Mothers' Jobs after Childbirth and Earnings

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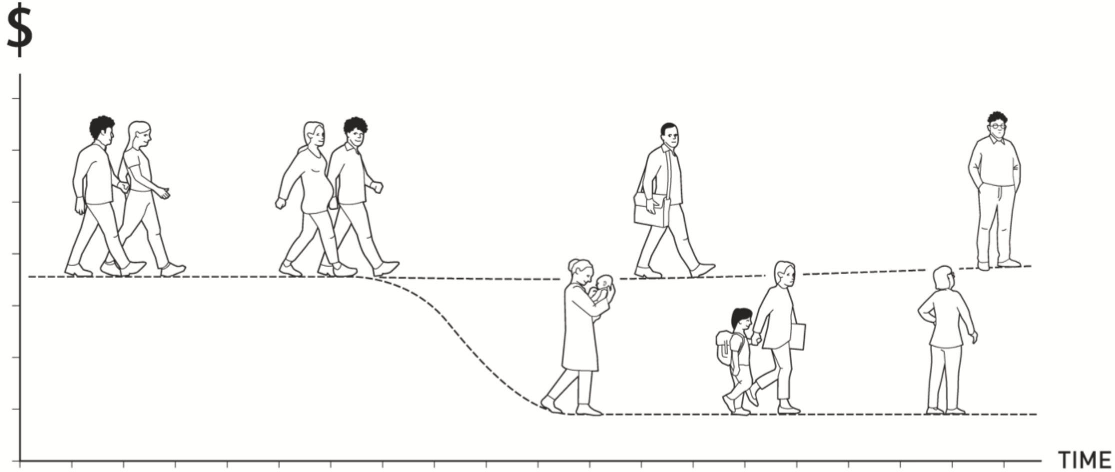
This presentation is based on a joint project with Bernhard Schmidpeter (Vienna University of Economics and Business and IZA).

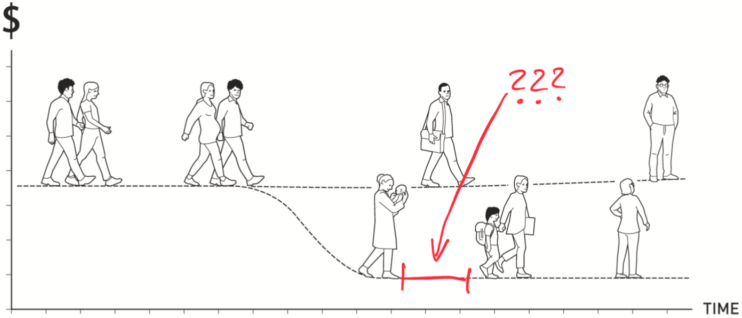
Motivation


$
TIME

Motivation

- Persistent gender pay gap in most countries (Goldin, 2014, Blau and Kahn, 2017)
- Many possible explanations for existing gender pay gaps
  - Lower aspirations, pressure, occupational sorting (e.g. Azmat et al. 2020, Cai et al. 2019)
- "Motherhood Penalty" has received particular attention
  - Divergence in earnings with onset of motherhood (e.g. Angelov et al. 2016)
  - Motherhood driving force of pay gaps (Kleven et al. 2019)

How do mothers behave in the labor market after childbirth?



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Mothers in the Labor Market

- Strong labor market attachment of mothers – between 50% and 80% in Europe within 3 years (OECD 2006)
- Large share of working mothers do not return to pre-birth employer
  - Around 20% of first-time mothers in the U.S. (Laughlin 2011)
  - Around 25% of mothers in Germany and Austria (Rupp 2013)
- Mothers' return behavior suggests a role for job search during maternity leave
- Changing employer can have important implications for wage growth and future career

Mothers and the Decision to Change Employer

- Job-to-job transition may be associated with
  - higher wages (e.g. Delacroix and Shi 2006)
  - more stable jobs (e.g. Jarosch 2015)
- Implications unclear
  - Moving to family friendly jobs?
  - Moving to better career opportunities?

Open questions

Open questions:

- Is switching employer important for mothers' labor market careers?
- Do mothers gain from job-to-job transitions?
- If so, who gains and why?
- What are the channels through which the change operates?

Our Research

- We estimate returns to job-to-job transitions during maternity leave
  - We bound distribution of gains/losses
  - Impose intuitive assumptions inherent in many job-search models
- We explore why only some of the mothers gain from the switch.

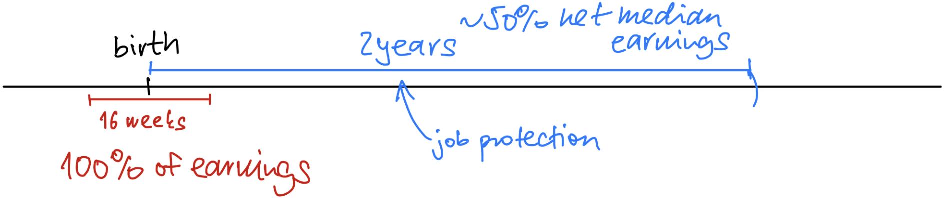
  We provide evidence on the role of
  - $\rightarrow$ **firms**
  - $\rightarrow$ **formal/informal childcare**
  - $\rightarrow$ **husbands**
  - $\rightarrow$ **networks**

Our Contribution

- (Unintended) Consequences of family policies (Lalive et al. 2014, To 2018, Thomas 2019, Karimi et al. 2020)
- "Motherhood Penalty" (Angelov et al. 2016, Kuziemko et al. 2018, Kleven et al. 2019)
- Determinants of labor market inequality (Juhn et al. 1993, Fernandez-Val et al. 2020)

Maternity Legislation in Austria

- Maternity protection
- Maternity leave
- Similar legislation in many countries (Germany, UK, US...)



Data

Data

- Austrian Social Security Database
- Daily labor market spells and annual earnings
- Mothers who gave birth July 1990 - Dec 1995
  - Leave benefits and leave duration aligned
  - Simple leave legislation
- Select all mothers
  - with some labor attachment prior to birth - 365 days with employer
  - who return to the labor market within maternity leave of 2 years - around 65% of all mothers in sample
- Changing employer: Determine if mother left pre-birth employer or not

Return Pattern Sample characteristics

Defining Returns to Changing Employer

- Y - earnings
- L - if mother leaves ($L = 1$) or returns ($L = 0$) to pre-birth employer
- Z - pre-birth earnings
- X - education, age-at-birth, firm size, share of females in pre-birth job

Parameter of interest: $\Delta^D(y) = P(Y(1) > y|L = 1) - P(Y(0) > y|L = 1)$

$\Delta^D(y)$ gives the change in probability of obtaining earnings **greater** than y due to job switch

Identification

Identification

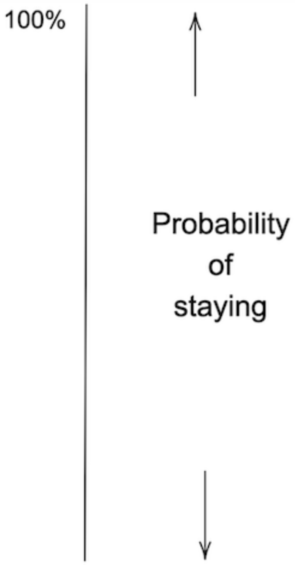
(M1) Mothers with higher pre-birth earnings less likely to switch

