Publication and Identification Biases in Measuring the Intertemporal Substitution of Labor Supply

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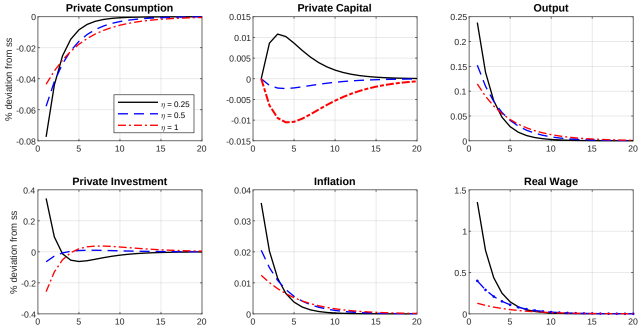
Why the Frisch **extensive margin** elasticity?

- Heckman (1984): the larger part of the fluctuations of labor supply during business cycles is due to adjustment along the extensive margin, not to the variation at the intensive margin.
- Hansen (1985) and Rogerson (1988): the *indivisible* nature of labor supply makes extensive margin response the main component of labor supply elasticity.
- Prescott (2004): plays a major role in explaining aggregate differences in total hours worked across countries.
- Chetty et al. (2011): unlike the Hicksian and Marshallian elasticities, the macroeconomic calibrations imply much larger Frisch labors supply elasticities than microeconometric studies.

Policy implications

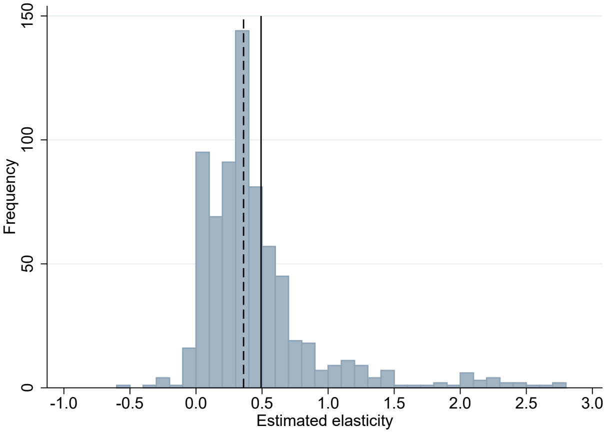
Impulse responses to a government spending shock in the standard New Keynesian setting



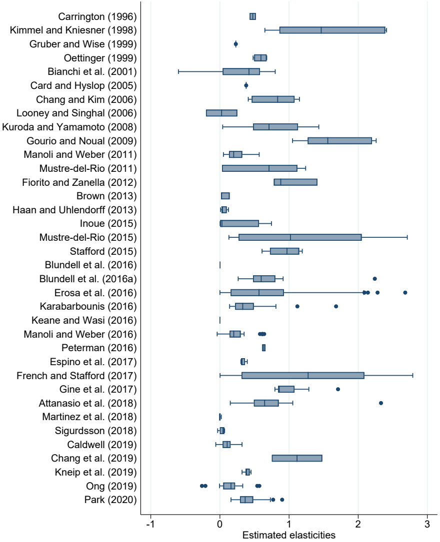
Data

- 36 primary studies (published and unpublished)
- Published between 1996-2020
- 723 estimates
- Sample mean = 0.49
- Sample median = 0.36
- 22 explanatory variables

Distribution of estimates



Estimates vary within and between studies



Publication Bias

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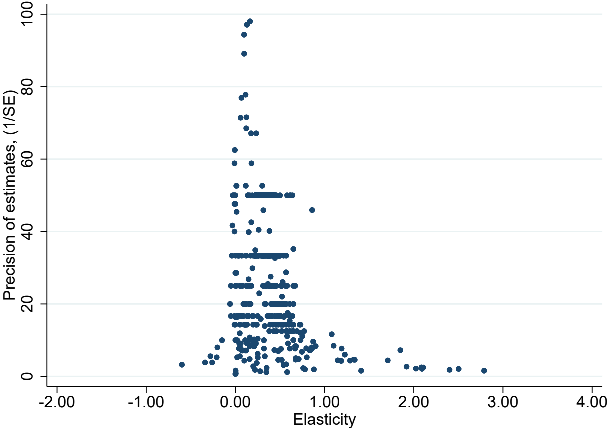
Different methods to assess publication bias:

- Visual tools
- Linear techniques
- Non-linear techniques

Funnel plot suggests publication bias



Linear techniques I

Regression-based funnel asymmetry tests:

$$\hat{\eta}_{ij} = \eta_0 + \delta \cdot SE(\hat{\eta}_{ij}) + e_{ij}, \tag{1}$$

$\hat{\eta}_{ij}$: the i-th estimate of the Frisch extensive elasticity in the j-th study

η_0: the mean elasticity corrected for the bias

δ: the size of publication bias

$SE(\hat{\eta}_{ij})$: the corresponding standard error

Can be used with various model specifications, e.g., OLS, fixed effects, etc.

