The Cognitive Load of Financing Constraints: Evidence from Large Scale Wage Surveys

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Motivation

"**What is your monthly wage ?**"

- Your answer is probably not the exact wage you earn...
- It is probably not random either
- This is a standard LFS survey item that we re-interpret as a cognition exercise
- **Intuition :** informative of worker level uncertainty/attention and of other potential behavioral/ reporting biases

Research Intuition :

Measure of Workers' Attention to their Own Wages

Idea : Turn survey data on their head
and investigate what they say about workers' perceptions of their own wages :

- **Workers' errors are informative, rather than noise !** (Pishke, 1995)
- Same interpretation of un-incentivized surveys as in **Ferrario and Stantcheva (2022)**
- **Direct** measure of **attention** via overall accuracy of wage perception
- Also allows documenting furhter potential behavioral biases

Requires a **novel methodology** :

- Empirical "structural" model of attention/uncertainty,
  flexible enough to address rounding and potential reporting biases
- Non-trivial (mixture) model, requiring EM(ML) techniques :
  unsupervised clustering

Application to the Relationship between Attention and Financing Constraints/Poverty

Research idea :

- Use distance to payday as an **exogenous** variation of financing constraints (ensured by LFS sampling scheme)
- Take our **new measure of attention** and investigate its monthly variations : New test of the above hypothesis :

  Does attention (aka cognitive load) correlate with financing constraints ?
  - (MUCH) larger population than previous literature, developped country
  - Real world data (ie. non-experimental setting)
- Implement **revealed preference approach** on these patterns :
  $\Longrightarrow$ We are able to identify **shape of the attention cost function !**
- **Additional by-product :**
  new measure of the population of financially constrained workers

Take-Aways for French Workers, 2005/2015

- French workers perceive their wage with a degree of uncertainty of $\approx$ 10%
- Through the lens of a signal extraction model (Gabaix, 2018) : Attention index averages at 63% and ranges between 30% and 84%, depending on the wage level, education, tenure or gender
- Low-wage workers actually feature suggestive patterns of monthly cyclicality that are indicative of financing constraints
  - Attention is minimal in the middle of the month
  - It increases steadily until payday, by ca. 20%, then drops **immediately**
  - $\Longrightarrow$ not consistent with a pure passive information exposure story
  - $\Longrightarrow$ well rationalized by a simple model of financing constraints
  - Reveals : **costs of maintaining attention over time are convex**, **costs of achieving high levels are not too concave** (or convex)
- All other behavioral biases are stable (Stango and Zinman, 2020)
- The **bottom 30%** of French workers are subject to these cycles

Related Literature

- Previously mentioned literature in
  psychology, economics and cognitive sciences
  - Models of rational inattention surveyed in Gabaix (2018)
  - Empirical papers on inattention to the characteristics of goods : Gabaix and Laibson (2016), Lacetera et al. (2012)...
  - Empirical papers on inattention to their prices : Chetty et al. (2009), Taubinsky and Rees-Jones (2017), Ito (2014) or Allcott (2011)...
- Literature in **labor economics**
  - Measurement issues in survey data (vs. administrative data) : Hampers the analysis of wage dynamics or wage rigidities
  - Pischke (1995), Biscourp et al. (2005), Dickens et al. (2007)
- Literature in **macro** :
  - Uncertainty : Bloom (2009) or Bloom et al. (2012)
  - Macro implications of rational inattention :
    Sims (2003), Luo (2008) vs Reis (2006)
- Also related : **behavioral household finance**
  - Determinants of attention to financial accounts
    (eg. Olafsson and Pagel, 2017)

Outline of Paper

- Theoretical framework in a nutshell
- Data and descriptive evidence
- Measures of worker level uncertainty :
  - Empirical set-up
  - Results from the variance analysis exercise
- Payday (financing constraints) and the monthly cycle of attention

Theoretical Framework

Model of Financing Constraints (1)