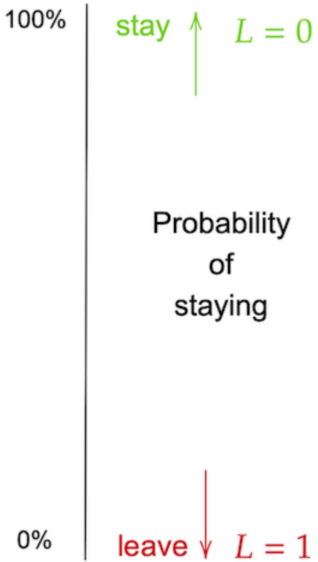
$$P(L = 0 | Y(0), Z = z, X = x) \text{ is increasing in } z \text{ almost surely, for all x.}$$

(M2) Mothers with higher <u>potential</u> re-employment earnings at her pre-birth employer less likely to switch

$$P(L = 0 | Y(0) = y, Z, X = x) \text{ is increasing in } y \text{ almost surely, for all x.}$$

(REL) There needs to be a dependence between Z and $Y(0)$


100%
Probability
of
staying


100%
stay
$L = 0$
Probability
of
staying
0%
leave
$L = 1$

$$P(L = 0 | Z, Y(0), X)$$

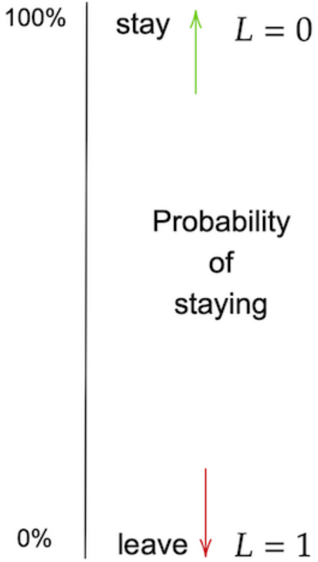
100% stay $L = 0$

Probability
of
staying

0% leave $L = 1$

Z pre-birth €

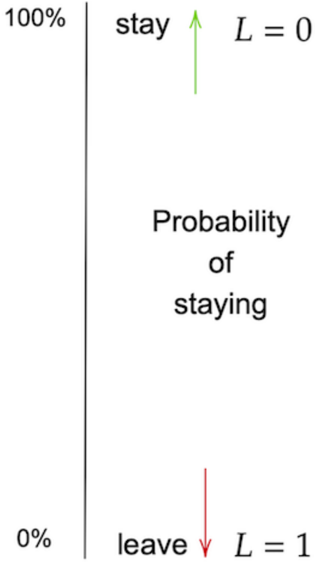
$$P(L = 0 | Z, Y(0), X)$$



Z pre-birth €

$Y(0)$ future €

$$P(L = 0 | Z, Y(0), X)$$

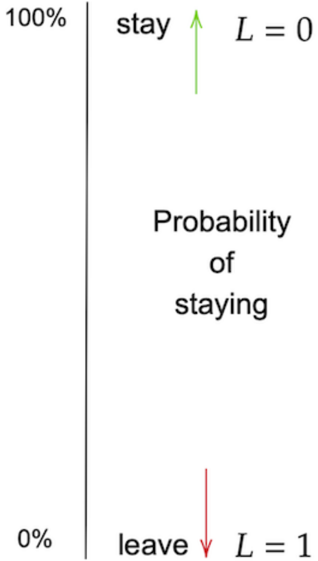


Z pre-birth €

$Y(0)$ future €

$$P(L = 0|Z, Y(0), X)$$

X
- age
- education
- firm size
- share of ♀



Z pre-birth €

$Y(0)$ future €

$$P(L = 0 | Z, Y(0), X)$$

X
- age
- education
- firm size
- share of ♀

100%

stay $L = 0$

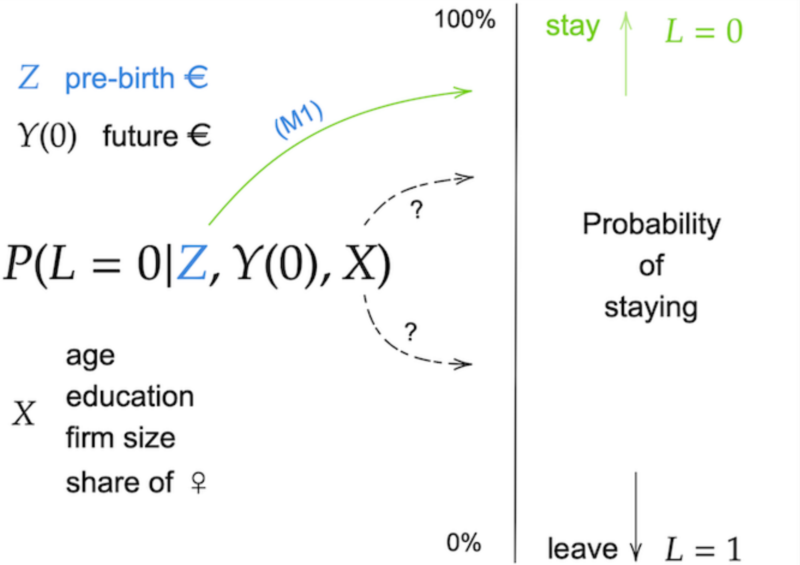
?

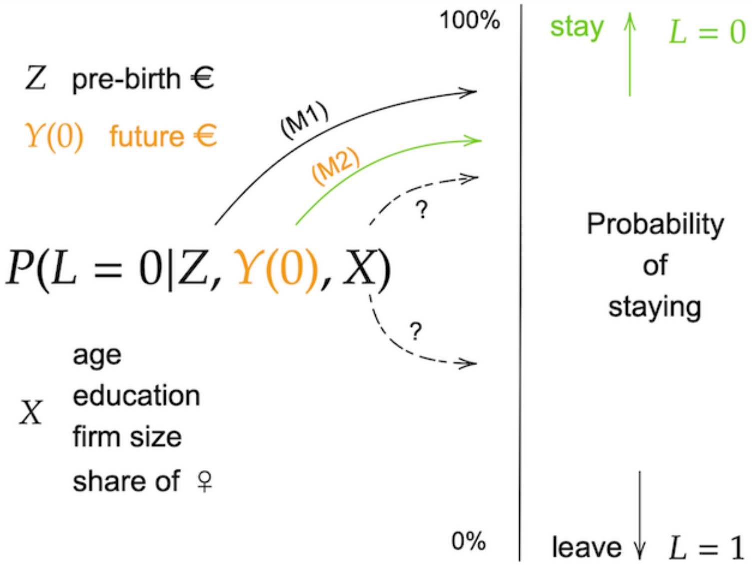
Probability of staying

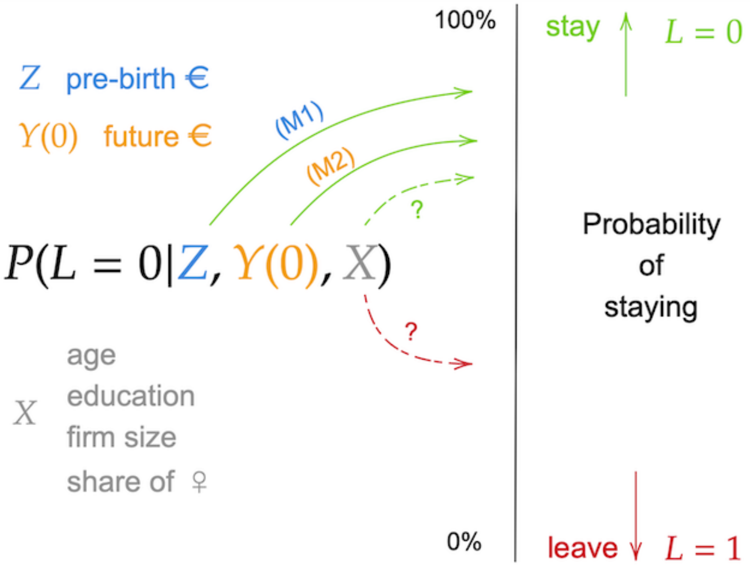
?

