stimuli and lottery wins. Second, the magnitude of the change in results, when shifting from a non-robust to a robust estimator implies some caution in the use of semi-structural techniques that are not robust to a departure from the random walk assumption to estimate other parameters, including the pass-through of permanent shocks.

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