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A Meta-Analysis of the Frisch Extensive Margin Elasticity

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Abstract:
A key parameter in structural models is the Frisch elasticity of labor supply at the extensive margin, but empirical estimates vary greatly. We provide a quantitative synthesis of the literature. To this end, we collect 723 estimates from 36 studies along with 22 explanatory variables reflecting studies' characteristics and address model uncertainty by Bayesian and frequentist model averaging. Using linear and non-linear techniques, we find that publication bias exaggerates the mean of reported elasticities in the literature from 0.25 to 0.49. Our findings also suggest that two principal characteristics affect the magnitude of estimated elasticities systematically. First, identification bias: studies that follow a quasi-experimental approach tend to report smaller estimates. Second, aggregation bias: studies using macro data tend to report larger estimates. Furthermore, estimates associated with prime age or male workers tend to be systematically smaller, while studies relying on specific-industry data, near retirement workers, and probit regression tend to be larger.

JEL: E24, J20, J21, C83
Keywords: Frisch elasticity, extensive margin, meta-analysis, publication bias, Bayesian model averaging

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1 Introduction

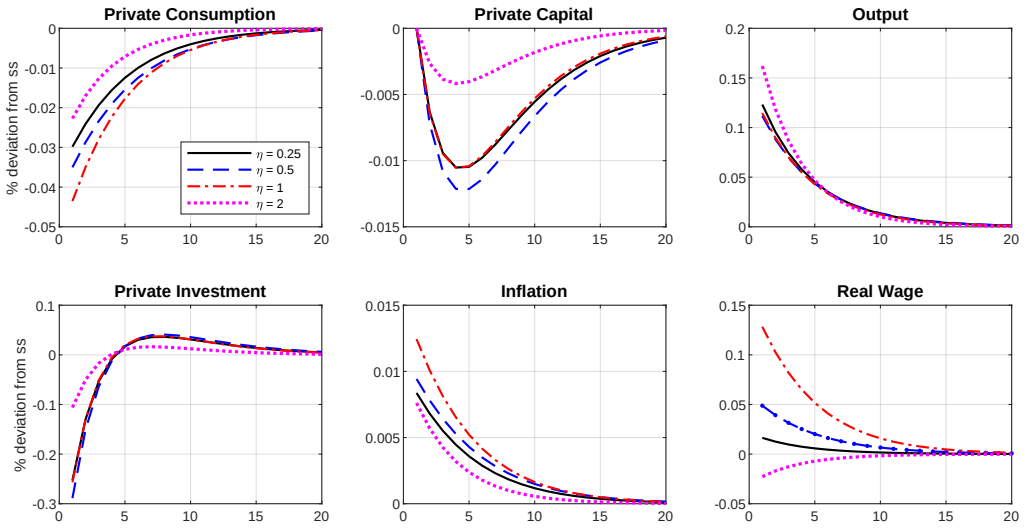
Understanding labor supply elasticity is crucial in macroeconomics and economic policy. Among the different types of labor supply elasticity, the Frisch elasticity is widely used in equilibrium macro models (e.g., DSGE models). The elasticity reflects the labor supply response to transitory changes in tax or wage rates and is needed to calibrate most of the modern DSGE models. Along with life cycle models, these models are salient tools in analyzing fiscal and monetary policies. The magnitude of labor supply elasticity is crucial in conducting the policies mentioned above, as it substantially affects the behavior of other economic variables such as consumption and output. Figure 1 shows how the response of economy to a shock in government expenditures varies when we employ different values of the Frisch labor elasticity in the New Keynesian setting. For instance, the Frisch labor elasticity significantly affects the response of private capital and consumption to the government spending shock. Heckman (1984) argues that 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. The reason is that the extensive margin takes into account the participation (employment) decisions, while the intensive margin captures only hours elasticity.

There is also a disagreement in the literature regarding the micro and macro elasticities. Chetty et al. (2011) show that macroeconomic calibrations imply much larger Frisch labor supply elasticities than microeconometric studies since extensive margin responses are usually not captured in micro studies. Hansen (1985) and Rogerson (1988) argue that because of the indivisible nature of labor supply, the extensive margin response (participation decision) is the main component of labor supply elasticity.

Furthermore, a substantial fraction of the macroeconomic literature refers to the aggregate Frisch elasticities as macro elasticities, while micro elasticities imply only the intensive margin elasticity. Following Chetty et al. (2013), we use a different classification in which both micro and macro elasticities refer to the extensive margin elasticity using data on different aggregation levels. Although the micro and macro estimates are consistent among the Hicksian and Marshallian elasticities[1], Frisch extensive margin elasticities using macro data are not consistent with those of micro data.

[1] Attanasio et al. (2018), Chetty et al. (2013), and Keane (2011), among others address more details on the estimations of other types of labor elasticity, i.e., Hicksian and Marshallian.

Figure 1: Policy implications with different values of the Frisch elasticity



Notes: The figure presents different economic variables' impulse responses to a government spending shock in the New Keynesian setting. When the Frisch elasticity of labor supply (η) changes, ceteris paribus, economic variables respond to the shock differently. The vertical axis denotes the percentage of deviation from the steady state. The horizontal axis is the number of quarters after a one-percentage-point increase in government spending.

In this paper, accounting for publication bias and other studies' characteristics, we explore the heterogeneity among estimates in different studies. Our results show that different sources of bias conspire to exaggerate the reported magnitude of the mean Frisch elasticity of labor supply at the extensive margin (0.49). The first decisive factor impacting the magnitude of the Frisch extensive elasticity reported in the literature is publication bias. We employ linear methods to examine the presence of publication bias in our primary studies. The linear techniques give us a corrected mean of the Frisch extensive elasticity in the range of 0.25-0.37. Applying non-linear techniques such as those suggested by Andrews and Kasy 2019 and Furukawa 2020, we obtain the mean effect corrected for publication bias between 0.19 and 0.36. After averaging over the values obtained from linear and non-linear techniques, the result suggests that the estimate of Frisch extensive elasticity corrected for publication bias is around 0.25. In line with Ioannidis et al. (2017), the finding confirms that publication bias leads to a twofold exaggeration in the mean of reported estimates in the literature.

Collecting 22 extra explanatory variables, we examine other aspects of studies to achieve a more robust conclusion regarding the source of heterogeneity in the reported estimates of Frisch elasticity at the extensive margin. We use Bayesian model averaging model (BMA; Eicher et al. 2011) and frequentist model averaging (FMA; Hansen 2007) to address the model

uncertainty. We find two decisive characteristics affecting the magnitude of estimates elasticities. First, identification bias: studies that do not follow a quasi-experimental approach tend to report estimates that are larger by 0.3 on average. Second, aggregation bias: studies using macro (aggregated) data tend to report estimates that are larger by 0.2 on average. Besides, our results suggest more explanatory variables that are, to a lesser extent, accountable for the systematic variation among estimates reported in the literature. The estimates of Frisch extensive elasticity of males tend to be smaller than those for females, which is line with a large body of the literature (Keane, 2011). Similarly, estimates associated with the prime age group (workers between 25-55 years old) are smaller on average, while estimates based on near retirement workers (older than 55 years old) tend to be larger. Regarding dataset characteristics, studies using industry-specific data tend to report systematically larger estimates. Furthermore, our results suggest that elasticities estimated within a probit model setting tend to be larger on average. However, we find no evidence of the systematic impact of other types of econometric techniques. We also find that, among publication characteristics, the number of citations can be useful in explaining the systematic variation among estimates. Our findings regarding biases and key variables remain robust after applying sensitivity checks in different settings.

The remainder of the paper is structured as follows. Section 2 provides a brief overview of the Frisch elasticity and its estimation methods. Section 3 describes how we collect data from primary studies. In section 4, we apply different techniques to control for publication bias in the literature. Section 5 investigates the source of heterogeneity among estimates using Bayesian model averaging. Section 6 concludes the paper.

2 Estimating the Frisch Elasticity of Labor Supply

In this section, we provide a brief review of the Frisch elasticity and its estimation method. The Frisch (λ-constant) elasticity measures anticipated changes in the wage and taxes. Since it takes into account transitory changes in wages and taxes without wealth effect, it is the right concept to discuss the impact of business cycle fluctuations on employment.

Moreover, elasticities are estimated with two different data types: macro (aggregate) data used in macroeconomic and equilibrium models, and micro data that are usually used in quasi-experimental studies and surveys.

The Frisch labor supply elasticity is defined as follows:

$$\eta = \frac{\partial h}{\partial w}\frac{w}{h}\|_{\lambda}, \tag{1}$$

where h and w are hours of work and wage rate, respectively. Under a dynamic setting without uncertainty where a temporally separable utility function represents the household's preferences over a life cycle, the elasticity is typically estimated by the following basic empirical labor equation for each individual

$$\ln h_t = \eta \ln w_t + \theta x_t + \varepsilon_t, \tag{2}$$

where x is a vector of individual characteristics, and ε is the error term. The estimated elasticity based on Equation 2 corresponds to the response at the intensive margin. There is an extensive use of the instrumental variable (IV) approach to encounter wage endogeneity in the literature. One also needs to instrument to deal with the measurement error in w_t. Assuming labor indivisibility, we can abstract from the intensive margin to address only the participation decision that operates at the extensive margin. Hence, the dependant variable can only take values 1 or 0, and the elasticity can be estimated by using a probit model for the participation decision.

In the case of macro models, the participation (employment) decision can be written as:

$$h_t = \begin{cases} \bar{h}, & \text{if } w_t \geq w_t^R \\ 0, & \text{if } w_t \leq w_t^R. \end{cases} \tag{3}$$

The worker participates in the labor market if the offered wage w_t is equal or larger than the reservation wage, w_t^R. Hence, the distribution of reservation wages plays a crucial role in determining the aggregate level elasticity's magnitude at the extensive margin. However, it cannot be observed in the data and must indirectly be included in the structural models.

Alternatively, one can decompose the aggregate elasticity into the intensive and extensive margins. As in Fiorito and Zanella (2012), the variance of the log of aggregate labor can be decomposed as:

$$\text{var}\,(\ln H_t) = \text{var}\,(\ln n_t) + \text{var}(\ln \bar{h}_t) + 2\,\text{cov}(\ln n_t, \ln \bar{h}_t), \tag{4}$$

where n_t is the number of employed individuals, $\bar{h}_t$ is the average number of hours worked, and aggregate labor is $H_t = n_t \bar{h}_t$. Using Equation 4, the decomposition of aggregate Frisch elasticity can be written as:

$$\eta = \frac{\text{cov}(\Delta \ln H, \Delta \ln W)}{\text{var}(\Delta \ln W)} = \frac{\text{cov}(\Delta \ln \bar{h}, \Delta \ln W)}{\text{var}(\Delta \ln W)} + \frac{\text{cov}(\Delta \ln n, \Delta \ln W)}{\text{var}(\Delta \ln W)}, \tag{5}$$

where Δ is the first-difference operator, and W is the aggregate wage rate. The first term on the right-hand side is the macro intensive margin, and the second term corresponds to the extensive margin. In the extreme case, where there is no heterogeneity among workers and employment is constant over the population, the extensive margin is eliminated as $\text{cov}(\Delta \ln n, \Delta \ln W) = 0$. In other words, micro and macro (aggregate) elasticities coincide.