0%

leave $L = 1$


Z pre-birth €
$Y(0)$ future €
(M1)
?
?
$P(L = 0|Z, Y(0), X)$
X
age
education
firm size
share of ♀
100%
0%
stay
$L = 0$
Probability
of
staying
leave
$L = 1$


100%
stay
$L = 0$
Z pre-birth €
$Y(0)$ future €
(M1)
(M2)
?
$P(L = 0|Z, Y(0), X)$
?
X
age
education
firm size
share of ♀
Probability
of
staying
0%
leave
$L = 1$


100%
stay
$L = 0$
Z pre-birth €
$Y(0)$ future €
(M1)
(M2)
?
$P(L = 0|Z, Y(0), X)$
?
Probability
of
staying
age
X
education
firm size
share of ♀
0%
leave
$L = 1$

Assumptions (M1) and (M2) inherent in many (theoretical) job-search models with endogenous search effort

- Decreasing returns to search in own earnings (e.g. Christensen et al. 2005)
- Higher earning workers spent less time searching (Fabermann et al. 2017)
- (Survey on the directed search: Wright et al., 2021)

What assumptions we **do not make** (besides (M1) and (M2)):

- ~~restrictions on mothers' abilities~~
- ~~restrictions on mothers' preferences~~
- ~~restrictions on the structure on the underlying selection mechanism~~

What we **allow for**:

- higher paid mothers gain more
- higher educated mothers move to lower paying jobs as they under-estimate cost of having children (Kuziemko et al., 2018)
- higher educated mothers prefer family friendly firms (Hotz et al., 2018)
- firms make job offers based on (unobserved) productivity
- higher educated mothers using outside options to renegotiate their contracts (Cahuc et al., 2016)

- $P(Y(1) > y|L = 1, X = x) = P(Y > y|L = 1, X = x)$ is observed
- $P(Y(0) > y|L = 1, X = x)$ is not observed

We bound

$$P(Y(0) > y|L = 1, X = x)$$

- lower bound following the idea in d'Haultfoeuille (2010) (using (M1))
- upper bound using a matching idea (using (M2)) Intuition

Bounding Returns to Search

- Under (M1) and (M2) we obtain bounds on $\Delta_x^D(y)$

$$\underbrace{P(Y(1)>y|L=1,X=x)-E\left[P(Y>y|L=0,Z,X=x)|L=1,X=x\right]}_{LB_x(y)}$$

$$\leq \Delta_x^D(y) \leq$$

$$\underbrace{P(Y(1)>y|L=1,X=x)-\frac{\pi_x}{1-\pi_x}E\left[\frac{1-P_x(Y)}{P_x(Y)}\mathbb{1}(Y>y)|L=0,X=x\right]}_{UB_x(y)}$$

- $\pi_x = P(L=0|X=x)$
- $P_x(Y)$ satisfies

$$E\left[\frac{1-L}{P_x(Y)}-1|Z,X=x\right]=0$$

Bounding Returns to Search

- Under (M1) and (M2) we obtain bounds on $\Delta_x^D(y)$

$$\underbrace{P(Y(1) > y|L = 1, X = x) - E\left[P(Y > y|L = 0, Z, X = x)|L = 1, X = x\right]}_{LB_x(y)}$$

$$\leq \Delta_x^D(y) \leq$$

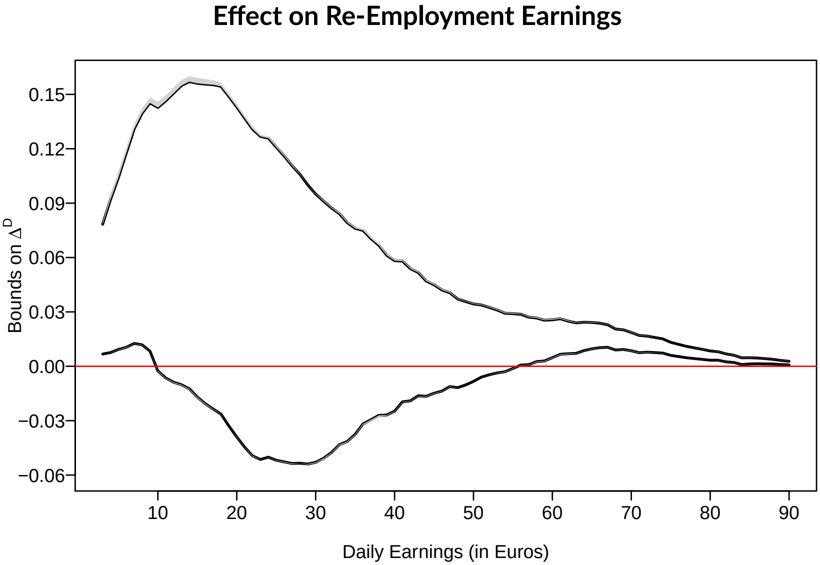
$$\underbrace{P(Y(1) > y|L = 1, X = x) - \frac{\pi_x}{1-\pi_x} E\left[\frac{1 - P_x(Y)}{P_x(Y)} \mathbb{1}(Y > y)|L = 0, X = x\right]}_{UB_x(y)}$$

- All components of the bounds can be estimated from the data
- To obtain unconditional effect $\Delta^D(y)$ we integrate over the distribution of X given $L = 1$
- Inference is based on the non-parametric bootstrap with 500 replications and Imbens-Manski (2004) critical value adjustment

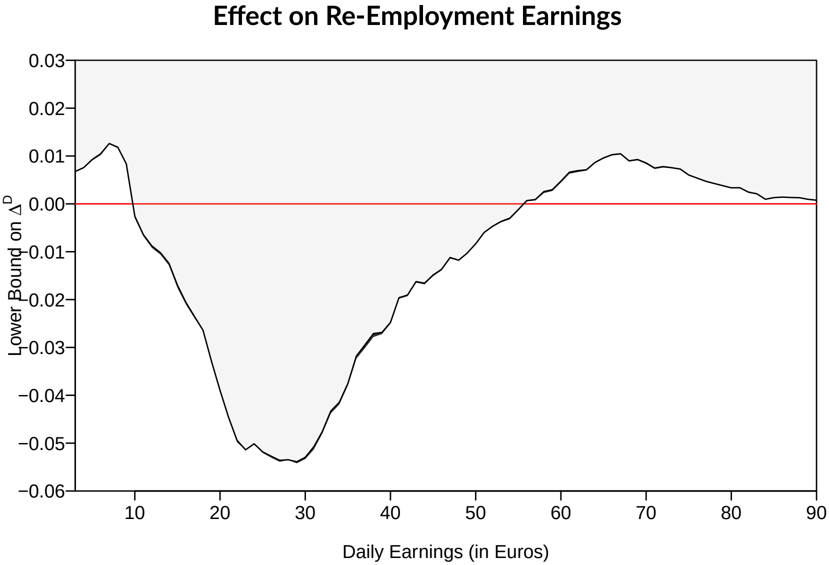
▸ Estimation details ▸ Support for (M1) ▸ Support for (M2) ▸ Support for REL