Utility of a worker within a month :

$$
\begin{aligned}
U^{(0)}(C_t) \quad &= \quad \int_0^1 u(C_t)\mathrm{d}t \\
&\quad -R_A. \int_{\mathbb{R}} \left(\bar{C} - W\right) F_0(W)\mathrm{d}W - R_B. \int_0^{\bar{C}} \left(\bar{C} - W\right) F_0(W)\mathrm{d}W
\end{aligned} \tag{1}
$$

with :

- u concave $\Longrightarrow$ consumption smoothing
- R_A : cost of transferring income symmetrically across time
- R_B : assymetric cost ; captures financing constraints / risk aversion
- F assumed to be lognormal with STD σ
  - Main parameter to be estimated : measure of uncertainty
  - Parametric assumption corresponds to least informative distribution of given variance σ^2 (maximum entropy)

Model of Financing Constraints (2)

Introducing endogenous attention at day $\tau \in [0;1]$:

$$\begin{aligned} U^{(m)}(C_t) \quad &= \quad \int_0^{\tau} u(C_t)\mathrm{d}t + \int_{\tau}^{1} u(C_t)\mathrm{d}t \\ &\quad -R_A.\int_{\mathbb{R}} \left(\bar{C} - W\right) F_m(W)\mathrm{d}W - R_B.\int_0^{\bar{C}} \left(\bar{C} - W\right) F_m(W)\mathrm{d}W \\ &\quad -K(m).h(1-\tau) \end{aligned} \tag{2}$$

where m is attention :

- Intuition in a signal extraction model
- Workers gather (orthogonal) signal s to lower σ
- F_m is the bayesian posterior probability distribution, computed from the prior F and the new signal s

Model of Financing Constraints (3)

Empirical predictions :

- Financially constrained / risk averse workers pay more attention overall
- They have an incentive to vary their attention over the month and pay more attention as the budget constraint tightens

Setting that is informative of the cost function for m :
FOC are informative of the :

- **Cost of maintaining attention over time :**

$$\frac{\mathrm{d}m}{\mathrm{d}\tau} \approx \frac{h''(1-\tau).K(m)}{h'(1-\tau).K'(m)} \tag{3}$$

  Since K, K', and h' are strictly positive,
  the sign of $\frac{\mathrm{d}m}{\mathrm{d}\tau}$ is informative of the the sign of h''
- **Cost of achieving high levels of attention :**
  - If $\frac{\mathrm{d}m}{\mathrm{d}\tau} < 0$ then K'' is necessarily negative and large in absolute value
  - If $\frac{\mathrm{d}m}{\mathrm{d}\tau} > 0$, then K'' is either positive or negative but small in absolute value

Data

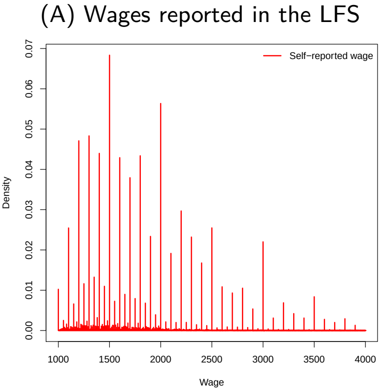
Main Data Source : ERFS = LFS + Fiscal files

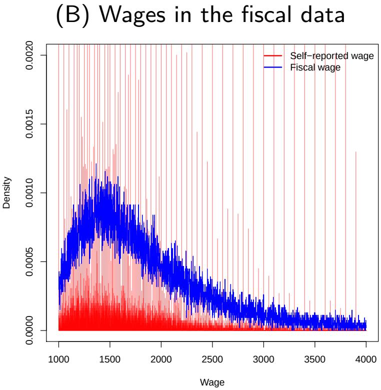
French “Survey on Fiscal and Social Earnings” (ERFS) :

- Labor Force Survey : rotating panel, self-reported wage
- Matched with fiscal files, in particular : taxable wage income
- Scientific sampling scheme insuring that
  day of interview is (broadly) orthogonal to workers’ characteristics