A sizable fraction of literature explicitly models the employment rate using reduced form labor supply equations. Following this approach, most quasi-experimental studies calculate the Frisch elasticity at the extensive margin as the change in log employment rates over the change in the net of tax wage rates (see e.g., Bianchi et al. 2001; Card and Hyslop 2005; Martinez et al. 2018).

Additionally, apart from the conventional estimation methods, part of studies use non-parametric or simulation-based methods to estimate the Frisch elasticity at the extensive margin (Erosa et al. 2016; Kneip et al. 2013). We include these estimates together with other estimates mentioned above, with different specifications and environments since each of them captures the labor force's decision on employment (i.e., the extensive margin). Furthermore, we control the various aspects of the framework in which researchers estimate elasticities at the extensive margin. We discuss these aspects in detail in Section 5.

3 Data

We use Google Scholar to search for the estimated Frisch elasticities at the extensive margin. We choose this database since it provides a full-text search, which is absent in other search engines. We design our search query to download and examine the abstracts of the first 500 studies returned by the search. If the abstract explicitly addresses any other elasticities rather than the Frisch elasticity, we move to the next abstract. We add the study to our meta-analysis

if its abstract explicitly states that the study estimates the Frisch elasticity at the extensive margin. If the abstract is not clear about the estimated elasticities in the study, we go through the paper to inspect the estimated Frisch extensive elasticities. If we do not find the relevant estimate, we drop the study and move to the next abstract. We also investigate each study's references and citations to make sure that we cover all relevant studies that are not shown in our baseline search. The PRISMA diagram in Figure A1 shows the detailed process of including studies in this meta-analysis.

Table 1: Primary studies used in the meta-analysis

Attanasio et al. (2018)	Inoue (2015)
Bianchi et al. (2001)	Karabarbounis (2016)
Blundell et al. (2016a)	Keane and Wasi (2016)
Blundell et al. (2016b)	Kimmel and Kniesner (1998)
Brown (2013)	Kneip et al. (2013)
Caldwell (2019)	Kuroda and Yamamoto (2008)
Card and Hyslop (2005)	Looney and Singhal (2006)
Carrington (1996)	Manoli and Weber (2011)
Chang and Kim (2006)	Manoli and Weber (2016)
Chang et al. (2019)	Martinez et al. (2018)
Erosa et al. (2016)	Mustre-del Río (2011)
Espino et al. (2017)	Mustre-del Rio (2015)
Fiorito and Zanella (2012)	Oettinger (1999)
French and Stafford (2017)	Ong (2019)
Giné et al. (2017)	Park (2020)
Gourio et al. (2009)	Peterman (2016)
Gruber and Wise (1999)	Sigurdsson (2019)
Haan and Uhlendorff (2013)	Stafford (2015)

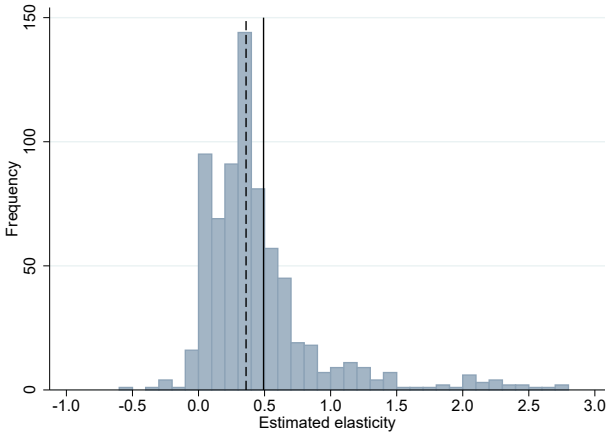
To be included in our meta-analysis, the study must contain at least one estimate comparable with the estimates described in section 2. If the estimate of Frisch elasticity at the extensive margin is not reported in a study and can be calculated by other presented results, we derive it and include it in our database. We also include estimates from unpublished studies. Since researchers intend to publish their papers eventually, the estimates are unlikely to reduce publication bias (Rusnák et al., 2013). Moreover, the majority of unpublished studies included in our meta-analysis are working papers of the National Bureau of Economic Research (NBER), which indicates their high quality.

Using the search algorithm, we collect 723 estimates from 36 studies. We terminate the search on July 26, 2020, and do not add additional studies. The full list of papers is presented

in Table 1. The oldest study in our database is published in 1996 and the last one in 2020. It means that our meta-analysis covers a quarter-century of research in the field. Fifty percent of 36 primary studies are published in the so-called *"top five"* or top field journals in economics. As of our search's termination date in Google Scholar, all the studies receive 3830 citations combined, indicating the importance of the studies.

Figure 2 shows the distribution of the estimated Frisch extensive elasticities. The mean and median of reported estimates of the Frisch elasticity at the extensive margin are 0.49 and 0.36, respectively. One can notice that even though the Frisch elasticity cannot be negative by definition, there are few negative estimates in our sample, indicating the contradictory results in part of empirical studies. Furthermore, the distribution exhibits outliers on both sides. We address the influence of the outliers by winsorizing at the 5% level (The results are consistent with other winsorizing levels).

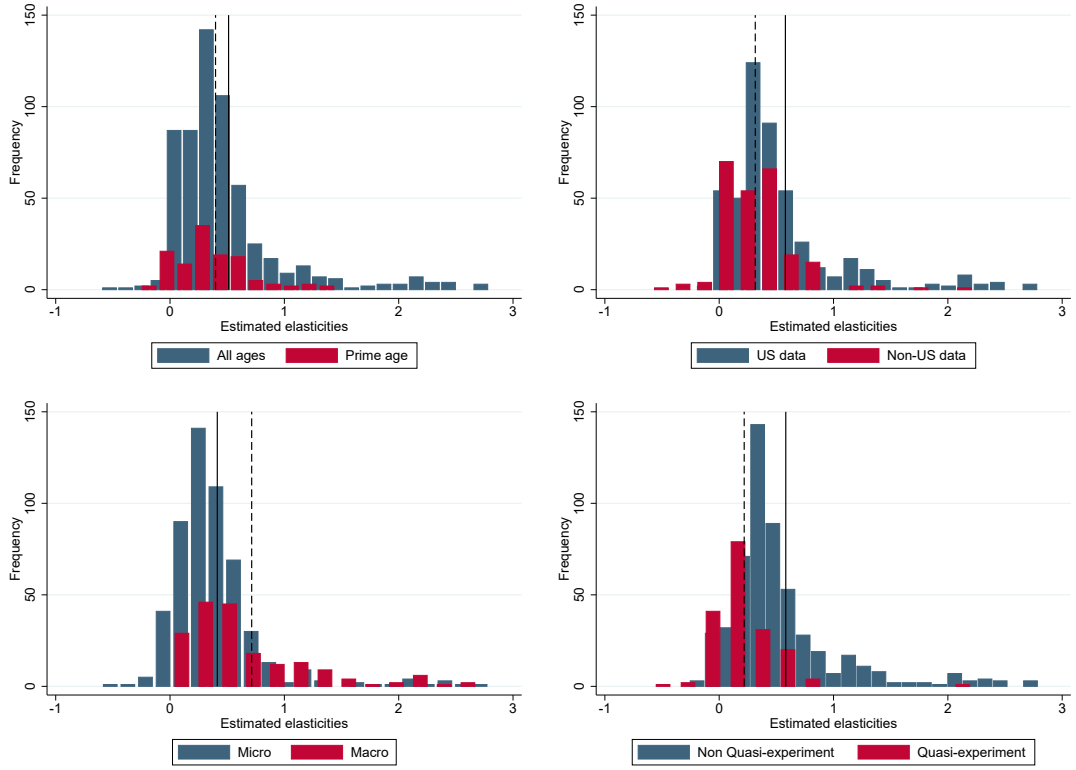
Figure 2: Distribution of the Frisch extensive margin elasticity estimates



Notes: The solid line denotes the sample mean (0.49); the dashed line denotes the sample median (0.36). Estimates smaller than -1 and larger than 4 are excluded from the figure but included in all regressions.

In addition to reported estimates and their standard errors, we add explanatory variables to cover all aspects affecting the magnitude of the estimated elasticities. We define 22 additional explanatory variables leading us to collect more than 15,000 data points. We control for demographic characteristics by including dummy variables whether the reported elasticity is for a specific gender or age group, as well as marital status and income level. We further control for the data characteristics. We control if the frequency of data used in the primary studies is annual, quarterly, or monthly. Moreover, we check whether the reported elasticity

Figure 3: Patterns in the data



Notes: The solid line is the mean elasticity relevant to the first variable (blue), and the dashed line denotes the mean elasticity relevant to the second variable (red) in each sub-figure. Estimates smaller than -1 and larger than 3 are excluded from the figure but included in all regressions.

is based on the US data or if the study employs industry-specific data. More importantly, we control whether the data used are at the aggregate level (macro). We also include dummy variables indicating econometric techniques (e.g., probit, IV, non-parametric methods) used in studies in our collected variables. We include dummy variables to control whether the labor supply is indivisible, and if the study is quasi-experimental. Additionally, we consider publication characteristics by controlling the study age (publication year), number of citations, and if the study is published in the top five leading journals. Lastly, we control whether the study mainly focuses on the Frisch extensive elasticity or reports the elasticity as a byproduct of other results.

The precision of individual estimates (standard error) is a crucial element to conduct modern meta-analysis methods. However, standard errors are not reported for a fraction of the collected elasticities in our sample. Standard errors are available for 538 of 723 estimates in our sample. In order to resolve the issue, we apply the bootstrap re-sampling technique. We

further combine the reported standard errors with those obtained from re-sampling. Hence, we use all the estimates reported in our meta-analysis. Looking at the data, one can notice that the reported elasticities vary both across and within studies, based on different data types and methodologies. Figure 3 shows, in an evident pattern, macro elasticity estimates tend to be larger than those based on micro data. The mean reported elasticity for macro and micro estimates is 0.71 and 0.41, respectively. Furthermore, the mean of reported quasi-experimental estimates is 0.22, while the mean reported elasticity is 0.58 for non-quasi-experimental studies. These numbers from the primary studies are consistent with other results in the literature, highlighting the impact of quasi-experiment design on the size of the estimated Frisch extensive elasticity (Chetty et al., 2013). Estimates based on US data is 0.58, indicating a mean elasticity almost twice larger than the one derived from non-US data. Lastly, the difference between elasticities for the prime age group and the whole population is noticeable. Elasticities for the prime age group vary less than those of all age groups. The mean elasticity from the studies based on the whole population is 0.51, which is 25% larger than the mean reported elasticity for the prime age group. Besides, Figure 4 depicts the variation of estimates in the primary studies used in this meta-analysis as a whole picture.