Results

Short-Term Returns

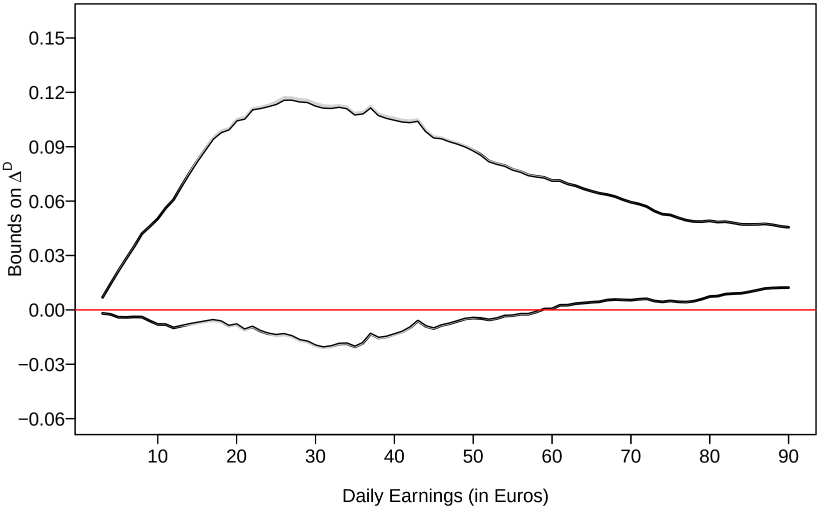


Short-Term Returns - Lower bound



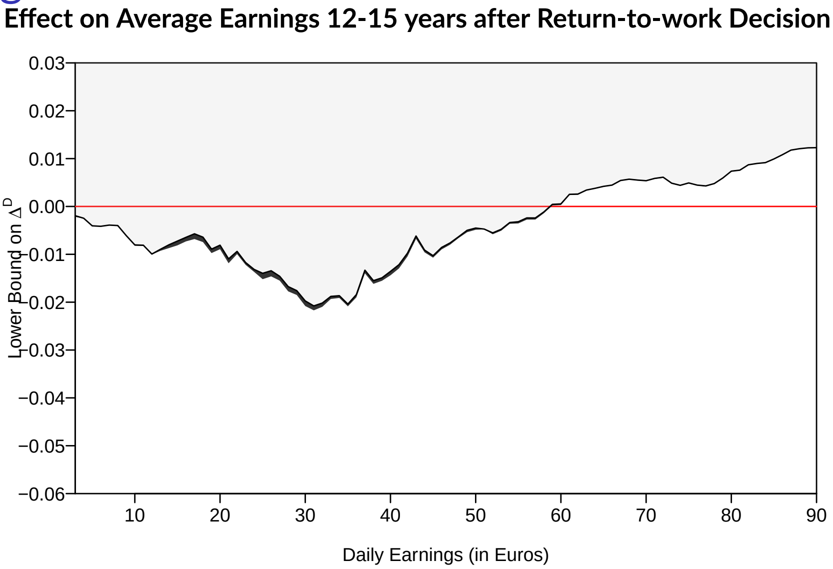
Long-Term Returns

Effect on Average Earnings 12-15 years after Return-to-work Decision



▸ Results for Uni

Long-Term Returns - lower bound



Results for Uni

Results for Tenure as Z

Why do we see these results?

Possible channels:

- Firms and mobility
- Formal/informal childcare
- Role of husbands
- Network of co-workers

The Role of the New Firm

- What types of firms do mothers move to after childbirth?
  - Firms' hiring strategy indicator of future success
  - Pay gaps as sign for equal opportunities
- Does geographic mobility play a role?
  - Mobility to obtain better firm-worker matches elsewhere
  - Trading lower commuting time for higher earnings

Approach

- We order mothers into five groups G according to their earnings
- For members in group $G = g$ we estimate simple linear model for leavers $L = 1$ and stayers $L = 0$ separately

$$M_i = X_i' \beta^{g,L} + \varepsilon_i$$

- $\widehat{E}[\widehat{M}|G = g, L = 1] - \widehat{E}[\widehat{M}|G = g, L = 0]$ reflects estimated difference in outcome *associated with* changing employer

The Role of Jobs and Firms

The Role of Firms & Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm Characteristics				Geographic Mobility	
	Δ Log Employees		Δ Log Pay Gap among Employees		Moved ZIP Code	Δ Log Commute Time
	Overall x 100	Females x 100	Incumbent x 100	New Hires x 100	x 100	x 100
€ $Y < 20$	22.62	19.13	−8.37	−13.94	3.78	−6.37
	(10.37)	(8.14)	(4.96)	(12.32)	(2.98)	(14.82)
$20 \leq Y < 40$	34.42	29.22	−1.18	−2.53	3.29	−5.94
	(11.26)	(8.55)	(4.59)	(12.33)	(2.98)	(13.99)
€€ $40 \leq Y < 60$	39.45	32.69	0.53	−2.37	6.03	−2.58
	(10.57)	(8.85)	(4.65)	(13.15)	(2.85)	(15.06)
$60 \leq Y < 80$	22.98	18.97	0.33	7.06	4.72	−3.51
	(10.79)	(8.34)	(4.77)	(12.79)	(2.89)	(14.96)
€€€ $80 \leq Y$	45.29	34.54	−1.98	20.51	5.60	25.34
	(10.75)	(8.54)	(4.60)	(12.64)	(2.81)	(14.23)

Leavers move to higher growing firms

The Role of Firms & Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm Characteristics				Geographic Mobility	
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Leavers move to firms with more women

The Role of Firms & Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm Characteristics				Geographic Mobility	
	Δ Log Employees	♀	Δ Log Pay Gap among Employees		Moved ZIP Code	Δ Log Commute Time
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Leavers move to firms with smaller pay gap

The Role of Firms & Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm Characteristics			$Y(♂) - Y(♀)$	Geographic Mobility	
	Δ Log Employees		Δ Log Pay Gap among Employees		Moved ZIP Code	Δ Log Commute Time
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Leavers are more likely to move

The Role of Firms & Mobility

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	Firm Characteristics				Geographic Mobility	
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	(10.75)	(8.54)	(4.60)	(12.64)	(2.81)	(14.23)

Leavers are willing to commute more

The Role of Firms & Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm Characteristics				Geographic Mobility	
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	(10.75)	(8.54)	(4.60)	(12.64)	(2.81)	(14.23)

The Role of Search Costs

- Does local provision of childcare affect mothers' returns changing employer?
- Can husbands explain mothers' returns from changing employer?
    - Support by adjusting labor market career to care for children
- Can networks explain mothers' returns from changing employer?