		Year $t-1$				Year t				Year $t+1$			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Panel 1	Wave of Labor Force Survey	1	2	3	4	5	6						
	Wage reported in LFS	×					×						
	Fiscal wage				×								
Panel 2	Wave of Labor Force Survey		1	2	3	4	5	6					
	Wage reported in LFS		×					×					
	Fiscal wage				×								
Panel 3	Wave of Labor Force Survey			1	2	3	4	5	**6**				
	Wage reported in LFS			×					×				
	Fiscal wage				×				×				
Panel 4	Wave of Labor Force Survey				**1**	2	3	4	5	6			
	Wage reported in LFS				×					×			
	Fiscal wage				×				×				

Wage Distributions

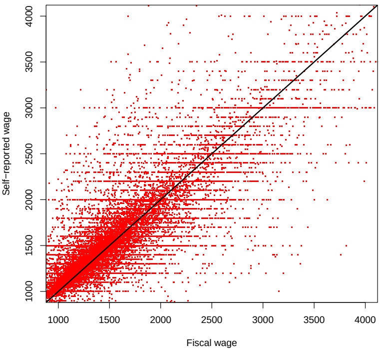




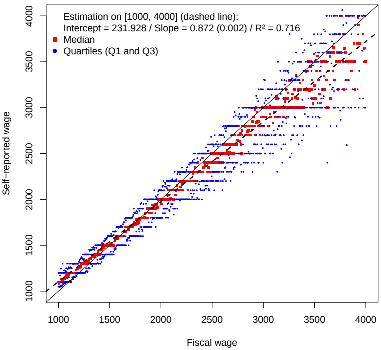
Shares of wages	at t		at $t+1$		at t and $t+1$	
Multiples of :	LFS	Fiscal files	LFS	Fiscal files	LFS	Fiscal files
€1	1	1	1	1	1	1
€10	0.794	0.008	0.877	0.008	0.727	0
€50	0.707	0.002	0.783	0.001	0.606	0
€100	0.619	0.001	0.677	0	0.478	0
€500	0.177	0	0.196	0	0.074	0
€1,000	0.077	0	0.084	0	0.031	0

Correspondence btw. Self-Reported and Fiscal Wages

(A) Raw Data



(B) Quartiles of Self-Reported Wages by Bins of €5 of Fiscal Wages



Empirical Set-Up

Baseline Variance Analysis Set-Up

Standard (orthogonal) random effect model :

$$\begin{aligned} w_{it}^{r} &= w_{it}^{f} + a_i + \upsilon_{it}, \\ a_i &\sim \mathcal{N}\left(\mu_a, \sigma_a^2\right) \\ \upsilon_{it} &\sim \mathcal{N}\left(0, \sigma_m^2\right) \\ \mathrm{Corr}\left(a_i, \upsilon_{it}\right) &= 0 \\ w_{it}^{f} &\perp a_i, \upsilon_{it} \end{aligned}$$

Main technical difficulty : non-standard limited dependent variable model

$$e^{w_{it}^{r}} = N_i \left\lfloor \frac{e^{w_{it}^{f}} e^{a_i} e^{\upsilon_{it}}}{N_i} + 0.5 \right\rfloor, \ t \in \{1, 2\}$$

Rounding potentially affects our estimates of the "errors" that workers make, therefore **our estimates of** σ_m **and** σ_a

Sketch of Estimation Strategy

Non-standard limited dependent variable model :

$$e^{w_{it}^r} = N_i \left\lfloor \frac{e^{w_{it}^f} e^{a_i} e^{\upsilon_{it}}}{N_i} + 0.5 \right\rfloor, \; t \in \{1, 2\}$$

General Structure of the Mixture Model (Ln-Likelihood)

$$l\left(\Omega_i, N_i | X_i, \theta, (\pi_n)\right) = \ln\left(\sum_{n \in \mathcal{N}} \pi_n \mathbb{P}\left(\Omega_i | N_i = n, X_i, \theta\right)\right) \tag{4}$$