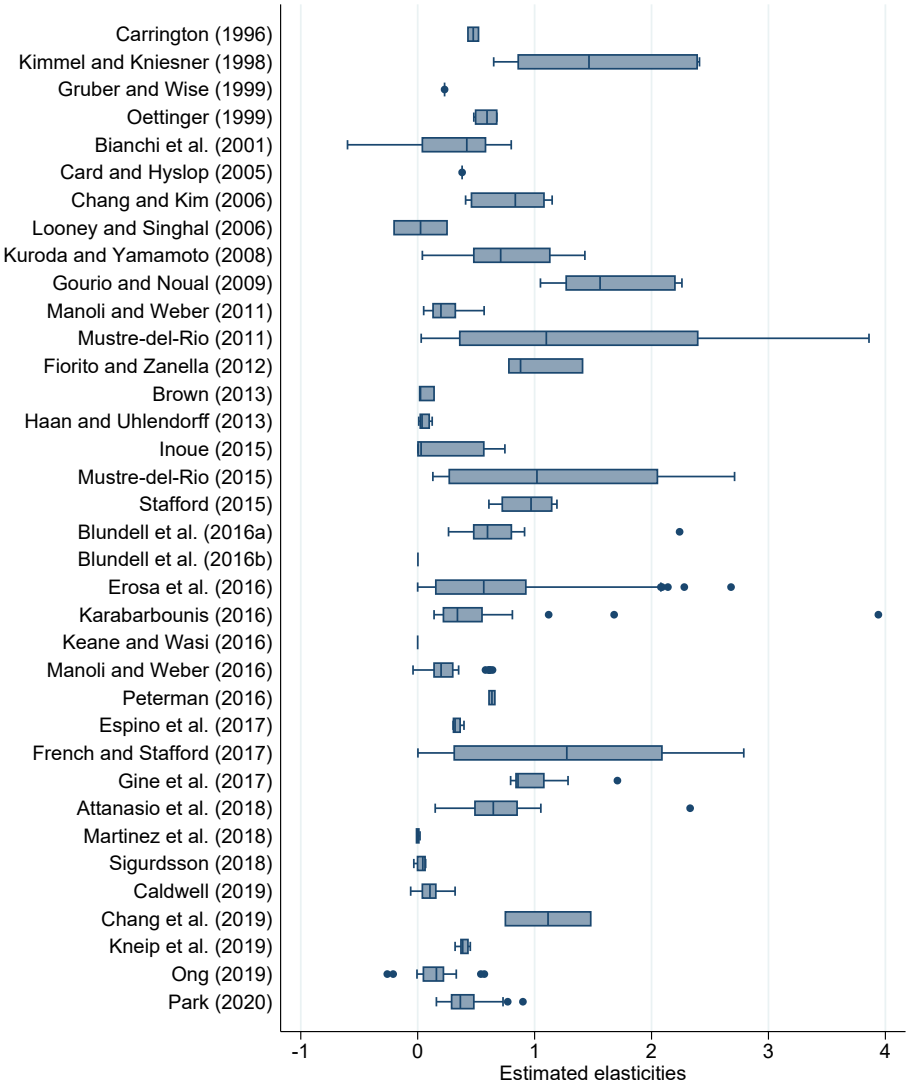
4 Publication Bias

Publication bias has a remarkable impact on reporting the empirical findings in different fields of science. In economics, hypothesis testing starts with studying the relationship between a dependant variable and a set of explanatory variables based on prior beliefs built upon the available literature. However, publication bias causes an increase in the importance of the relationship between the dependent variable and explanatory variables with each positive publication. Ioannidis et al. (2017) show that the effect of publication bias on exaggerated reported estimates in economics is twofold.[2] Researchers tend to discard statistically insignificant estimates or those with the wrong sign as it makes sense to focus only on statistically significant estimates with the right sign. This strategy increasingly and iteratively distorts our inference from the literature.

Moreover, employing various types of specifications, it is always possible to obtain statis-

[2]Other recent studies investigating the effect of publication bias in economics include Valickova et al. (2015), Havranek et al. (2016, 2017), Havranek and Irsova (2017), and Astakhov et al. (2019).

Figure 4: Variation of the estimates within and between studies

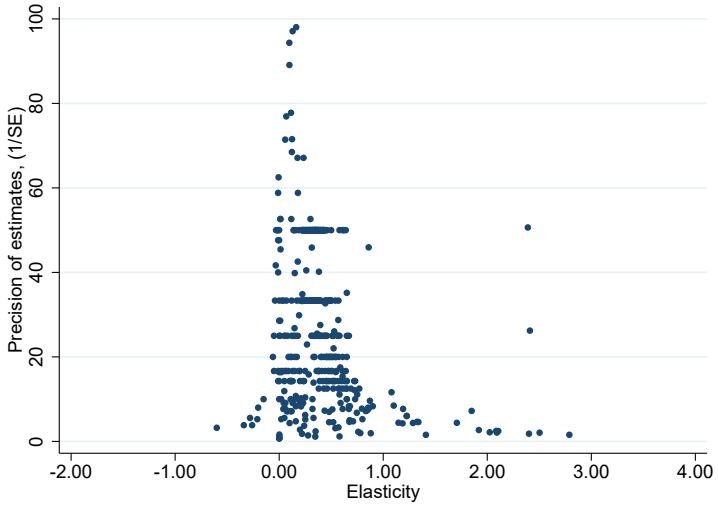


Notes: The figure shows a box plot of the Frisch elasticity estimates at the extensive margin reported in individual studies. Each box's length represents the inter-quartile range (P25-P75), and the dividing line inside the box is the median value. The dots are remaining (outlying) estimates in each study. The whiskers represent the highest and lowest data points within 1.5 times the range between the upper and lower quartiles. Estimates smaller than -1 and larger than 4 are excluded from the figure but included in all regressions.

tically significant estimates. McCloskey and Ziliak (2019) provide an analogy to the Lombard effect: speakers increase their vocal effort in the presence of noise. When publication requires statistical significance, reported estimates can indicate significance but not necessarily what the statistical theory recommends. In other words, publication bias indicates a correlation between the reported estimate and its standard error. In the case of Frisch elasticity, the theory ignores the negative values of the Frisch elasticity, which leads such estimates to be omitted in the literature. In this section, we document the strong presence of publication bias in reported elasticities. To the best of our knowledge, no other study addresses potential publication bias in the literature of the Frisch elasticity of labor supply at the extensive margin.

Figure 5 illustrates the so-called funnel plot (Egger et al., 1997), which is used to check the presence of publication bias. The horizontal axis measures the magnitude of the estimated extensive margin Frisch elasticity, and the vertical axis measures its precision. In the absence of publication bias, the most precise estimates are closer to the average effect, and the plot forms a symmetrical inverted funnel. In our case, the figure shows asymmetry indicating publication bias. To have a symmetrical funnel consistent with the absence of publication bias, we need to have more negative estimates.

Figure 5: Funnel plot suggests publication bias



Notes: In the absence of publication bias, the plot should form a symmetric inverted funnel. Extreme values of precision are excluded from the figure but included in the regressions.

The funnel plot is just a visual tool to check for publication bias and does not provide sufficient evidence regarding publication bias. Therefore, we use regression-based funnel asymmetry tests to investigate publication bias quantitatively:

$$\hat{\eta}_{ij} = \eta_0 + \delta \cdot SE(\hat{\eta}_{ij}) + e_{ij}, \tag{6}$$

where $\hat{\eta}_{ij}$ is the i-th estimate of the Frisch extensive elasticity in the j-th study, $SE(\hat{\eta}_{ij})$ is the corresponding standard error, δ represents the size of publication bias, and η_0 denotes the mean elasticity corrected for the bias. There is no publication bias if estimated elasticities and their standard errors are statistically independent ($\delta = 0$), while publication bias is present if there is a correlation between estimated elasticities and their standard errors ($\delta \neq 0$).

The first panel of Table 2 shows the results of Equation 6 with various model specifications. All standard errors are clustered at the study level. The first column presents the results from a simple OLS regression. The second column adds study-level fixed effects to capture study-specific characteristics. In the third column, as suggested by Stanley and Doucouliagos (2017), estimates are weighted by the inverse of their reported standard errors. Addressing the heteroskedasticity of Equation 6, we use the inverse number of estimates per study as the weight in the last column.

The results in the first panel of Table 2 show the presence of publication bias in line with the visual evidence in Figure 5. Three of the four specifications indicate that the correlation between estimates and standard errors is positive and statistically significant (publication bias). Although the result obtained from study-level fixed effects specification denotes a positive coefficient on standard error, it does not confirm that the correlation is statistically significant. Furthermore, the mean corrected for bias in all four specifications (0.25-0.37) is smaller than the uncorrected mean (0.49).

Although the linear techniques are intuitive in assessing publication bias, they can also be biased if the correlation between the estimates and their standard errors is not linear. Panel B of Table 2 presents the results obtained from applying non-linear techniques. The Weighted Average of Adequately Powered (WAAP) technique proposed by Ioannidis et al. (2017), takes into account the estimates when its statistical power is above an 80% threshold. Using the WAAP technique, we assign a weight to each estimate with adequate power to compute a

weighted mean corrected for bias. We find a mean elasticity of 0.26, consistent with the results of linear regressions. Furthermore, we employ the technique suggested by Andrews and Kasy (2019). The technique assumes that publication probability changes noticeably after crossing conventional t-statistic's thresholds. The technique re-weights estimates in each bracket based on how they are present in the literature. Andrews and Kasy (2019) model gives us a mean elasticity of 0.36, which is relatively larger than those of other non-linear models.

Table 2: Linear and non-linear funnel asymmetry tests

Panel A: Linear funnel asymmetry techniques				
	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
Panel B: Non-linear techniques				
	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

Notes: Panel A presents the results of regression $\hat{\eta}_{ij} = \eta_0 + \delta \cdot SE(\hat{\eta}_{ij}) + e_{ij}$, where $\hat{\eta}_{ij}$ and $SE(\hat{\eta}_{ij})$ are the i-th estimated Frisch extensive elasticity and its standard error reported in the j-th study. 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. If applicable, we report 95% confidence intervals from wild bootstrap clustering, in square brackets. Panel B shows the results from non-linear techniques. We cluster all standard errors at the study level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The third non-linear method we employ is the Endogenous Kink (EK) technique proposed by Bom and Rachinger (2019). Extending the linear funnel asymmetry test, they show that the selection of estimates for publication is constrained with particular precision cut-offs in each literature. This technique gives us a mean elasticity of 0.21. Using a non-parametric approach, Furukawa (2020) develops a stem-based method that concentrates only on the most precise estimates (i.e., the stem of the funnel plot). The method takes into account both efficiency (increasing in the number of included estimates) and bias (decreasing in the number of included more precise estimates) and optimizes the trade-off between them. The techniques

yield a mean elasticity effect of 0.19, which is by far the lowest among all results from linear and non-linear techniques. Lastly, as a robustness check, we use the "*Top10*" method of Stanley et al. (2010), where we take only the top 10% of most precise estimates. This method gives us an estimate of 0.26 for the mean elasticity, identical to what we obtained from the WAAP technique.

Table 2 shows a significant presence of publication bias in the literature. Both linear and non-linear techniques give us an estimate of the Frisch extensive elasticity corrected for publication bias with a lower magnitude than the simple uncorrected mean. Linear funnel asymmetry techniques yield a range of 0.25-0.37 for the mean estimate of the elasticity, while the results of non-linear techniques are relatively more heterogeneous and yield between 0.19-0.36. We conclude that the average of all estimates in Table 2, 0.25, is a reasonable estimate for the Frisch extensive elasticity after correcting for publication bias in the literature. The result is consistent with Ioannidis et al. (2017), as publication bias exaggerates the estimate of the elasticity almost twofold (i.e., corrected mean vs. uncorrected simple mean: 0.25 vs. 0.49).