The Role of Formal Childcare

Search Costs - The Role of Local Childcare Provision

	(1) No. Nurseries Available	(2) Places Available per Child 0-3
$Y < 20$	-4.00	-0.04
	(2.89)	(0.03)
$20 \leq Y < 40$	-1.74	-0.02
	(2.87)	(0.03)
$40 \leq Y < 60$	-0.23	-0.00
	(2.88)	(0.03)
$60 \leq Y < 80$	3.46	0.02
	(2.84)	(0.03)
$80 \leq Y$	1.44	0.03
	(2.85)	(0.03)

Formal childcare does not seem to matter much.

Search Costs - The Role of Local Childcare Provision

	(1) No. Nurseries Available	(2) Places Available per Child 0-3
$Y < 20$	-4.00	-0.04
	(2.89)	(0.03)
$20 \leq Y < 40$	-1.74	-0.02
	(2.87)	(0.03)
$40 \leq Y < 60$	-0.23	-0.00
	(2.88)	(0.03)
$60 \leq Y < 80$	3.46	0.02
	(2.84)	(0.03)
$80 \leq Y$	1.44	0.03
	(2.85)	(0.03)

small numbers

~ 0

The Role of Informal Childcare

Determinants of Moving Costs - The Role of Informal Care Arrangements

	(1)	(2)	(3)
	Any Daily Help	Daily Help from	
		Husband	Relatives
	x 100	x100	x100
$Y < 20$	1.90	1.62	-4.02
	(2.25)	(2.24)	(1.20)
$20 \leq Y < 40$	2.49	2.18	-1.02
	(1.85)	(1.85)	(1.08)
$40 \leq Y < 60$	4.96	5.03	-3.36
	(2.98)	(2.99)	(1.45)
$60 \leq Y < 80$	-1.85	-6.32	3.25
	(6.85)	(6.86)	(4.22)
$80 \leq Y$	21.31	22.86	6.78
	(11.98)	(11.99)	(7.52)

Based on **"synthetic selves"** using Austrian microcensus.

(Kuzmienko et al. 2018)

(mothers' age at birth, education, nationality, percentile in the earnings distribution, and industry in the pre-birth job)

Informal childcare does matter. Especially for higher earning mothers.

Determinants of Moving Costs - The Role of Informal Care Arrangements

	(1)	(2)	(3)
	Any Daily Help	Daily Help from	
		Husband	Relatives
	x 100	x100	x100
$Y < 20$	1.90	1.62	-4.02
	(2.25)	(2.24)	(1.20)
$20 \leq Y < 40$	2.49	2.18	-1.02
	(1.85)	(1.85)	(1.08)
$40 \leq Y < 60$	4.96	5.03	-3.36
	(2.98)	(2.99)	(1.45)
$60 \leq Y < 80$	-1.85	-6.32	3.25
	(6.85)	(6.86)	(4.22)
$80 \leq Y$	21.31	22.86	6.78
	(11.98)	(11.99)	(7.52)

The Role of Search Costs – Husbands

Husbands

- do not adjust their labor market attachment, nor earnings
- of mothers at the higher earnings distribution tend to switch employers more - suggesting "joint mobility"

The within-household pay gap shrinks more at the higher earnings distribution of mothers.

The Role of Search Costs – Networks

Can networks explain mothers' returns from changing employer?

- Better information about new job opportunities
- Mitigating information asymmetry between employer-employee

Leavers at the upper part of distribution

- have larger networks of former co-workers.
- have stronger networks (worked together for a longer time).
- have more quality networks (their peers were earning more).

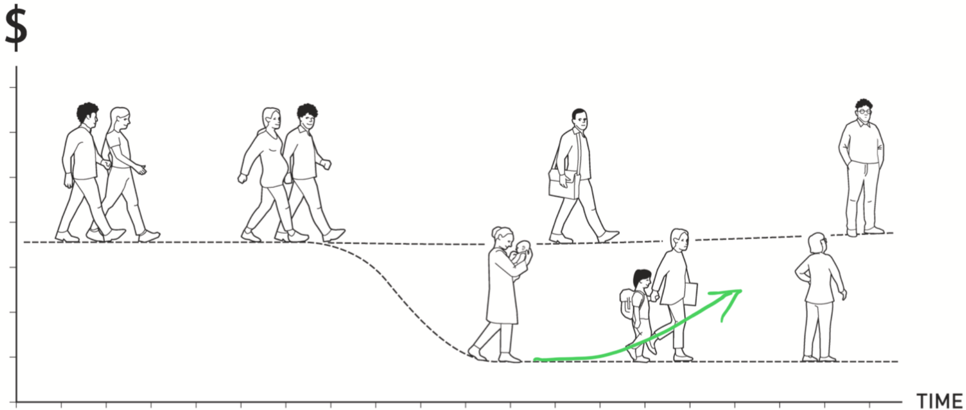
Conclusion

Key takeaways

- Unequal gains from changing employer after birth along earnings distribution
- Earnings Gains are associated with
  - move to firms offering better opportunities to newly hired female workers
  - move to firms which are likely more successful in future
  - higher geographical mobility
- Differences in gains likely reflect differences in search costs
  - No evidence for the role of formal childcare provision
  - Husbands also more mobile
  - Better networks facilitate information transmission

In one sentence

Encouraging job search one possibility to decrease gender gaps, but search costs an important obstacle!



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Thank you.

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Additional information

- Return to work patterns ▸ Return to work
- Sample characteristics ▸ Sample
- Intuition for Lower bound ▸ LB intuition
- Empirical support for (M1) ▸ Support for (M1)
- Empirical support for (M2) ▸ Support for (M2)
- Empirical support for (REL) ▸ Support for (REL)
- Other questions ▸ Estimation details
- Results for University graduates ▸ Res. Uni
- Results with Tenure as (monotone) instrument Z ▸ Results Tenure
- (Recent) Non-mothers ▸ Non-mothers

Possible questions

- General questions ▸ General
- Assumption (M1) ▸ (M1)
- Assumption (M2) ▸ (M2)
- Data questions ▸ Data
- Econometrics ▸ Econometrics
- Robustness checks ▸ Robustness
- Other questions ▸ Other

FAQs: General questions

- Why do (M1) and (M2) hold?

  We don't know if they hold. But we have good reasons to believe so. First of all, these assumptions are not at all exotic, yet they are a very standard part in a variety of job-search models. They are much weaker than having a proper instrument, which is challenging to obtain in this particular setup as it is difficult to find a variable satisfying an exclusion restriction. Also, we provide some empirical evidence that supports these monotonicity conditions even though they are not directly testable in a sense that there exists a test with asymptotic power of one. We provide a very detailed discussion about under what circumstances these assumptions do not hold.

- What variables do you control for?

  We control for a variety of information that may be important confounders in the relationship between job-transition and earnings. We control for age, education, firm size, share of female co-workers. (In the robustness section also: length of tenure.) Results without adjusting for X are actually qualitatively similar.

FAQs: General questions (2)

- Why do you particularly look at women at this particular career stage?

