Web Appendix to
"Habit Formation in Consumption: A Meta-Analysis"*

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Abstract

This appendix provides supplementary statistics and tests of publication bias. While we find some indications of publication selection related to the 0 and 1 thresholds that define the range consistent with habit formation, we find little evidence of any systematic bias resulting from this selection.

1 Box Plot

Figure 1 shows a box plot of the estimates that we include in our data set. Three features of the data stand out. First, most studies tend to report estimates lying between 0 and 1; that is, estimates that are consistent with the habit formation hypothesis (estimates above 1 are inconsistent with theory, while negative estimates reject habit formation in favor of durability of the consumption good under investigation). Second, even in the 0–1 range the estimates differ substantially within and between studies, with values around 0.5 being the most common. Third, estimates rejecting habit formation are not rare, and appear on both sides of the distribution. In the literature we generally encounter estimates lying between −2 and 2.

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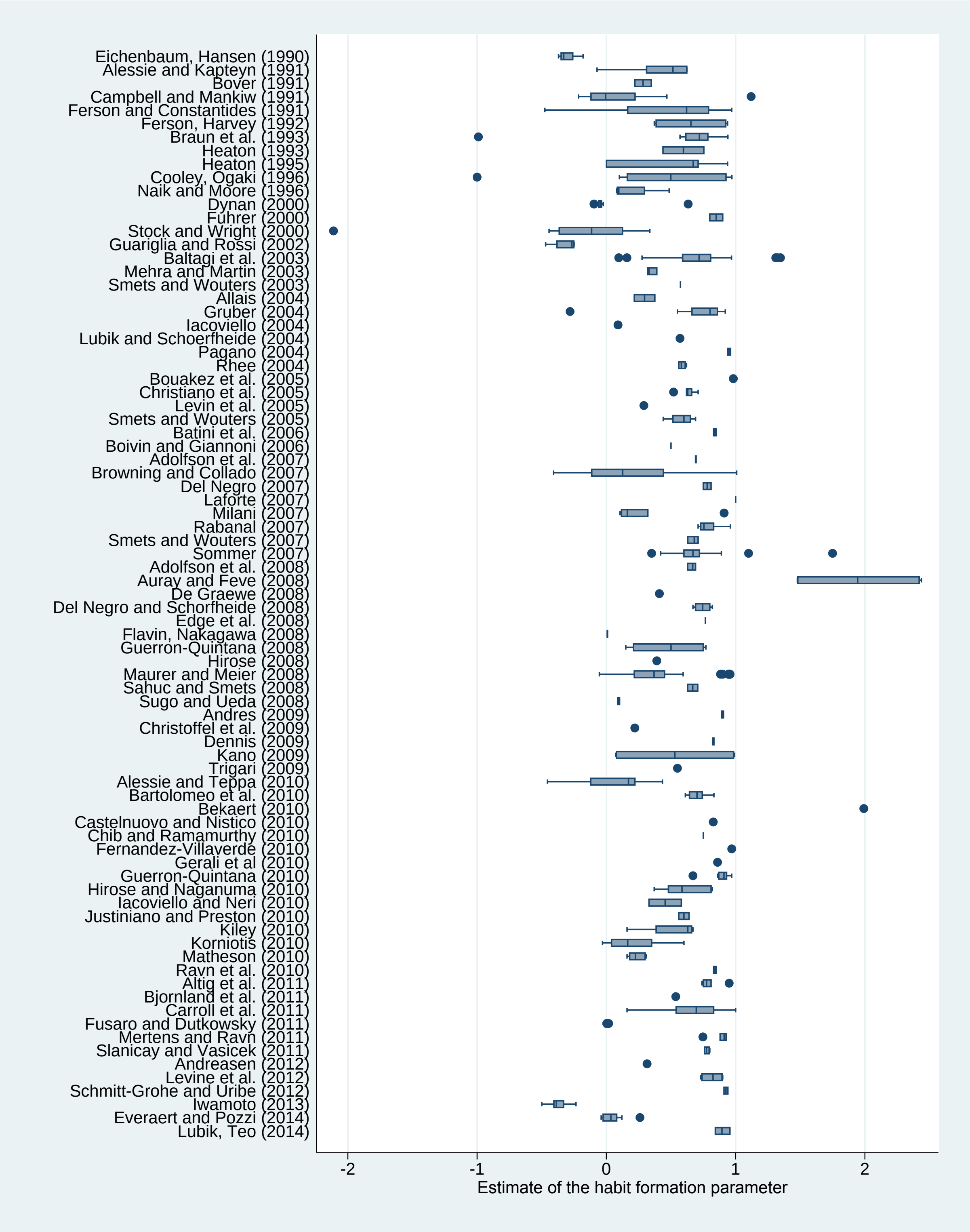
Figure 1: Estimated habit formation parameters vary considerably