5 Heterogeneity

As we argue in the previous section, publication bias is a salient factor affecting the systemic difference among the estimates of the Frisch extensive elasticity. However, other study characteristics can impact the magnitude of the estimated elasticities. In this section, we introduce 22 additional explanatory variables indicating various aspects of the framework in which the researchers obtain their estimates. These variables capture demographic characteristics together with the data and specification characteristics used in the primary studies. In addition, we use variables that reflect the publication characteristics of each study. Using standard errors and 22 additional variables, we run meta-regressions to shed light on heterogeneity sources in the Frisch elasticity literature. Table 3 lists the definition and summary statistics of the variables divided into four categories. Additionally, Figure 6 shows Pearson correlation coefficients for the variables reported in Table 3.

5.1 Variables

Demographics. A primary source of heterogeneity among the estimates of labor supply elasticity can be originated from the demographic characteristics of the sample study. We define seven dummy variables to control for possible features available in the literature. We include two dummy variables to capture the samples' age for estimating the Frisch extensive elasticity. Although different studies use various age groups in their estimation, two groups of workers are widely highlighted in the literature. First, prime age workers between 25 and 55 years old; second, workers near retirement age (i.e., older than 55 years old). There is a disagreement between macro and micro studies regarding the magnitude of the Frisch extensive elasticity for prime age workers. Micro studies show near-zero elasticity, while macro studies show similar to those for the whole population (Chetty et al., 2013). On the other hand, workers near retirement exhibit a larger Frisch extensive elasticity than other age groups (e.g., Erosa et al., 2016; Manoli and Weber, 2016). More than one-third of collected estimates (34%) are based on either group. In cases that the estimate is based on a subgroup with an age range close but not identical to the definition of prime age or near retirement (e.g., 20-55 years old for the prime age group, older than 50 years old for near retirement group, etc.), we still consider the estimate. Elasticities based on other age groups are not commonly addressed in the literature. Thus, we do not take into account other age groups in the analysis.

We codify two dummy variables denoting the gender of sample. Datasets that consist of only female workers are used in 18% of estimates, while this number is 42% for the estimates, including only male workers. There is a consensus in the literature that employment fluctuations are higher among female workers than their male counterparts. Confirming this pattern, the mean of Frisch extensive elasticities for these groups in the collected estimates are 0.40 and 0.56 for male and female workers, respectively. We further include a dummy variable to control for the estimates that are used only for worker groups with similar income levels. Almost 23% of estimates are based on a specific income group. Finally, two dummy variables control for the marital status of samples. Only 4% of estimates are based on only married workers, and 3% for single workers. It is worth mentioning that, although we consider two extra dummy variables: without children and self-employed workers, we are unable to collect enough estimates addressing these categories. Hence, we exclude them from the regressions.

Data characteristics. The second category of variables covers the characteristics of data used in estimations. We introduce a variable reflecting the time span of the data. Moreover, two dummy variables control for the frequency of data. We use annual data as the reference category since more than 74% of estimates employ annual data. Industry dummy variable controls if the estimate uses specific industry-level data. In our primary studies, 12% of estimates employ industry-level and daily data simultaneously. More than 67% of estimates utilize datasets based in the US, including The Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth 1979 (NLSY). We thus add a dummy variable for the use of US data. The majority of estimates (74%) use individual-level data, while others use aggregate level (macro) data. We use the former as the baseline category and define a dummy variable using the latter. The macro dummy variable refers only to the aggregation level of the dataset, not the nature of the study in which the elasticity is estimated since both macro and micro studies can use data on different aggregation levels. Fiorito and Zanella (2012) document the difference in using the same dataset at different aggregation levels to estimate the Frisch elasticity of labor supply.

Specifications. Defining five dummy variables, we control for specifications of estimates in different respects. The first dummy variable we include equals one if the estimate assumes the indivisibility of labor. In this case, since the labor force can either work or not work, all labor fluctuations happen at the extensive margin. We find that 35% of estimates employ the indivisible labor assumption. Furthermore, quasi-experimental estimates are one-fourth of all estimates in the primary studies. Quasi-experimental studies reflect a mean estimate of 0.22, substantially smaller than 0.58, which is the mean estimate from other studies. Additionally, three additional dummy variables control for the potential effect of econometric techniques used in estimating elasticities. The baseline category is OLS, as researchers use it to estimate more than 45% of estimates. Probit models are used only in 5% of estimates, while the instrumental variables (IV) and non-parametric methods are used in 14% and 37% of estimates, respectively. We consider both non-parametric and simulations of any kind in the same category to address less conventional methods in the literature.

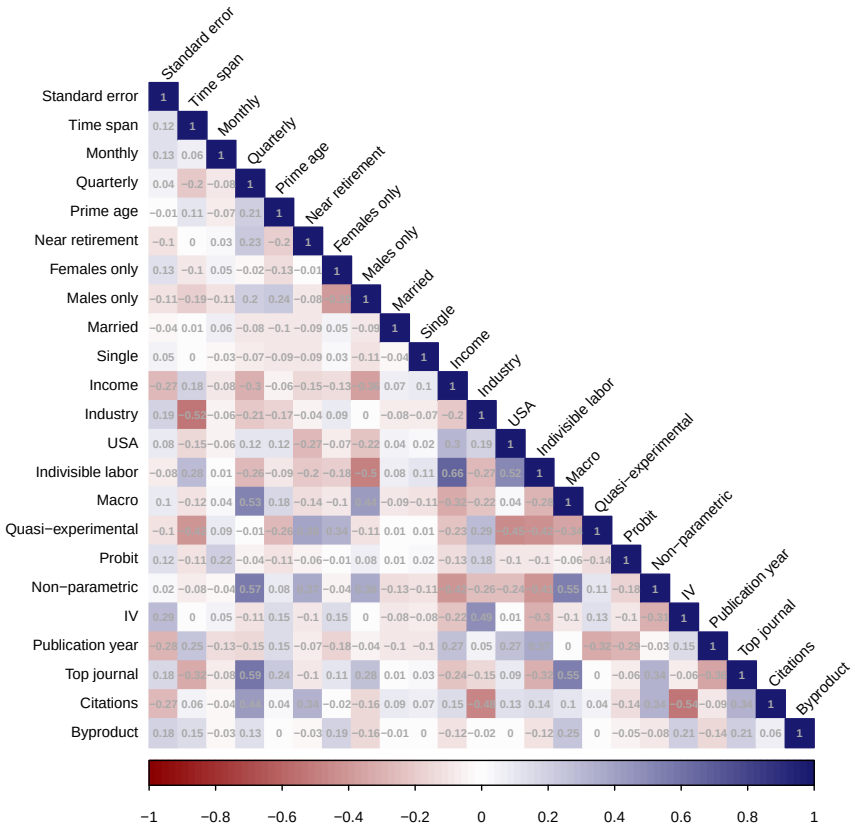
Table 3: Definition and summary statistics of explanatory variables

Variable	Description	Mean	SD
Frisch elasticity	The estimated extensive-margin Frisch elasticity.	0.49	0.64
Standard error	The standard error of the estimate.	0.10	0.17
Demographics			
Prime age	= 1 if the sample only consists of the prime working age population between 25 and 55.	0.17	0.38
Near retirement	= 1 if the sample only consists of the population older than 55.	0.17	0.38
Females only	= 1 if the sample consists of females only.	0.18	0.38
Males only	= 1 if the sample consists of males only.	0.42	0.42
Married	= 1 if the sample consists of married people only.	0.04	0.20
Single	= 1 if the sample consists of single people only.	0.03	0.18
Income	= 1 if the estimate is based on a specific income group.	0.23	0.42
Data characteristics			
Time span	The logarithm of the data time span used to estimate the elasticity.	2.22	0.89
Monthly	= 1 if the data frequency is monthly (reference category: annual).	0.02	0.15
Quarterly	= 1 if the data frequency is quarterly (reference category: annual).	0.24	0.43
Industry	= 1 if the sample consists of workers in a specific industry.	0.12	0.32
Macro	= 1 if the data is the aggregated individual data (reference category: micro).	0.26	0.44
USA	= 1 if the estimate is for the US.	0.67	0.47
Specifications			
Indivisible labor	= 1 if the labor supply is indivisible.	0.35	0.48
Quasi-experimental	= 1 if the estimate is quasi-experimental.	0.25	0.43
Probit	= 1 if the probit model is used for the estimate (reference category: OLS).	0.05	0.22
Non-parametric	= 1 if non-parametric simulation-based methods are used for the estimate (reference category: OLS).	0.37	0.48
IV	= 1 if $2sls$ or IV method are used for the estimate (reference category: OLS).	0.14	0.35
Publication characteristics			
Publication year	The logarithm of the publication year of the study minus the year when Heckman (1984) was published.	3.46	0.20
Top journal	= 1 if the estimate is in a study published in the top five journals.	0.22	0.41
Citations	The logarithm of the number of per-year citations of the study, according to Google Scholar.	1.75	1.06
Byproduct	= 1 if it is not the central focus or not directly reported in the study; = 0 if the estimate is the main study's focus.	0.04	0.20

Notes: SD = standard deviation. The table excludes the definition and summary statistics of the reference categories.

Publication characteristics. We use the last category to capture the factors that affect publication quality. First, we account for the publication year of the study and its distance from the seminal work of Heckman (1984) in which the importance of the extensive margin in the responsiveness of labor force is highlighted. The next variable takes into account the logarithm of the number of per-year citations of the study, according to Google Scholar. We also include a dummy variable if the study published in the top five journals. Eight studies produce 22% of estimates in our database. Finally, a dummy variable equals zero if the estimated Frisch extensive elasticity is explicitly reported in the study. If the estimate is either a byproduct of different analyses in the study or not reported at all, the dummy variable is equal to one. For example, Carrington (1996) and Brown (2013) do not directly report the estimated Frisch extensive elasticity, while Chang and Kim (2006) report the estimated Frisch extensive elasticity as a supplementary practice. We consider estimates in all three studies byproducts.

Figure 6: Correlation matrix



Notes: The figure shows Pearson correlation coefficients for 22 variables reported in Table 3 together with standard errors. The number of observations for each variable is 723.

5.2 Estimation

One can run a simple regression to relate all the collected variables to the magnitude of reported estimates. This method is problematic as not all the explanatory variables are equally important, and including all of them in the regression will ignore model uncertainty and consequently affect the precision of our results. To solve the issue, we can exclude the redundant variables by doing step-wise regression. Moreover, relying on the theory, we can have only a particular set of variables and discard the rest of them. However, these solutions are not optimal since some individual variables can be removed by accident in step-wise regression, and removing variables will ignore the difference between studies in multiple aspects, even if we follow the theory. We choose the Bayesian model averaging (BMA) to address model uncertainty in the Bayesian setting.