  We document that these women engage in a job-search much more that corresponding not-recent-mothers (transitions are 14% vs 7% respectively). So there is a lot of variation in the job-to-job transition here (acknowledged in recent reports) and this is the variable that we study. The job protection period is also interesting from policy perspective as it provides a reduced cost of search for these mothers, making this a potentially important tool to help climbing mothers up the career ladder.

  Non-mothers

- You claim that mothers change jobs more often during the first two years than non-mothers. But those women who are non-mothers are very different, right?

  Indeed, that is why we have **not-recent-mothers**. We look at a reference quarter and make 4 years around this date. So non-mother in our sample may have had children earlier or could be mother later. We use similar criteria as our baseline sample, we remove women with - tenure less than year, not employed for at least a day in the two years. Raw differences are sizable. Also, we run logit regressions with tenure in the previous job, earnings in the previous job, education and age.

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FAQs: Assumption (M1)

- What if a high earnings mom receives more acceptable job offers? What if their information about outside offers is better?

  New information lead to adjustment of wage expectation but does not lead to higher mobility (Schmidpeter 2023). There is also evidence that job mobility is decreasing with wages.

- Again what if their information about outside offers is better?

  We control for the size of the pre-birth employer, share of female co-workers, educational attainment of the mother.

- But don't higher earnings moms have higher negotiation power?

  Yes, indeed, and such renegotiation is in line with our bounding approach, as long as the current employer is willing to match potential outside options. Mothers can, therefore, reach higher wages with their current employer.

- What if mothers with high Z are negatively surprised by the cost of having kids?

  We control for age and education. Also, there is a positive "matching" on home production with partner.

▸ Back to overview

FAQs: Assumption (M2)

- What if a mother with higher Y(0) values non-monetary amenities more than the earnings potential?

  While non-monetary amenities (NMA) matter, there is no empirical evidence that the valuation depends on the earnings potential. Taber and Vejlin (2016) suggest that higher educated women value NMA equally to lower educated women. Cortes et al. (2020) show that earnings and NMA correlate positively (goes against compensating differentials). Notice that we do allow for the trade-off between NMA and wages. We only need that the value of NMA does not increase with earnings potential given our individual and firm characteristics.

- How about the renegotiation power?

  Indeed mothers with high Y(0) may have a high negotiation power. But, at the same time, they are more likely to be a very productive match and hence firms would find replacing them very costly. They may be more willing to increase their wages to keep them. This is fine with (M2), as long as the pre-birth employer is willing to match outside offers. We control for important negotiation determinants such as the firm size (the firm's ability to negotiate) or education (the mother's ability to negotiate).

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FAQs: Data

- **Why do you use such an old dataset?**

  Practical answer is that we have access to this particular dataset and a longer time frame allows us to look at long-term outcomes. However the Institutional setting remained largely unchanged and social norms are likely to change slowly.

- **Why Austria?**

  We have high quality admin data from Austria that allows us to look into long-term outcomes too. Also, job mobility of mothers has also been documented for other countries, e.g. Germany and USA.

- **How about the part-time jobs?**

  Unfortunately, we don't have such data. We only have daily spells and yearly earnings. Also, our dataset consists of mothers with children born in 1990-1995 and part-time jobs were much more uncommon than nowadays.

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FAQs: Econometrics

- **What is Y(0) and what is Y(1) ?**

  Y(0) is a counterfactual earnings if mother stayed with her current pre-birth employer Y(1) is a counterfactual earnings if mother left her current pre-birth employer Y(0) is unobserved for those who left.

- **How does the lower bound work?**

  Lower bound on our object of interest (difference in probability of crossing a particular value of daily earnings y) is based on the upper bound of mean counterfactual probability of crossing a particular value if L=0 for individuals with L=1. This quantity is naturally unobserved. We used a matching idea and (M2) to get the upper bound.

  ▸ Intuition LB

- **how does the upper bound work?**

  Upper bound on our object of interest (difference in probability of crossing a particular value of daily earnings y) is based on the lower bound of mean counterfactual probability of crossing a particular value if L=0 for individuals with L=1. This quantity is naturally unobserved. We used the idea of conditioning on the potential outcome in the spirit of d'Haultfoeuille (2010) and (M1) to obtain this lower bound. This bound is somewhat less interesting from the empirical point of view.

FAQs: Econometrics (2)

- How is (M1) different from (M2), they look similar

  Conditioning is different. We can say that in (M1) we condition on the Y(0) and hence earnings potential and look at how staying probability increases with pre-birth earnings. Whereas in (M2) we condition on pre-birth earnings and look how staying probability increases with the earnings potential.

- What is the Y(0) in the graph for (M2), Y(0) is unobserved for L=1

  Yes, we look only for the subsample of L=0 and plot the P(Y) from the moment condition. This can only be interpreted as the probability in the case of strict exogeneity (rather than (M2)). While imperfect, this is a feasible thing to do and was suggested by d'Haultfoeuille (2010) too.

- Are these bounds sharp?

  The bounds on the unobserved quantity are sharp (proven in d'Haultfoeuille (2010)) and this translates into sharpness of the bounds on our object of interest.

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FAQs: Robustness checks

- Alternative monotonicity: Tenure as Z

  Direction is the same, but wider in the mid-distribution.
- Results without covariates

  Similar but bounds are a bit wider (as expected).
- (M1) and (M2) support graphs - conditioning on X.

  Similar pattern.
- Return-to-work period: 24months $\rightarrow$ 30months

  Qualitatively similar results.
- Channels: Regression coeff. vs. Δ in predicted values

  Again, similar results.
- Functional form assumptions for P_X

  Logit regressions insensitive to inclusion of higher order terms.

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FAQs: Other questions

- **Why do you have non-significant results?**

  We show the results as they are, without any kind of p-hacking, fishing, specification searches or manipulation. Yes the bounds are wide, sometimes including zero, but this reflects the amount of information that is in the dataset.

- **Why are some of the graphs so non-smooth?**

  If we go from say daily earnings 37 euro to 38 euro, we include those that earned 37.5 euro. Given the non-parametric (semi-parametric) nature of the bounds, there is a jump. But notice that a similar jump is on the lower and upper bound - this suggests that we indeed show variation in the data and this is not an estimation quirk, e.g. say due to unstable $\hat{P}_x(Y)$ estimator. We aim to show the data as raw as possible minimizing smoothing to stay completely transparent.

- **How come kindergartens don't matter(?)**

  This is actually in line with the previous literature. While formal childcare does not seem to matter all that much (notice that we only claim associations not causality), informal childcare matters a great deal.