Notes: The figure shows a box plot of the estimates of the habit formation parameter reported in individual studies. Following Tukey (1977), the box shows the interquartile range (P25–P75) with the median highlighted. Whiskers cover the interval from (P25 − 1.5 · interquartile range) to (P75 + 1.5 · interquartile range) if such estimates exist. The dots show the remaining (outlying) estimates reported in each study. Full references for the individual studies used in the meta-analysis are available in Appendix B of the paper.

2 Publication Bias

The majority of the estimates in our sample are obtained via estimation methods presupposing that the ratio of the estimate to the corresponding standard error has a t-distribution. These methods do not place explicit constraints on the estimates that force them to lie between 0 and 1; therefore, the estimates can lie outside the $(0,1)$ interval even if the underlying habit parameter lies within, given sufficient imprecision in estimation. Yet our sample also contains estimates from DSGE and other structural models that are often obtained under *a priori* restrictions. For example, some studies estimate DSGE models using maximum likelihood or minimum distance techniques, explicitly restricting the set of admissible values of the habit formation parameter to lie within the $[0,1]$ range (see Bouakez *et al.*, 2005). Other studies use Bayesian techniques, but employ prior distributions for the habit parameter that are bounded to the $[0,1]$ interval (e.g., Smets & Wouters, 2003; Levine *et al.*, 2012, who assume Beta distribution). Such structural estimates could generate spurious evidence for publication bias, so we exclude them from the analysis in this section.

In what follows we assess the extent of the bias and try to uncover the underlying mean estimate of habit formation. Our specification is based on Card & Krueger (1995) and Stanley (2008):

$$H\widehat{AB}IT_{ij} = \alpha_0 + \delta \cdot SE(H\widehat{AB}IT_{ij}) + \varepsilon_{ij}, \tag{1}$$

where $H\widehat{AB}IT_{ij}$ is the i-th estimate from j-th study, $SE(H\widehat{AB}IT_{ij})$ is the reported standard error of this estimate, and ε_{ij} is the disturbance term. As we have mentioned, most empirical methods estimating habit formation are based on the assumption that the ratio of the estimate to the standard error is t-distributed. This property implies that the numerator and the denominator of the ratio should be statistically independent quantities. Correlation between the two variables arises because of publication bias: suppose that researchers would only like to report estimates that are positive and statistically significant. Given the particular data and estimation technique (and thus given the standard error), they would need to search for a specification that delivers a point estimate of habit formation large enough to offset the standard error and show significance. Therefore, coefficient δ in regression (1), capturing the relation between estimates and their standard errors, indicates the magnitude of publication bias. α_0 is the mean estimate of the habit formation parameter conditional on the standard error approaching zero: it shows the mean reported habit formation parameter corrected for publication bias.