Using all possible subsets of explanatory variables (i.e., 2^k, where k is the number of explanatory variables), BMA runs numerous regression models. Analogous the information criteria in frequentist econometrics, posterior model probability (PMP) is assigned to each model. PMP assesses the performance of a model compared to other models. BMA uses weights based on PMPs to construct a weighted average over the estimated coefficients across all the models. Furthermore, posterior inclusion probability (PIP) for each variable indicates the sum of posterior model probabilities of the models in which the variable is included. Further details on BMA can be found in, e.g., Raftery et al. (1997) and Eicher et al. (2011), among other studies. Recent applications of BMA in meta-analysis can be found in, e.g., Havranek et al. (2018a,b) and Cazachevici et al. (2020).

Estimating millions of models (2^{23} in our case) is a task taking months to be done by a standard computer available today. Hence, we apply the Markov chain Monte Carlo algorithm (Madigan and York, 1995) to solve the infeasibility of BMA. The algorithm goes through the models with the highest posterior model probabilities. Moreover, we use the programming language R and the BMS package developed by Zeugner and Feldkircher (2015).

In the baseline specication, we employ the dilution prior suggested by George (2010). The dilution prior takes into account the colinearity of variables in each model. The prior multiply the model probabilities by the determinant of the correlation matrix of the variables included in the model. The higher collinearity means the determinant is closer to zero, which results in

a model with less weight. On the other hand, if the model exhibits low collinearity, the determinant is closer to one, and the model has a larger weight. We also use the unit information prior (UIP) for Zellner's g-prior, in which all regression coefficients are zero the same weight as one observation of the data.

Furthermore, we run a frequentist check, which is a hybrid frequentist-Bayesian model, including substantial variables with PIPs higher than 70% obtained from the baseline BMA specification. We then estimate the model using the OLS method and clustered standard errors in the study level.

5.3 Results

Figure 7 illustrates the results of Bayesian model averaging. Each column represents an individual regression model. They are sorted on the horizontal axis by their posterior model probabilities. The vertical axis shows the explanatory variables listed in the descending order of their posterior inclusion probabilities. The blue color (darker in gray-scale) indicates that the coefficient is positive, while the red color (lighter in gray-scale) denotes the negative sign of coefficient. The individual blank cell means that the corresponding variable is not included in the model. At first glance, Figure 7 indicates that 10 variables seem to be systematically important in forming the heterogeneity of estimated Frisch extensive elasticity in the literature as they have high PIPs and unchanging signs across regression models.

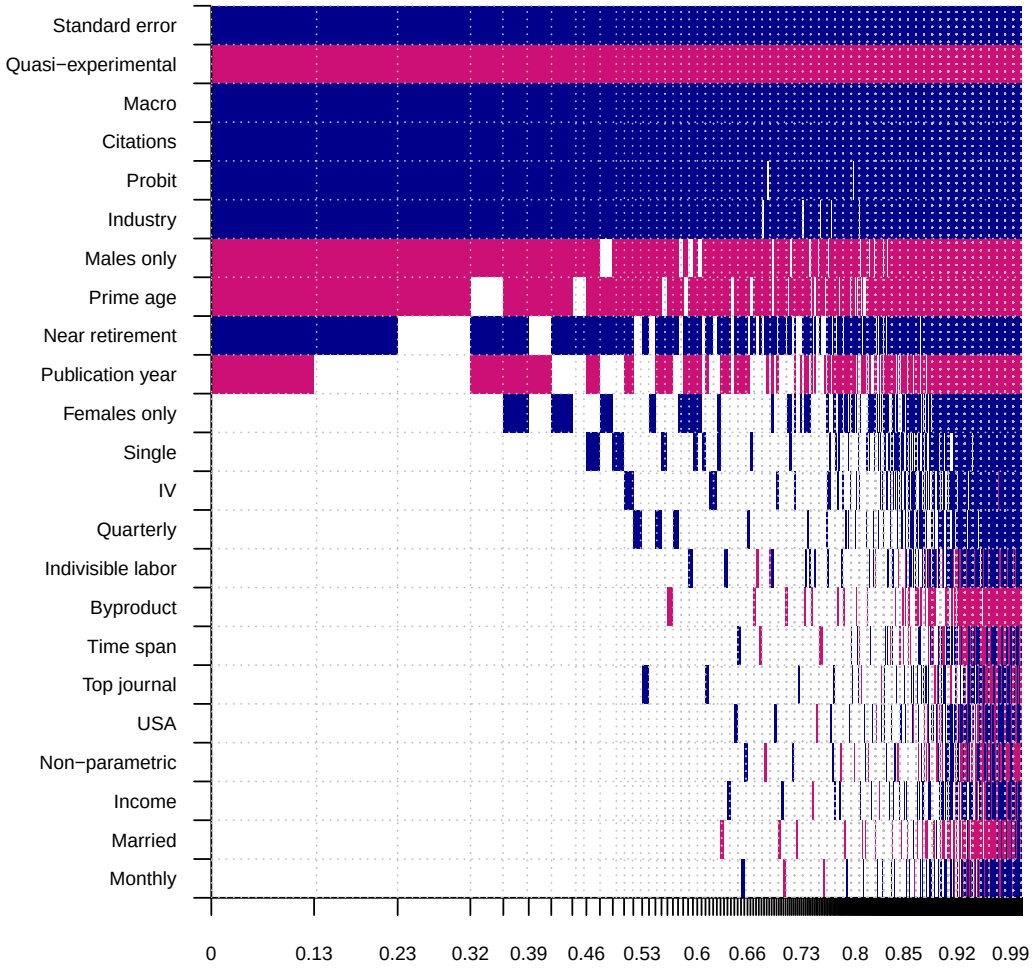
Table 4 presents the numerical results of Bayesian model averaging. The left panel reports the posterior inclusion probability, posterior mean, and standard deviation for each explanatory variable. Excluding the intercept, three variables have PIP equal to 1, indicating that they are decisive variables; three variables are *strong* as their PIPs are between 0.95 and 0.99, and two can be labeled as *substantial* with PIPs more than 75 but lower than 95. Moreover, there are two variables with PIPs between 50 and 75, indicating their *weak* effect. The right panel of Table 4 shows the results of an OLS regression model, including the variables with PIP 75 and higher. The estimated coefficients in both panels have the same sign and similar magnitude, and apart from one variable, they display the same significance (PIP in BMA and its equivalent, p-value shown in the right panel). Hence, the results in the right panel are consistent with the baseline BMA.

The first important conclusion from the results is that publication bias remains robust even when we take into account the context in which the elasticity is estimated by adding extra 22 explanatory variables to our regression model. The effect of publication bias in BMA results is in line with our findings in the previous section. BMA results show that publication bias exaggerates the estimated Frisch extensive elasticities, confirming that the significant correlation between standard errors and estimates is not due to excluding different aspects of data from the regression.

Demographics. We find evidence that demographic characteristics affect the estimates of the Frisch extensive elasticity in different aspects. First, the estimates of Frisch extensive elasticity of males tend to be smaller than those for females. This is in line with the consensus in part of the literature. Card and Hyslop (2005), Keane (2011) and Keane and Rogerson (2015), for instance, document the subgroups with more elastic labor supply elasticity at the extensive margin, which females (typically single mothers) and near retirement workers are among them since they are less attached to the labor market. However, our finding contrasts with studies reporting larger elasticities of male workers than female workers (see e.g., Bianchi et al. 2001). Our results suggest that estimates based on near retirement workers are systematically larger. We find this variable fairly substantial, with a PIP of 75. Next, BMA results suggest that estimating elasticities based on the prime age group results in smaller estimates, which is systematically different from the whole population. The finding confirms the pattern in the literature shown in Figure 3. On the other hand, we do not find enough evidence that estimates associated with the female gender can explain the difference between reported estimates in the primary studies. Moreover, our results do not provide any evidence suggesting that marital status can explain the variation in reported estimates. Similarly, we find no evidence that income level is an essential variable in explaining the heterogeneity between estimates.

Data characteristics. We find no substantial effect for the time span of the data used in the estimation of the Frisch extensive elasticity. The results also suggest that differences in data frequency cannot influence the systematic variation of reported estimates in the primary studies. As shown in Figure 3, the pattern in the literature shows a larger magnitude for estimates relying on datasets based in the US. Controlling for other aspects of data in BMA,

Figure 7: Model inclusion in BMA (Dilution prior)



Notes: The response variable is the estimate of the Frisch extensive elasticity in a primary study. The columns denote individual models; variables are sorted by posterior inclusion probability in descending order. The horizontal axis denotes the cumulative posterior model probabilities. The estimation is based on the unit information prior (UIP) recommended by Eicher et al. (2011) and the dilution prior suggested by George (2010), which captures collinearity. Blue color (darker in gray-scale) = the variable has a positive estimated sign. Red color (lighter in gray-scale) = the variable has a negative estimated sign. No color = the variable is excluded from the given model. Table 3 presents a detailed description of all variables. The numerical results are reported in Table 4.

Table 4: Explaining heterogeneity (BMA: Diluation prior)

	Bayesian Model Averaging			Frequentist Check (OLS)		
Variable	Post. Mean	Post. SD	PIP	Coeff.	S.E.	P-val.
Intercept	0.558	N.A.	1.000	0.210	0.048	0.000
Standard error	1.331	0.146	1.000	1.407	0.135	0.000
Demographics						
Prime age	-0.092	0.048	0.864	-0.103	0.035	0.005
Near retirement	0.082	0.057	0.749	0.093	0.071	0.200
Females only	0.020	0.041	0.243			
Males only	-0.102	0.043	0.911	-0.110	0.055	0.054
Married	-0.001	0.011	0.032			
Single	0.012	0.040	0.118			
Income	0.000	0.007	0.035			
Data characteristics						
Time span	0.000	0.006	0.044			
Monthly	0.001	0.015	0.031			
Quarterly	0.004	0.017	0.071			
Industry	0.174	0.058	0.968	0.160	0.069	0.027
Macro	0.197	0.036	1.000	0.207	0.050	0.000
USA	0.001	0.010	0.040			
Specifications						
Indivisible labor	0.003	0.021	0.068			
Quasi-experimental	-0.293	0.049	1.000	-0.270	0.049	0.000
Probit	0.244	0.068	0.989	0.277	0.131	0.041
Non-parametric	0.000	0.009	0.038			
IV	0.005	0.021	0.075			
Publication characteristics						
Publication year	-0.099	0.114	0.497			
Top journal	0.001	0.012	0.043			
Citations	0.076	0.016	0.999	0.076	0.020	0.001
Byproduct	-0.003	0.018	0.048			
Observations	723			723		
Studies	36			36		

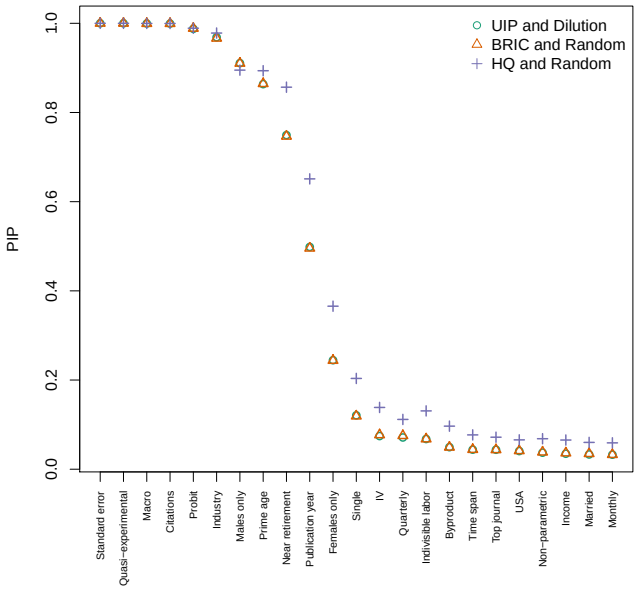
Notes: Response variable = The Frisch extensive elasticity, S.D. = standard deviation, PIP = Posterior inclusion probability, S.E. = standard error. In the left panel, we apply BMA based on the UIP g-prior and dilution model (Eicher et al. 2011; George 2010). The right panel reports frequentist check results, which includes substantial variables with PIPs higher than 70% obtained from the baseline BMA specification. Standard errors in the frequentist check are clustered at the study level. Table 3 presents a detailed description of all variables.

we do not find supporting evidence that the US-based estimates are systematically different from other reported estimates. Our results also provide strong evidence that using macro data has a systematically significant effect on the magnitude of estimates. The reported elasticities estimated based on macro data tend to be larger than their micro counterparts by 0.2. This is in line with the pattern in the literature depicted in Figure 3. In addition, our analysis suggests that there is a systematic relationship between industry-specific data and reported estimates of Frisch extensive elasticity. Industry-specific estimates are systematically larger than estimates that are not associated with particular industries.