Linear techniques II

Table 1: Linear and funnel asymmetry tests

	OLS	FE	Precision	Study
Standard error	1.595***	0.788	2.222***	2.106***
(*publication bias*)	(0.262)	(0.767)	(0.484)	(0.258)
	[0.93, 2.20]	-	[1.23, 3.31]	[1.53, 2.56]
Constant	0.301***	0.370***	0.247***	0.252***
(*mean beyond bias*)	(0.044)	(0.066)	(0.065)	(0.109)
	[0.12, 0.42]	-	[0.11, 0.31]	[0.13, 0.38]
Observations	723	723	723	723
Studies	36	36	36	36

OLS = ordinary least squares, FE = study fixed effects, Precision = the estimates are weighted by the inverse of their standard errors, Study = the inverse number of estimates per study is used as weight. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Non-linear techniques I

- Weighted Average of Adequately Powered (WAAP), Ioannidis et al. (2017): statistical power above an 80% threshold
- Andrews and Kasy (2019): publication probability changes noticeably after crossing conventional t-statistic's thresholds
- Endogenous Kink (EK), Bom and Rachinger (2019): the selection of estimates for publication constrained with particular precision cut-offs in the literature
- Furukawa (2020):
  - non-parametric method
  - only the most precise estimates
  - optimizes the trade-off between:
    i efficiency (increasing in the number of included estimates)
    ii bias (decreasing in the number of included more precise estimates)

Non-linear techniques II

Table 2: Non-linear tests

	Ioannidis et al. (2017)	Andrews and Kasy (2019)	Bom and Rachinger (2019)	Furukawa (2020)
Effect beyond bias	0.260***	0.356***	0.207***	0.187***
	(0.041)	(0.010)	(0.094)	(0.112)
Observations	723	723	723	723
Studies	36	36	36	36

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Explanatory variables

Demographics	*Data characteristics*	*Specifications*	*Publication characteristics*
Prime age	Time span	Indivisible labor	Publication year
Near retirement	Monthly	Quasi-experimental	Top journal
Females only	Quarterly	Probit	Citations
Males only	Industry	Non-parametric	Byproduct
Married	Macro	IV	
Single	USA		
Income			

Bayesian model averaging (BMA)

Using all possible subsets of explanatory variables, BMA runs numerous regression models (i.e., 2^k, where k is the number of explanatory variables).

- different priors
- posterior model probability (PMP): assigned to each model.
- posterior inclusion probability (PIP): or each variable indicates the sum of posterior model probabilities of the models in which the variable is included.

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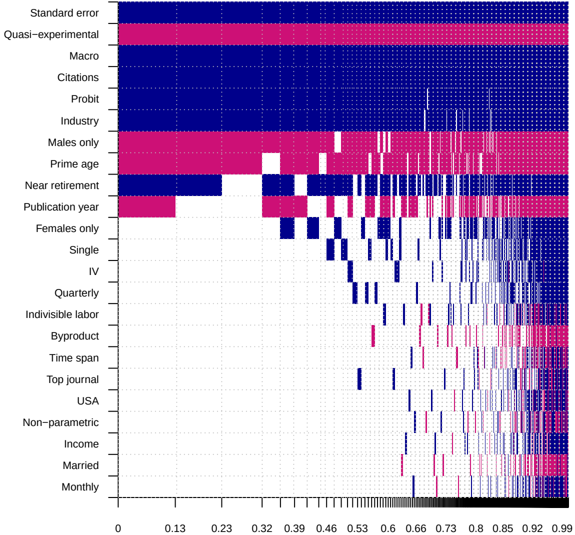
Our case includes 2^{23} models.

- Markov chain Monte Carlo (MCMC)
- dilution prior, George (2010)
- other priors for robustness checks, e.g., BRIC, HQ, etc.

Model inclusion in BMA



Explaining heterogeneity with BMA

- **Standard error** +
- **Demographics:**
  - Prime age -
  - Near retirement +
  - Males only -
- **Data characteristics:**
  - Industry +
  - Macro +
- **Specifications:**
  - Quasi-experimental -
  - Probit +
- **Publication characteristics:**
- Citations +

Conclusion

Principal parameters distorting the reported magnitude of the Frisch extensive elasticity of labor supply in the literature:

1. Publication bias:
   - the mean of reported elasticities (0.49) is exaggerated twofold in the primary studies
   - 0.25 is a reasonable estimate for the Frisch extensive elasticity after correcting for publication bias
2. Aggregation bias: studies using macro data tend to report estimates that are larger by 0.2 on average
3. Identification bias: studies that follow a quasi-experimental approach tend to report smaller estimates by 0.3 on average.

References

Andrews, I. and Kasy, M. (2019). Identification of and correction for publication bias. *American Economic Review*, 109(8):2766–94.

Bom, P. R. and Rachinger, H. (2019). A kinked meta-regression model for publication bias correction. *Research Synthesis Methods*, 10(4):497–514.

Chetty, R., Friedman, J. N., Olsen, T., and Pistaferri, L. (2011). Adjustment costs, firm responses, and micro vs. macro labor supply elasticities: Evidence from Danish tax records. *The quarterly journal of economics*, 126(2):749–804.

Furukawa, C. (2020). Publication bias under aggregation frictions: from communication model to new correction method. Working paper, MIT, mimeo.

George, E. I. (2010). Dilution priors: Compensating for model space redundancy. In *Borrowing Strength: Theory Powering Applications–A Festschrift for Lawrence D. Brown*, pages