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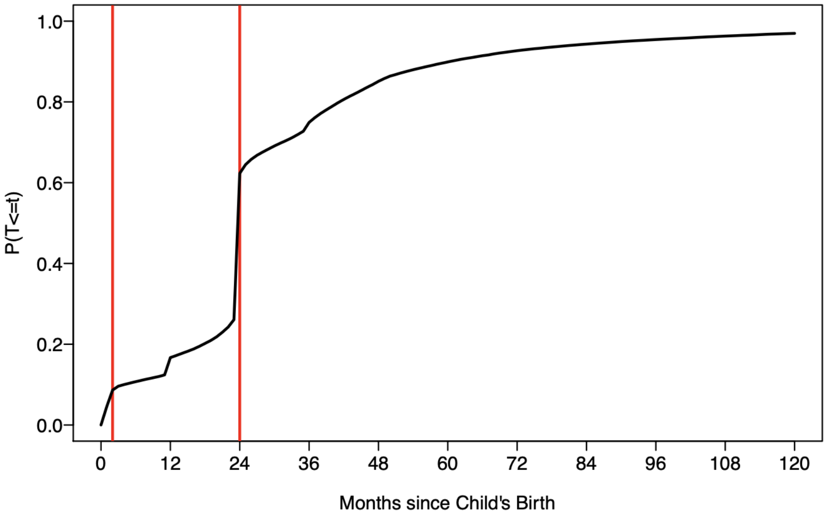
Mothers' Labor Market Return Patterns



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Data – Summary of Sample

	Overall Sample	Leavers $L = 1$	Stayers $L = 0$	Raw Difference
Personal Characteristics				
Age at Birth (Years)	27.80	26.65	28.01	$-1.37\dagger$
No. of Children	1.80	1.77	1.81	$-0.04\dagger$
Non-Austrian (Shares)	0.05	0.05	0.05	-0.00
University Degree (Shares)	0.10	0.07	0.10	$-0.03\dagger$
Pre-Birth Labor Market Outcomes				
Daily Earnings (Euros)	24.77	22.27	25.24	$-2.96\dagger$
Tenure (Days)	1,238.40	1,116.34	1,261.16	$-144.82\dagger$
White Collar (Share)	0.72	0.69	0.73	$-0.04\dagger$
Pre-Birth Employer				
Firm Size (Median)	79.50	39.75	92.50	$-52.75\dagger$
Share Females (Median)	0.64	0.68	0.63	$0.05\dagger$
Log Pay Gap (Median)	-0.31	-0.34	-0.31	$-0.03\dagger$
No. of Mothers	59,229	9,307	49,922	

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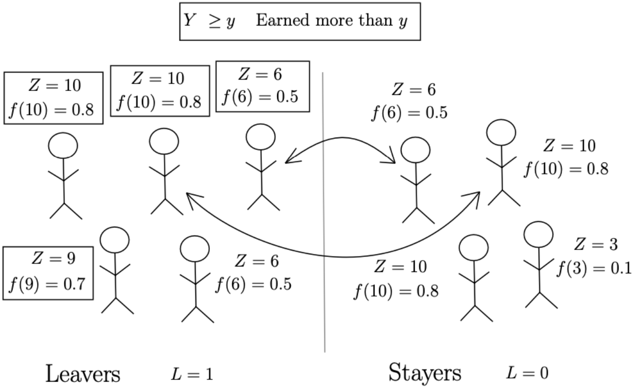
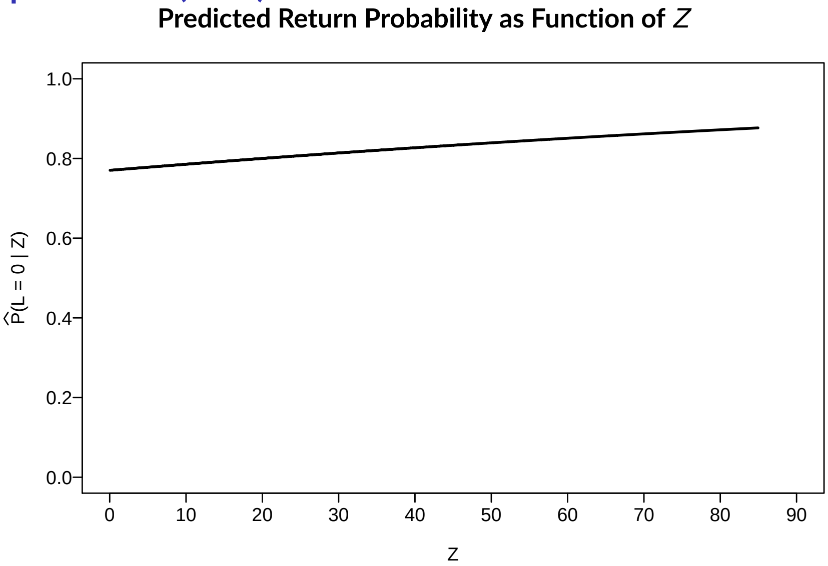
$$P(Y(0) \geq y | L = 1) \leq E\left[\underbrace{P(Y \geq y | L = 0, Z)}_{\equiv f(Z)} | L = 1\right].$$



Support for (M1)



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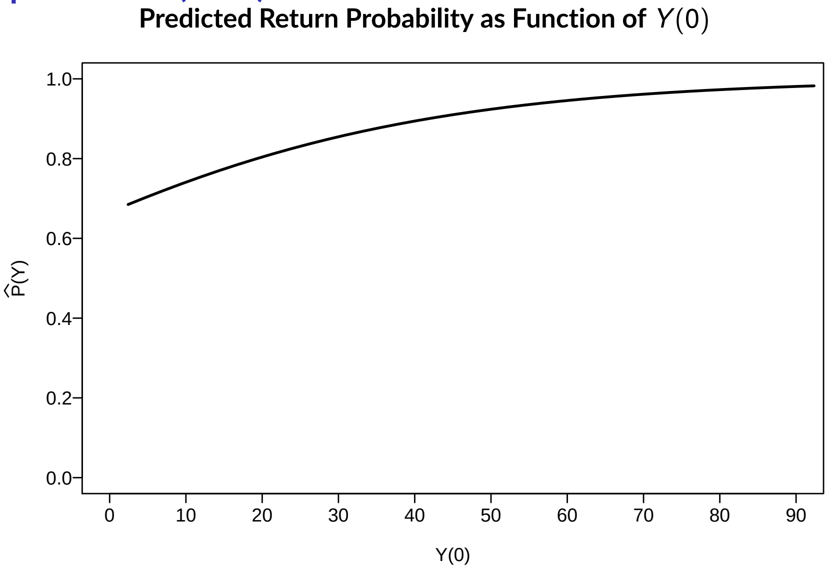
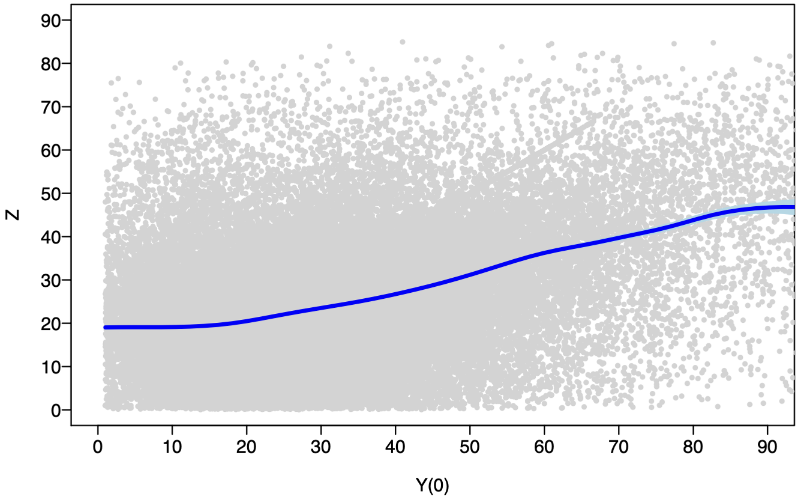
Support for (M2)



Support for (REL)