Specifications. Our results suggest that accounting for labor indivisibility cannot influence the resulting size of the Frisch extensive elasticity. This finding disagrees with a segment of macro literature, initiated by Hansen (1985) and Rogerson (1988), highlighting the importance of indivisible labor supply in determining the Frisch extensive elasticity.We find little evidence that either IV or non-parametric techniques used in estimating elasticity are substantially effective in differences among the reported estimates. Estimates that use these two techniques do not differ from other estimates using the reference technique, OLS. On the other hand, having a PIP of 0.99, elasticities estimated by the probit technique tend to be systematically larger by 0.24 on average. Finally, our results suggest that a quasi-experimental research design is a significant factor in the systematic variation of estimates in primary studies. Studies that do not follow a quasi-experimental approach tend to report larger estimates by 0.3 on average. This finding corroborates the pattern of reported estimates in the literature, depicted in Figure 3.

Publication characteristics. Among the factors affecting study quality, our results suggest that the number of citations, to a great extent, is responsible for the reported estimates. Furthermore, the age of study (publication year) can be considered a weak variable affecting the systematic difference between estimates as it indicates PIP equal to 50. Our results do not suggest that publication in a top journal can explain the heterogeneity among estimates. Lastly, estimates reported as byproducts are not systematically different from estimates reported as the main results in the primary studies.

Figure 8: Posterior inclusion probabilities across different prior settings



Notes: UIP and dilution prior = priors according to Eicher et al. (2011) and George (2010). BRIC and Random = the benchmark g-prior for parameters with the beta-binomial model prior (each model size has equal prior probability). HQ prior asymptotically mimics the Hannan-Quinn criterion.

In addition to the baseline BMA, we conduct a series of robustness checks to confirm if the results of our baseline BMA specification are valid in different settings. First, we employ alternative priors and g-priors. We apply the beta-binomial random model prior, which gives an equal prior probability to each model size (Ley and Steel, 2009). We also use BRIC g-prior suggested by Fernandez et al. (2001) and also HQ prior. Figure 8 depicts how the relative importance of the variables changes when different priors are used for BMA. The visual and numerical results obtained from alternative BMA settings are presented in Appendix B. As another sensitivity check, while we use unweighted data in the baseline specification, we run BMA on an alternative weighted data to evaluate the robustness of our results. We also run a version of the baseline BMA in which standard errors are excluded. The results of this exercise and the weighted BMA alternative are presented in Table B3 of Appendix B. Lastly, we apply frequentist model averaging (FMA), which ignores using priors. In order to reduce the number of estimated models, we use Mallow's criterion for model averaging estimator (Hansen, 2007), and the orthogonalization of covariate space suggested by Amini and Parmeter (2012). Table C1 in Appendix C reports the results of FMA exercise.

6 Concluding Remarks

In this study, we explore sources of heterogeneity among estimates in different studies by accounting for publication bias and other characteristics of studies. We analyze 723 estimates of the Frisch extensive elasticity from 36 studies published in the past three decades. The mean elasticity reported in the primary studies is 0.49. Using various specifications, we find that the mean of reported elasticities is exaggerated twofold after controlling for publication bias. We argue that 0.25 is a reasonable estimate for the Frisch extensive elasticity after correcting for publication bias in the literature. It means that the labor force is less responsive to transitory changes in wages and taxes than what one can conclude from the mean elasticity reported in the literature.

The estimates vary not only because of publication bias, but also the context in which they are estimated. We collect 22 additional variables that reflect different aspects of data used in the estimation of the Frisch elasticity at the extensive margin. These variables capture demographics, specifications, as well as data and publication characteristics of primary studies. Using Bayesian model averaging, we run several regressions to measure the importance of these explanatory variables in affecting the magnitude of the Frisch extensive elasticity reported in the literature. Our results from BMA and further sensitivity analysis suggest that two decisive variables can explain the systematic differences between estimates. First, studies using macro data tend to report estimates that are larger by 0.2 on average (aggregation bias). Second, studies that do not follow a quasi-experimental approach tend to report larger estimates by 0.3 on average (identification bias).

Moreover, the results suggest other explanatory variables affecting the magnitude of the reported elasticities in the literature. The estimates of Frisch extensive elasticity of males tend to be smaller than females or the whole population. Similarly, estimates associated with the prime age group lead to a substantial smaller values on average. On the other hand, studies that are based on industry-specific data or near retirement workers data, and use probit regression tend to report systematically larger estimates. We also find that, among publication characteristics, the number of citations is essential in explaining the systematic variation among estimates. Hence, we conclude that publication bias, aggregation bias, identification bias, and to a lesser extent, the other six explanatory variables conspire to exaggerate the reported

magnitude of the mean Frisch elasticity of labor supply at the extensive margin. Our findings regarding the biases are robust to applying various sensitivity checks to our baseline BMA specification.

The results are important as understanding the elasticity of labor supply is a crucial part of every macroeconomic model. The Frisch extensive elasticity particularly is needed to calibrate most of the modern DSGE models. Having a more realistic measure of labor supply responsiveness to wage changes will help both researchers and policymakers. However, there are some essential aspects of micro data such as self-employed workers, and young men and women without children, that we are unable to address in this study, due to the lack of availability in the primary studies. Moreover, further analysis of macro models' specifications can also be useful to explain the complex heterogeneity of reported estimates in the literature. Future studies can control these variables if sufficient data are available in the Frisch extensive elasticity literature.

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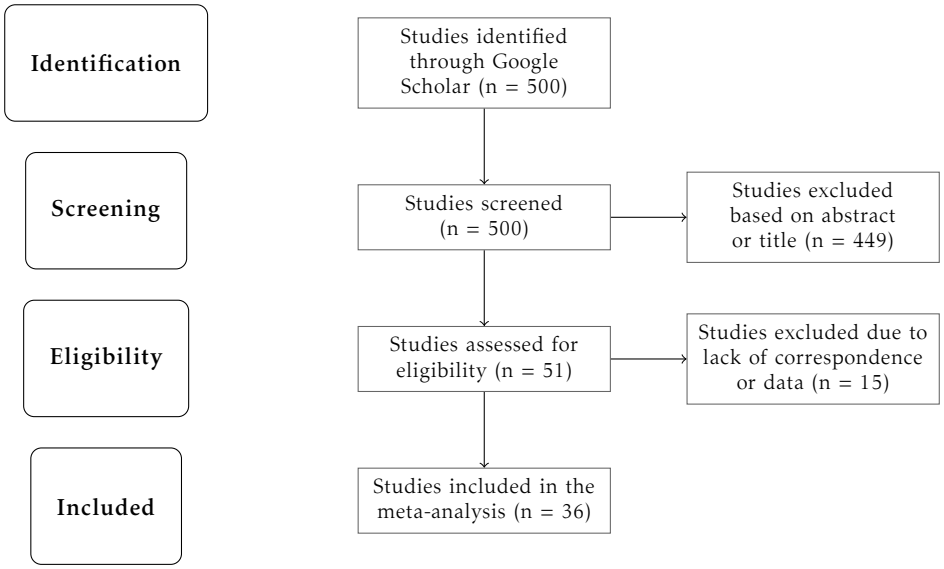
Appendices

A Systematic review progress

Figure A1: PRISMA flow diagram



Notes: Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) is an evidence-based minimum set of items for reporting in systematic reviews and meta-analyses.

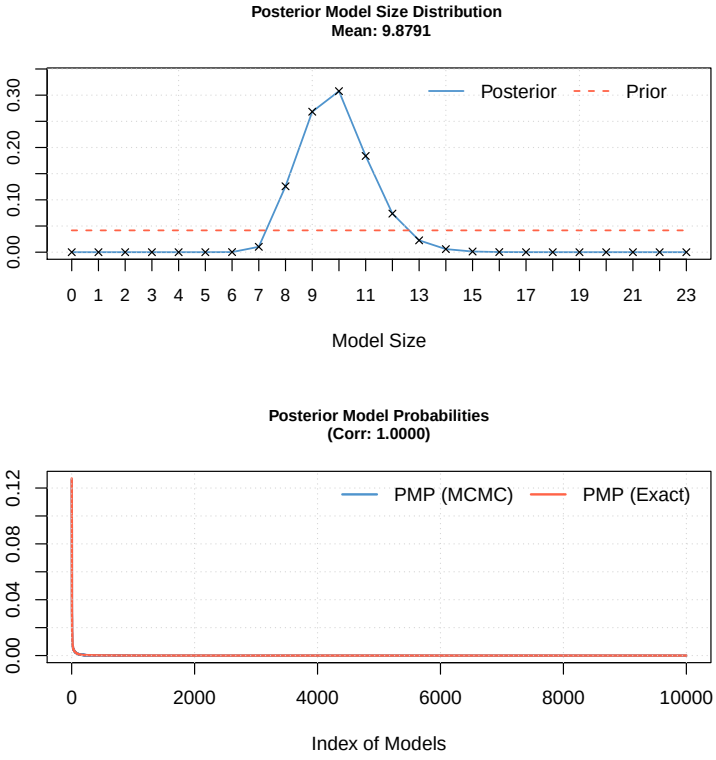
B Robustness checks to BMA

Table B1: Summary of the benchmark BMA estimation

Mean no. regressors	*Draws*	*Burn-ins*	*Time*	*No. models visited*
9.8721	$3 \cdot 10^6$	$1 \cdot 10^6$	5.506014 mins	567,495
Modelspace	*Models visited*	*Topmodels*	*Corr PMP*	*No. Obs.*
8,388,608	6.8%	100	1.0000	723
Model prior	*g-prior*	*Shrinkage-stats*		
random / 11.5	UIP	Av=0.9986		