Table 1: Funnel asymmetry tests indicate no publication bias

	Baseline	Instrument	Study	Precision	Median
SE (publication bias)	-0.222	-0.133	-0.214	0.174^{***}	0.276
	(0.211)	(0.854)	(0.165)	(0.0315)	(0.207)
Constant (effect beyond bias)	0.397^{***}	0.380^{**}	0.444^{***}	0.000679^{***}	0.345^{***}
	(0.0397)	(0.161)	(0.0405)	(0.0000417)	(0.0858)
Observations	462	462	462	462	38

Notes: The table presents the results of regression $\widehat{HABIT}_{ij} = \alpha_0 + \delta \cdot SE(\widehat{HABIT}_{ij}) + \varepsilon_{ij}$. $\widehat{HABIT}_{ij}$ and $SE(\widehat{HABIT}_{ij})$ are the i-th estimates of the habit formation parameter and their standard errors reported in the j-th studies. As in the funnel plot, we only use non-restricted estimates. The standard errors of the regression parameters are clustered at study level. All estimations except for the last include study fixed effects. *Instruments*: we use the inverse of the square root of the number of observations in the individual study as an instrument for the standard error of the estimate of the habit formation parameter. *Study*: we weight the estimates by the inverse of the number of estimates reported in the study. *Precision*: we weight the estimates by the inverse of the reported estimate's standard error. *Median*: we estimate the equation by including the median estimate of the habit formation parameter and the median standard error of the estimated habit formation parameter reported in the individual studies.

While several studies report very small standard errors, other studies report standard errors that are many orders of magnitude greater. To account for these outliers we winsorize the data on standard errors at 5% on both sides of the distribution. Our main results are not sensitive to the choice of the fraction of data to be winsorized at each tail (as long as the largest outliers are discounted: winsorizing at 0.5% delivers largely similar results). The results are also robust to dropping the observations from the 5% tails on each side of the distribution.

Table 1 presents the results of regression (1) for non-restricted estimates; these results can also be interpreted as a test of funnel plot asymmetry. We consider several versions of the test. First, we estimate an OLS regression with study fixed effects and standard errors clustered at the study level. We include fixed effects to filter out unobservable study-specific factors that influence the reported estimates. Second, to address the potential endogeneity problem in meta-analysis we estimate the regression using the instrumental variable technique, while also including study fixed effects. Some method choices are likely to affect both the estimate and its standard error in the same direction, thus creating correlation between the disturbance term ε_{ij} and $SE(\widehat{HABIT}_{ij})$ and resulting in an inconsistent estimate of δ. As an instrument, we use the inverse of the square root of the number of observations used in each primary study: this variable is roughly proportional to the standard error, but not likely to be correlated with the method choice. Third, we estimate the regression by weighting each estimate by the inverse of the number of estimates reported in the corresponding study, thereby giving each study an equal weight in the regression. Fourth, we weight the estimates by their precision to remove heteroskedasticity. Finally, we exploit between- (instead of within-) study variation in the data using the median estimates and median standard errors reported in the primary studies.

The results can be summarized as follows. Four methods out of five yield insignificant estimates of δ (the magnitude of publication bias) and significant and large estimates of α_0 (the underlying mean habit formation parameter corrected for publication bias). We estimate the mean corrected habit formation to be around 0.4, close to the sample mean and median reported in the previous section. These results suggest that publication selection does not create a substantial bias in the reported habit formation parameters.

In contrast, the precision-weighted specification delivers a statistically significant estimate of publication bias and a much smaller underlying mean for habit formation. While precision-weighting removes heteroskedasticity, it is highly sensitive to small values of the standard error. Moreover, this specification yields a positive estimate of δ, suggesting an upward publication bias, which is at odds with the intuition suggested by the funnel plot. According to the guidelines by Doucouliagos & Stanley (2013), the estimate of δ around 0.174 can be classified as "little to modest" publication bias, and would have to be more than five times larger to be classified differently. Finally, the results of the precision-weighted specification do not hold if we employ instrumental variable estimation, using the inverse of the square root of the number of observations as an instrument for the standard error (this specification is not reported). Therefore, we argue that precision-weighted estimation overstates the effect of publication bias.

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