Summation within “ln” term renders ln-lik numerically difficult to maximize

- Standard problem of mixture models, standard solution : EM algorithm
- Within interation : gaussian random effect a_i, approximated with Gauss-Hermitte quadrature

Results

Estimates in Pooled Sample

Model Structure : Probabilities of Rounding, (π_n)

Classes	€1	€10	€50	€100	€500	€1,000	Average	LnLik
Specifications	(A) Probabilities of rounding, π						*Coarsening*	
1 class	1.000						1.000	-262,023
	-						-	
2 classes	0.523			0.477			48.272	-191,222
	(0.005)			(0.005)			(0.501)	
3 classes	0.395		0.178	0.427			52.013	-176,802
	(0.005)		(0.004)	(0.005)			(0.507)	
4 classes	0.280	0.119	0.174	0.426			52.799	-170,421
	(0.004)	(0.003)	(0.004)	(0.005)			(0.507)	
5 classes	0.281	0.119	0.176	0.369	0.055		74.833	-169,485
	(0.004)	(0.003)	(0.004)	(0.005)	(0.002)		(1.051)	
6 classes	0.280	0.119	0.175	0.369	0.049	0.007	78.716	-169,437
	(0.004)	(0.003)	(0.004)	(0.005)	(0.002)	(0.001)	(1.311)	
left-digit bias	0.281	0.119	0.176	0.370	0.048	0.005	76.625	-169,902
	(0.004)	(0.003)	(0.004)	(0.006)	(0.002)	(0.001)	(1.273)	

NB Model with left digit bias for comparison with literature only
(Busse et al, 2013 and Lacetera et al, 2012)

Perceived Volatility Premium, σ_m

Classes	€1	€10	€50	€100	€500	€1,000	Average	
	(B) Perceived volatility premium, σ_m							AIC
1 class	0.105						0.105	524,053
	(0.000)						(0.001)	
2 classes	0.104			0.105			0.104	382,457
	(0.000)			(0.000)			(0.001)	
3 classes	0.108		0.082	0.109			0.104	353,623
	(0.000)		(0.001)	(0.000)			(0.001)	
4 classes	0.121	0.068	0.081	0.109			0.103	340,867
	(0.001)	(0.001)	(0.001)	(0.000)			(0.001)	
5 classes	0.122	0.068	0.080	0.114	0.042		0.101	339,000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)		(0.001)	
6 classes	0.122	0.068	0.080	0.113	0.046	0.077	0.101	338,910
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	0.013	(0.001)	
left-digit bias	0.122	0.068	'0.080	0.112	0.037	0.086	0.100	339,840
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	-0.016	(0.001)	

Uncertainty is is NOT correlated with rounding (contrasts with Ruud et al., 2014 or Binder, 2017)

Mapping with the index of attention : $m = 1 - \frac{\sigma_m^2}{\sigma^2}$

For $\sigma \approx 0.167$ (DADS), this implies that attention $m \approx 0.633$

Comparison with Previous Literature (Gabaix, 2018)

Study	Good or quantity	Opaque attribute	Attribute importance (τ/p)	Attention estimate (m)
Allcott and Wozny (2014)	Expense associated with car purchase	Present value of future gasoline costs	0.58	0.76
Hossain and Morgan (2006)	Price of CDs sold at auction on eBay	Shipping costs	0.38	0.82
DellaVigna and Pollet (2009)	Public company equity value	Value innovation due to earnings announcements	0.30	0.54
DellaVigna and Pollet (2009)	Public company equity value	Value innovation due to earnings announcements *that occur on Fridays*	0.30	0.41
Hossain and Morgan (2006)	Price of CDs sold at auction on eBay	Shipping costs	0.24	0.55
Taubinsky and Rees-Jones (2018)	Price of products purchased in laboratory experiment	Sales tax, *tripled relative to standard tax*	0.22	0.48
Lacetera et al. (2012)	Mileage of used cars sold at auction	Mileage left-digit remainder	0.10	0.69
Chetty et al. (2009)	Price of grocery store items	Sales tax	0.07	0.35
Taubinsky and Rees-Jones (2018)	Price of products purchased in laboratory experiment	Sales tax	0.07	0.25
Chetty et al. (2009)	Price of retail beer cases	Sales tax	0.04	0.06
Brown et al. (2010)	Price of iPods sold at auction on eBay	Shipping costs	0.03	0.00
Mean	–	–	0.21	0.44
Standard deviation	–	–	0.18	0.28
This study :	wages	transitory components	0.17	0.63