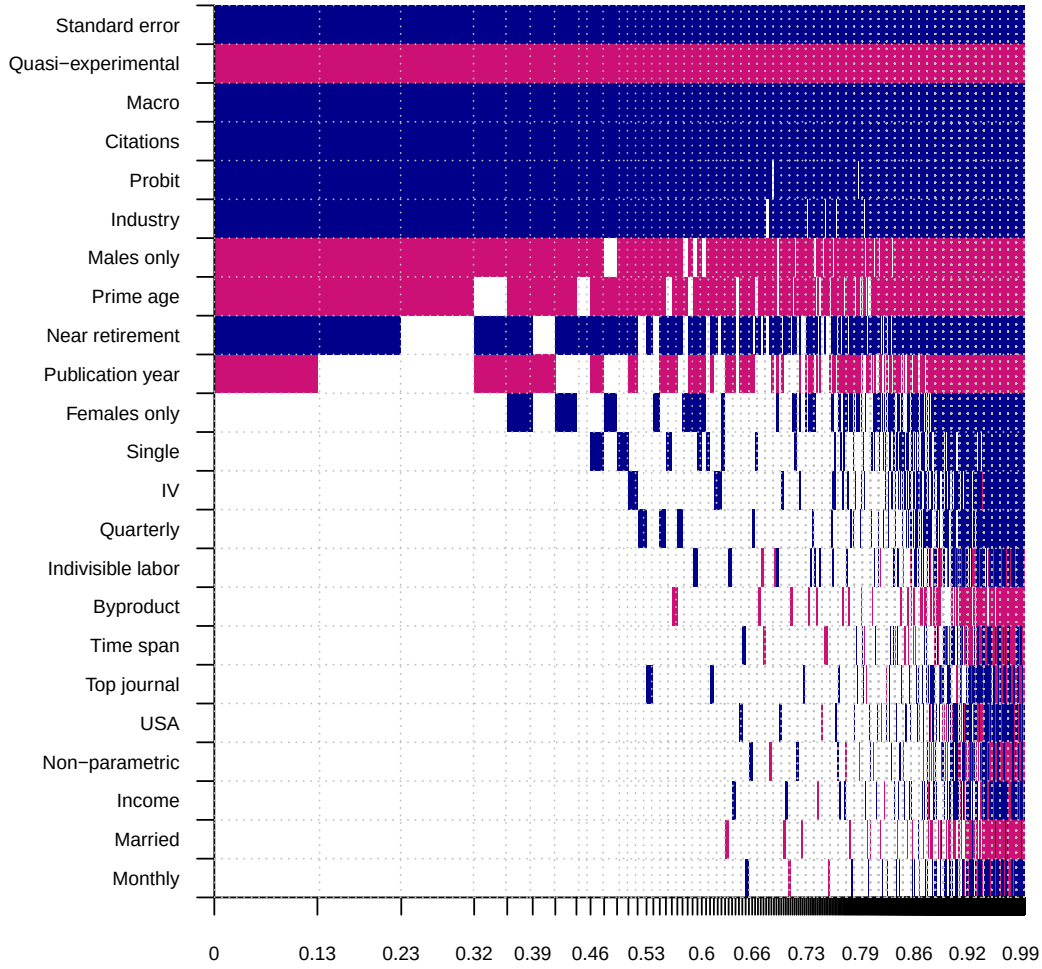
Notes: The corresponding results of this BMA specification are reported in Table 4. Considering Eicher et al. (2011), we employ unit information prior and as suggested by George (2010), the dilution prior which captures potential collinearity.

Figure B1: Model size and convergence for the benchmark BMA model (Dilution prior)



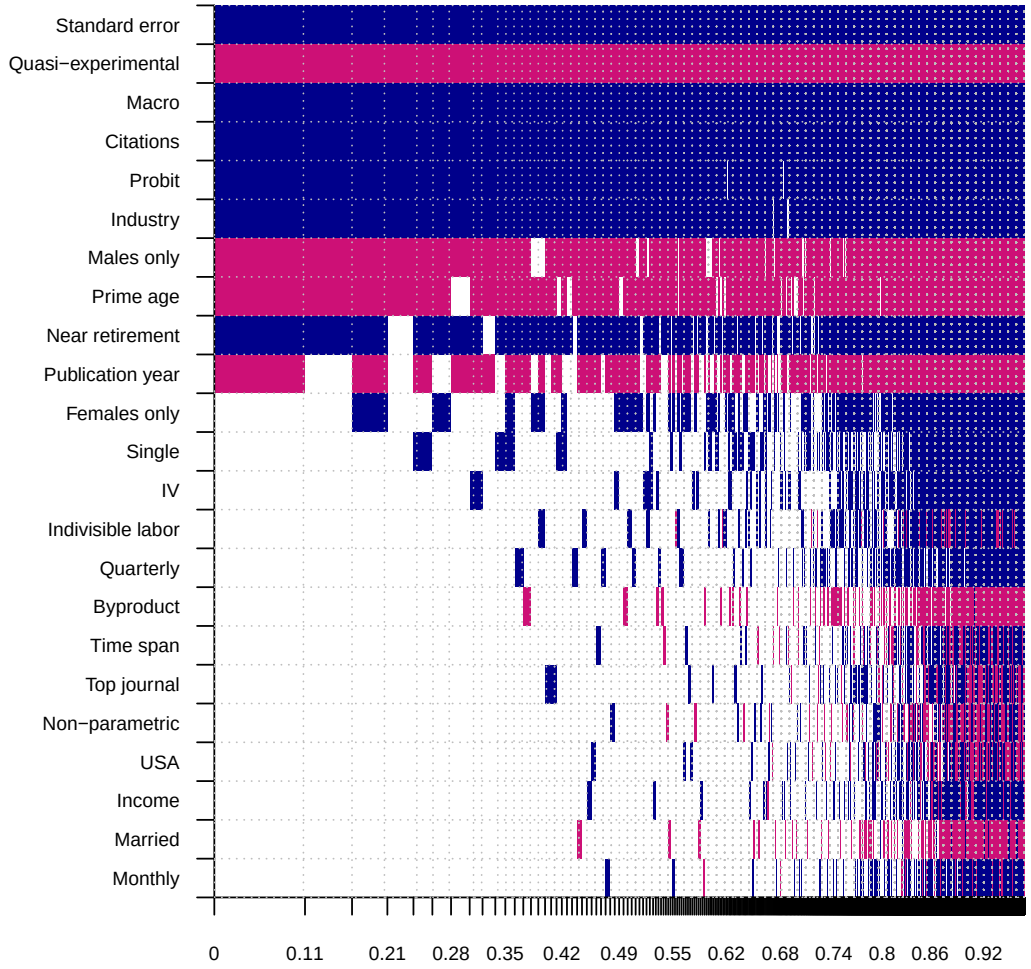
Notes: The figure depicts the posterior model size distribution and the posterior model probabilities of the BMA exercise reported in Table 4.

Figure B2: Model inclusion in BMA (BRIC g-prior)



Notes: The response variable is the estimate of the Frisch extensive elasticity in a primary study. The columns denote individual models; variables are sorted by posterior inclusion probability in descending order. The horizontal axis denotes the cumulative posterior model probabilities. The estimation is based on BRIC g-prior (the benchmark g-prior for parameters with the beta-binomial model prior) and random model prior. Blue color (darker in gray-scale) = the variable has a positive estimated sign. Red color (lighter in gray-scale) = the variable has a negative estimated sign. No color = the variable is excluded from the given model. The numerical results are reported in Table B2.

Figure B3: Model inclusion in BMA (HQ g-prior)



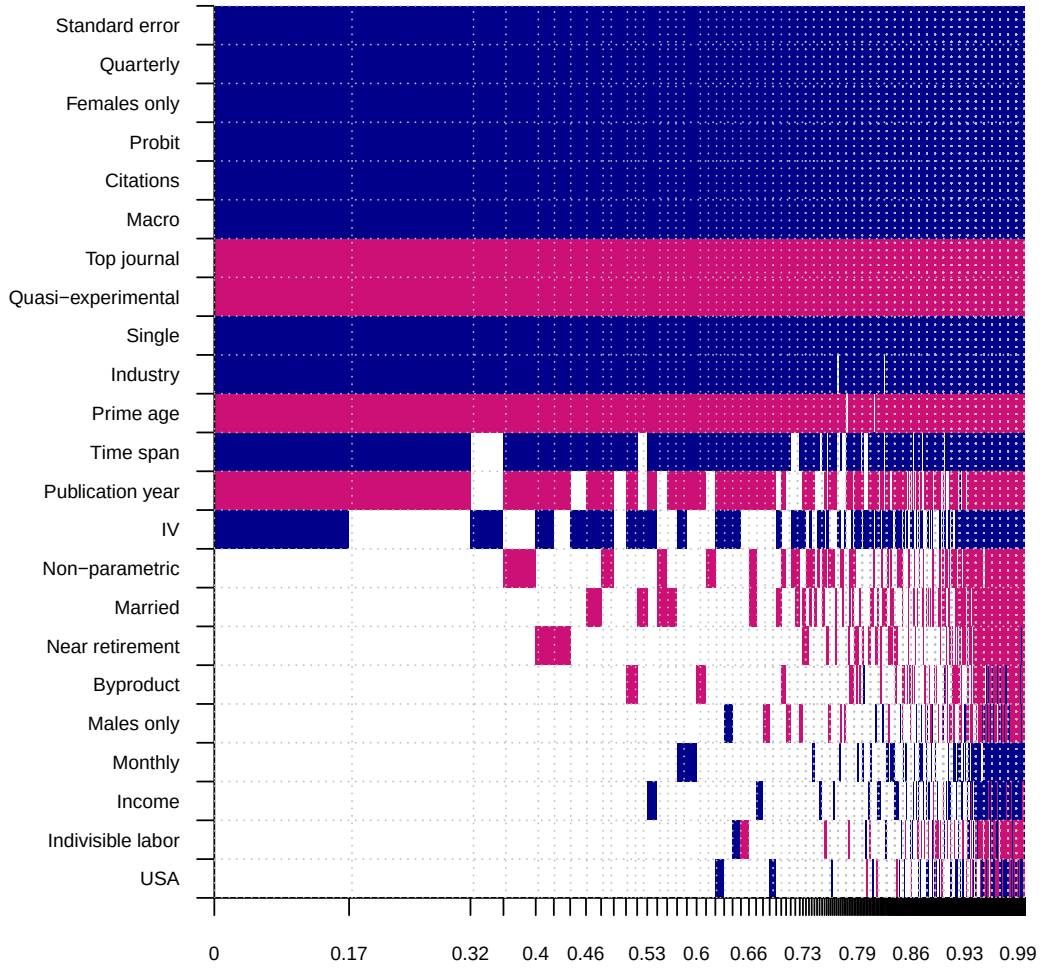
Notes: The response variable is the estimate of the Frisch extensive elasticity in a primary study. The columns denote individual models; variables are sorted by posterior inclusion probability in descending order. The horizontal axis denotes the cumulative posterior model probabilities. The estimation is based on HQ g-prior that asymptotically mimics the Hannan-Quinn criterion and random model prior. Blue color (darker in gray-scale) = the variable has a positive estimated sign. Red color (lighter in gray-scale) = the variable has a negative estimated sign. No color = the variable is excluded from the given model. The numerical results are reported in Table B2.

Table B2: Alternative BMA priors

	BRIC g-prior			HQ g-prior		
Variable	Post. Mean	Post. SD	PIP	Post. Mean	Post. SD	PIP
Intercept	0.561	N.A.	1.000	0.670	N.A.	1.000
Standard error	1.330	0.146	1.000	1.298	0.147	1.000
Demographics						
Prime age	-0.092	0.048	0.862	-0.093	0.045	0.893
Near retirement	0.082	0.057	0.750	0.096	0.052	0.856
Females only	0.020	0.041	0.244	0.030	0.046	0.362
Males only	-0.102	0.043	0.911	-0.098	0.045	0.897
Married	-0.001	0.011	0.034	-0.001	0.014	0.059
Single	0.013	0.040	0.121	0.021	0.050	0.202
Income	0.001	0.008	0.037	0.001	0.010	0.066
Data characteristics						
Time span	0.000	0.006	0.045	0.000	0.008	0.076
Monthly	0.001	0.015	0.033	0.001	0.020	0.057
Quarterly	0.004	0.017	0.071	0.005	0.019	0.111
Industry	0.174	0.058	0.968	0.182	0.059	0.976
Macro	0.197	0.036	1.000	0.197	0.037	1.000
USA	0.001	0.011	0.043	0.001	0.013	0.069
Specifications						
Indivisible labor	0.003	0.021	0.069	0.008	0.031	0.129
Quasi-experimental	-0.293	0.049	1.000	-0.306	0.048	1.000
Probit	0.243	0.068	0.988	0.232	0.067	0.989
Non-parametric	0.000	0.009	0.039	0.000	0.012	0.068
IV	0.005	0.021	0.075	0.009	0.029	0.139
Publication characteristics						
Publication year	-0.100	0.114	0.501	-0.132	0.115	0.650
Top journal	0.001	0.012	0.043	0.001	0.014	0.072
Citations	0.076	0.016	0.999	0.075	0.016	0.999
Byproduct	-0.003	0.018	0.049	-0.006	0.026	0.094
Observations	723			723		
Studies	36			36		

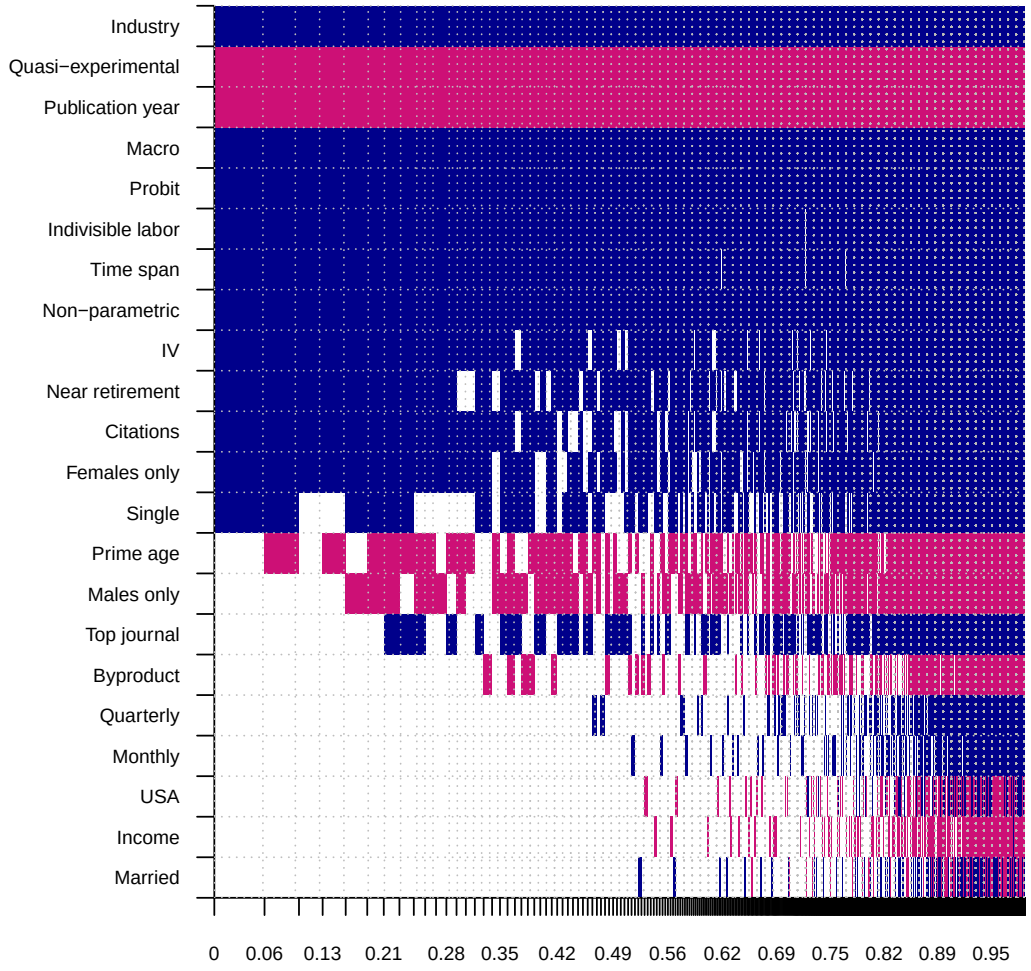
Notes: Response variable = The Frisch extensive elasticity, S.D. = standard deviation, PIP = Posterior inclusion probability. In the left panel, we apply BMA based on BRIC g-prior (the benchmark g-prior for parameters with the beta-binomial model prior). The right panel reports the results of BMA based on HQ g-prior, which asymptotically mimics the Hannan-Quinn criterion. Table 3 presents a detailed description of all variables.

Figure B4: Model inclusion in BMA, weighted by the inverse of the number of estimates per study



Notes: The response variable is the estimate of the Frisch extensive elasticity in a primary study. The columns denote individual models; variables are sorted by posterior inclusion probability in descending order. The horizontal axis denotes the cumulative posterior model probabilities. The estimation is based on the unit information prior (UIP) recommended by Eicher et al. (2011) and the dilution prior suggested by George (2010), which captures collinearity. The data used in BMA are weighted by the number of estimates per study. Blue color (darker in gray-scale) = the variable has a positive estimated sign. Red color (lighter in gray-scale) = the variable has a negative estimated sign. No color = the variable is excluded from the given model. Table B3 reports the numerical results.

Figure B5: Model inclusion in BMA without including standard errors



Notes: The response variable is the estimate of the Frisch extensive elasticity in a primary study. The columns denote individual models; variables are sorted by posterior inclusion probability in descending order. The horizontal axis denotes the cumulative posterior model probabilities. The estimation is based on the unit information prior (UIP) recommended by Eicher et al. (2011) and the dilution prior suggested by George (2010), which captures collinearity. In this setting, we exclude standard errors from the regressions. Blue color (darker in gray-scale) = the variable has a positive estimated sign. Red color (lighter in gray-scale) = the variable has a negative estimated sign. No color = the variable is excluded from the given model. Table B3 reports the numerical results.

Table B3: Alternative specifications of the baseline BMA model

	BMA (weighted)			BMA (without SE)		
Variable	Post. Mean	Post. SD	PIP	Post. Mean	Post. SD	PIP
Intercept	0.013	N.A.	1.000	2.250	N.A.	1.000
Standard error	1.615	0.117	1.000	N.A.	N.A.	N.A.
Demographics						
Prime age	-0.182	0.050	0.991	-0.053	0.053	0.589
Near retirement	-0.005	0.021	0.112	0.112	0.062	0.853
Females only	0.211	0.032	1.000	0.109	0.063	0.832
Males only	-0.002	0.013	0.081	-0.064	0.066	0.578
Married	-0.014	0.038	0.177	0.000	0.016	0.071
Single	0.266	0.062	0.998	0.094	0.090	0.602
Income	0.002	0.020	0.069	-0.001	0.011	0.076
Data characteristics						
Time span	0.064	0.033	0.882	0.091	0.027	0.987
Monthly	0.003	0.019	0.079	0.004	0.028	0.083
Quarterly	0.209	0.031	1.000	0.005	0.022	0.117
Industry	0.228	0.068	0.992	0.470	0.077	1.000
Macro	0.216	0.046	1.000	0.248	0.057	0.999
USA	0.000	0.008	0.064	0.000	0.016	0.082
Specifications						
Indivisible labor	-0.001	0.014	0.067	0.246	0.070	0.991
Quasi-experimental	-0.196	0.044	1.000	-0.324	0.054	1.000
Probit	0.347	0.047	1.000	0.264	0.063	0.998
Non-parametric	-0.013	0.029	0.214	0.165	0.054	0.975
IV	0.054	0.059	0.535	0.182	0.084	0.904
Publication characteristics						
Publication year	-0.055	0.039	0.748	-0.679	0.101	1.000
Top journal	-0.164	0.036	1.000	0.050	0.067	0.439
Citations	0.087	0.016	1.000	0.050	0.028	0.842
Byproduct	-0.003	0.014	0.087	-0.019	0.050	0.186
Observations	723			723		
Studies	36			36		

Notes: Response variable = The Frisch extensive elasticity, S.D. = standard deviation, PIP = Posterior inclusion probability. In the left panel, variables are weighted by the inverse of the number of estimates per study. The right panel reports the results of BMA when standard errors are excluded. In both panels, we employ BMA based on the UIP g-prior (Eicher et al., 2011) and dilution model suggested by George (2010). Table 3 presents a detailed description of all variables.

C Frequentist Model Averaging (FMA)

Table C1: Results of frequentist model averaging

	Coeff.	S.E.	P-value
Intercept	1.203	0.316	0.000
Standard error	1.087	0.165	0.000
Demographics			
Prime age	-0.092	0.035	0.008
Near retirement	0.119	0.041	0.003
Females only	**0.101**	**0.039**	**0.009**
Males only	-0.060	0.039	0.122
Married	-0.003	0.056	0.961
Single	**0.111**	**0.061**	**0.068**
Income	0.023	0.038	0.549
Data characteristics			
Time span	0.028	0.027	0.292
Monthly	0.016	0.086	0.857
Quarterly	0.048	0.044	0.276
Industry	0.300	0.081	0.000
Macro	0.235	0.056	0.000
USA	-0.035	0.048	0.468
Specifications			
Indivisible labor	**0.112**	**0.059**	**0.057**
Quasi-experimental	-0.332	0.062	0.000
Probit	0.212	0.069	0.002
Non-parametric	0.025	0.048	0.605
IV	0.099	0.058	0.087
Publication characteristics			
Publication year	**-0.329**	**0.098**	**0.001**
Top journal	-0.005	0.048	0.923
Citations	0.080	0.020	0.000
Byproduct	-0.099	0.068	0.147
Observations	723		
Studies	36		

Notes: We use Mallow's weights Hansen (2007), and the orthogonalization of the covariate space suggested byAmini and Parmeter (2012) to conduct frequentist model averaging (FMA) exercise. The emboldened variables are deemed important in FMA but not in the benchmark BMA.

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