Mean and Standard Deviation of Bias, μ_a and σ_a

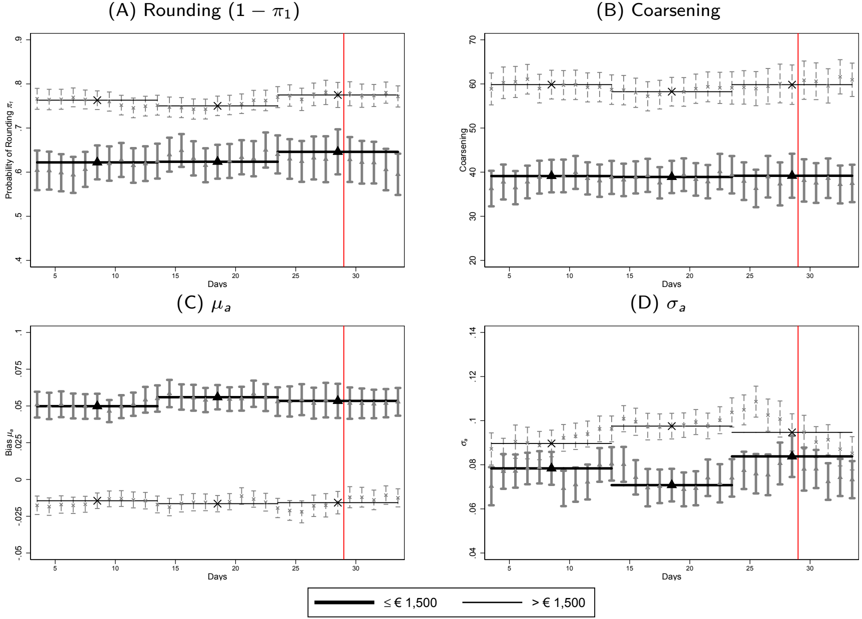
Classes	€1	€10	€50	€100	€500	€1,000	Average	
Specifications	(C) Mean of bias, μ_a							BIC
1 class	0.008						0.008	524,066
	(0.001)						(0.001)	
2 classes	0.020			-0.004			0.008	382,484
	(0.001)			(0.001)			(0.001)	
3 classes	0.025		0.003	-0.005			0.008	353,664
	(0.001)		(0.002)	(0.002)			(0.001)	
4 classes	0.030	0.012	0.003	-0.005			0.008	340,921
	(0.002)	(0.002)	(0.002)	(0.002)			(0.001)	
5 classes	0.030	0.012	0.003	-0.004	-0.018		0.008	339,068
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)		(0.001)	
6 classes	0.030	0.012	0.003	-0.004	-0.021	-0.007	0.008	338,992
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.023)	(0.001)	
left-digit bias	0.031	0.015	0.019	0.023	0.110	0.202	0.028	339,922
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.027)	(0.001)	
	(D) Standard deviation of bias, σ_a							
1 class	0.095						0.095	
	(0.001)						(0.001)	
2 classes	0.083			0.106			0.094	
	(0.001)			(0.001)			(0.001)	
3 classes	0.076		0.094	0.109			0.093	
	(0.001)		(0.001)	(0.001)			(0.001)	
4 classes	0.072	0.087	0.093	0.109			0.093	
	(0.001)	(0.001)	(0.001)	(0.001)			(0.001)	
5 classes	0.072	0.087	0.092	0.107	0.120		0.093	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)		(0.001)	
6 classes	0.072	0.087	0.092	0.107	0.113	0.160	0.093	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.019)	(0.001)	
Left-digit bias	0.072	0.087	0.091	0.107	0.117	0.178	0.093	
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.026)	(0.001)	

Correlations between Workers' Characteristics and Behavioral Parameters

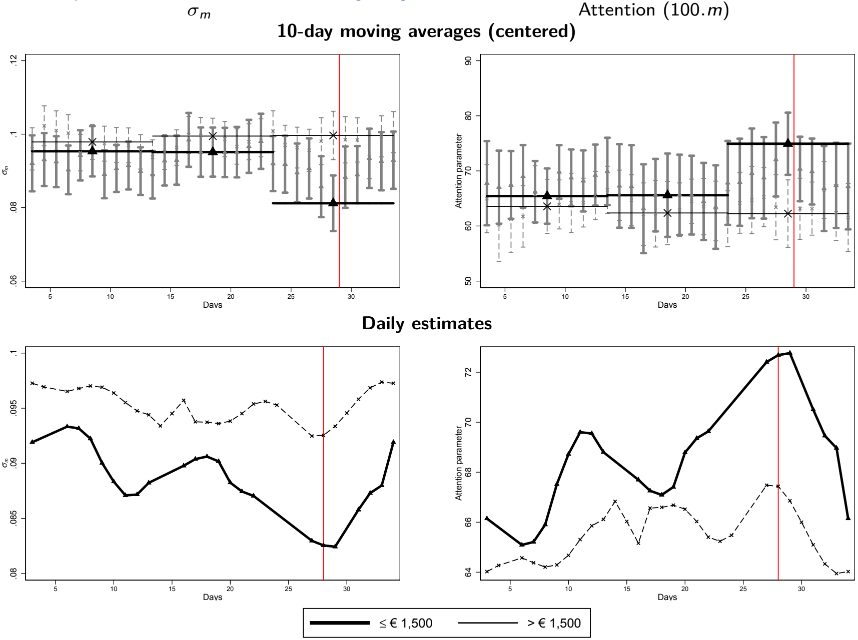
	Rounding	Coarsening	σ_m	μ_a	Attention
Wage :	0.105***	53.261***	0.004	-0.054***	0.046
high	(0.008)	(1.519)	(0.003)	(0.005)	(0.039)
Women	-0.041***	-13.243***	-0.015***	-0.012*	0.181***
	(0.009)	(0.604)	(0.002)	(0.006)	(0.035)
Education :	0.015*	4.757***	-0.002	0.011**	0.086*
high	(0.008)	(0.846)	(0.003)	(0.005)	(0.042)
Tenure :	-0.004	-13.327***	0.010***	0.011*	0.105**
short	(0.008)	(0.990)	(0.003)	(0.005)	(0.044)
Observations	15	15	15	15	15

Monthly Cycles

Stability of All Paramaters Across the Month...



... Except Attention : Monthly Cycle



What Do Attention Cycles Reveal ? (1)

Reminder of theoretical predictions :
Workers benefit from reducing σ_m iff they are **financially constrained**

What the data show :

- Workers earning less than €1,500 exert effort to reduce σ_m
- This reveals they are financially constrained

Quantification :

- The threshold corresponds to the bottom 30% of workers in the wage distribution
- Quantification of the population experiencing (at least temporarily) liquidity constraints

What Do Attention Cycles Reveal ? (2)

Reminder of theoretical predictions :

- The sign of $\frac{\mathrm{d}m}{\mathrm{d}\tau}$ is informative of the sign of h'', since :

$$\frac{\mathrm{d}m}{\mathrm{d}\tau} \approx \frac{h''(1-\tau).K(m)}{h'(1-\tau).K'(m)}$$

  and K, K', and h' are strictly positive
- Similarly, the theoretical FOC deliver bounds for K'' :
  - If $\frac{\mathrm{d}m}{\mathrm{d}\tau} < 0$ then K'' is necessarily negative and large in absolute value
  - If $\frac{\mathrm{d}m}{\mathrm{d}\tau} > 0$, then K'' is either positive, or negative but small in abs. value

What the data show : $\frac{\mathrm{d}m}{\mathrm{d}\tau} > 0$

- **The costs of maintaining attention over time are convex**
- **The costs of achieving high levels are not too concave** (or convex)
- Magnitude (per year) : equivalent to **bypassing between €10 and €50 of expected revenue**, depending on risk aversion

Concluding Remarks

Wrap-up :

- New methodology to measure attention in readily available and large datasets :
  - Allows reconsidering the correlation between cognitive load and financing constraints / poverty
  - Allows recovering the shape of the attention cost function

For future research ?

- **Quantitative implications for actual decision making (incl. implications for marketing), "performance" or productivity ?**
  So far, the previous literature suggests it would be non-negligible...
- What data ? ?
- **Investigate the disconnect btw bias and attention...**

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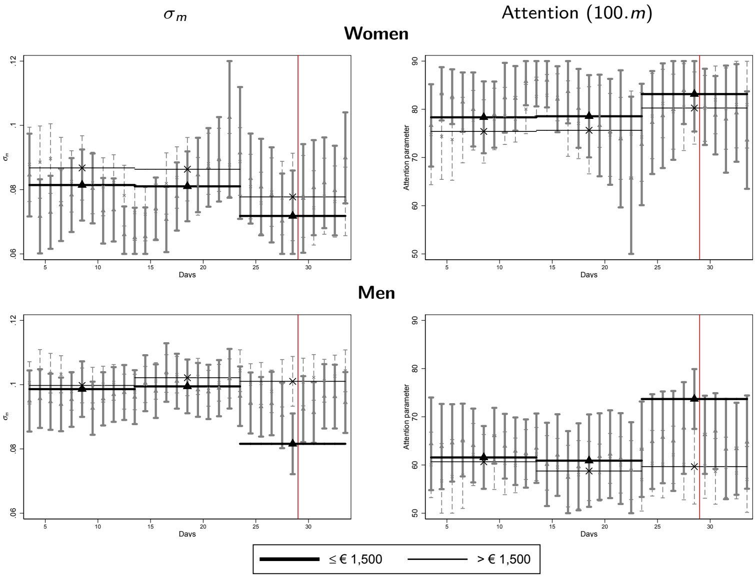
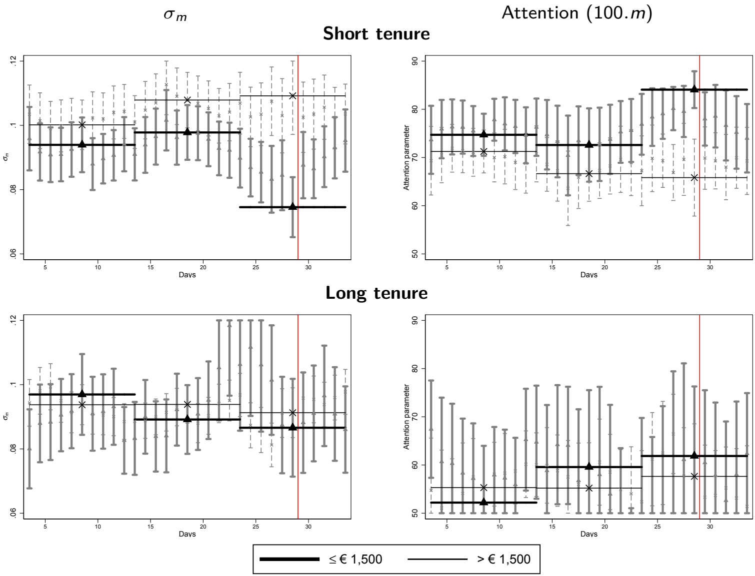
Heterogeneity across Workers (1) : Women *vs.* Men



Heterogeneity across Workers (2) : Short *vs.* Long Tenure



Heterogeneity across Workers (3) : High *vs.* Low Education