Relation between Z and $Y(0)$



Estimating $LB_x(y)$

- The quantity $P(Y > y|L = 1, X = x)$ is identified from the data alone
- $E[P(Y > y|L = 0, Z, X = x)|L = 1, X = x]$ can be estimated via distribution regression

$$\widehat{F}^*_{1|X=x}(y) = \frac{1}{N_{1,x}} \sum_{i:L_i=1,X_i=x} \widehat{F}_{Y|Z,L=0,X=x}(y|Z_i),$$

- We assume $F_{Y|Z,L=0,X=x}(y|Z_i)$ can be parameterized using the logit function
- $\widehat{F}^*_{1|X=x}(y)$ is estimated over fine grid of values y

Estimating $UB_x(y)$

- Upper Bound depends on selection probability $P_x(Y)$
- Following d'Haultfoeuille (2010), $P_x(Y)$ can be estimated by solving

$$E\left[\frac{1-L}{P_x(Y)} - 1 | Z, X = x\right] = 0$$

- $P_x(Y)$ is parameterized to have a logit form
- One we have $P_x(Y)$, upper bound can be estimated using weighted empirical cdf

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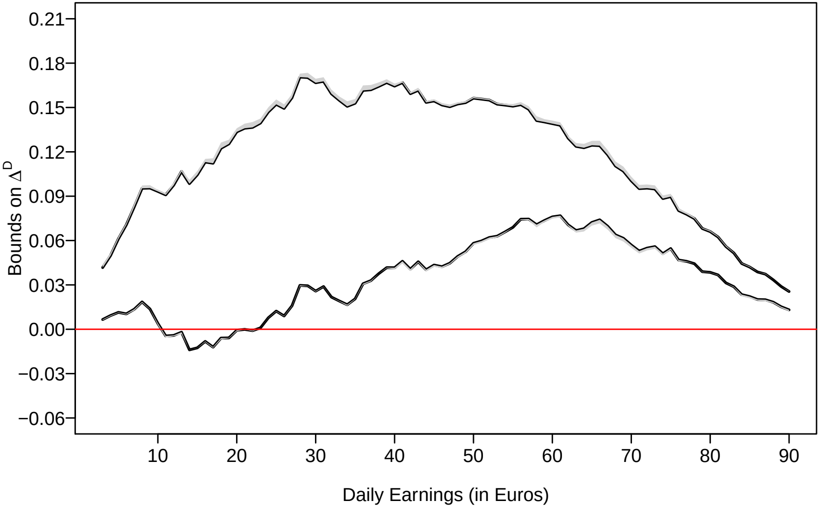
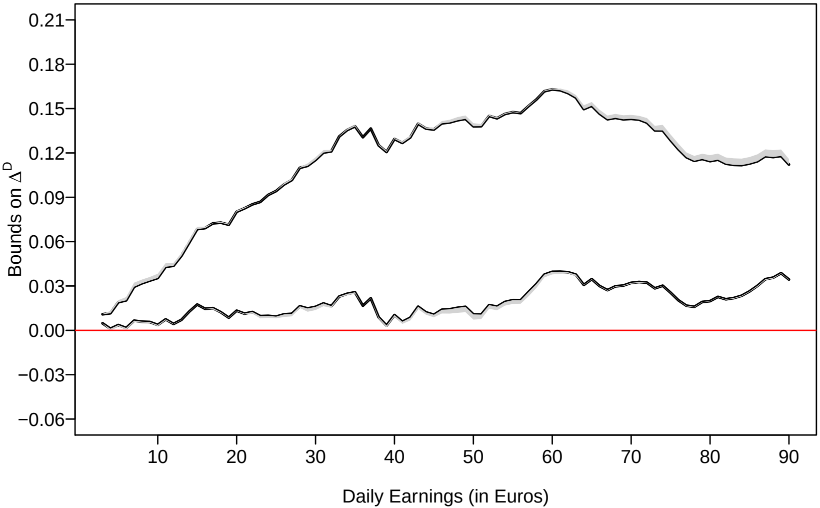
Job Search & Career Aspirations

Effect on Re-Employment Earnings – University Degree



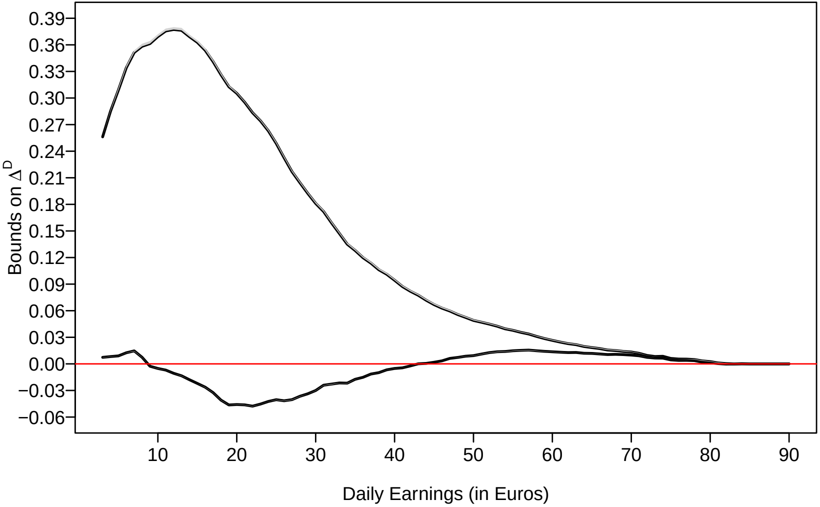
Job Search & Career Aspirations – Cont.

Effect on Average Earnings 12-15 years after Return-to-work Decision – University Degree

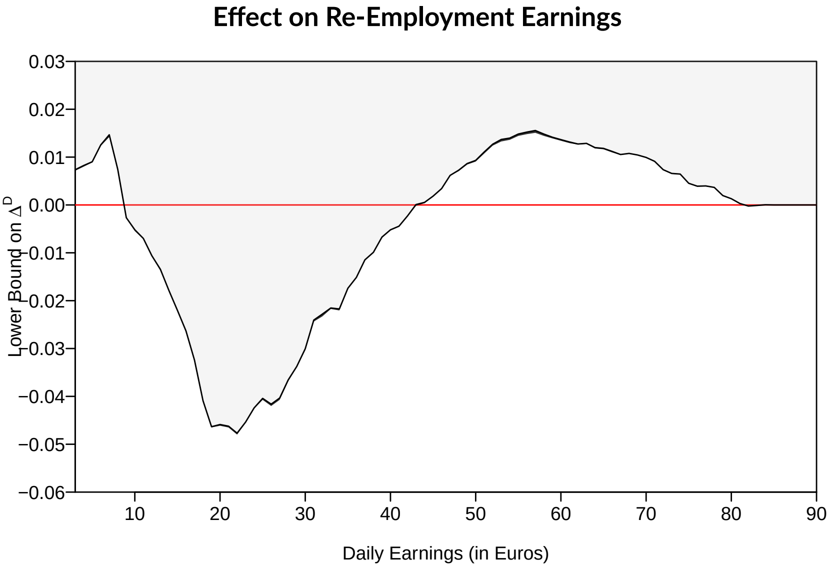


Short-Term Returns - Tenure as instrument

Effect on Re-Employment Earnings



Short-Term Returns - Lower bound - Tenure as instrument



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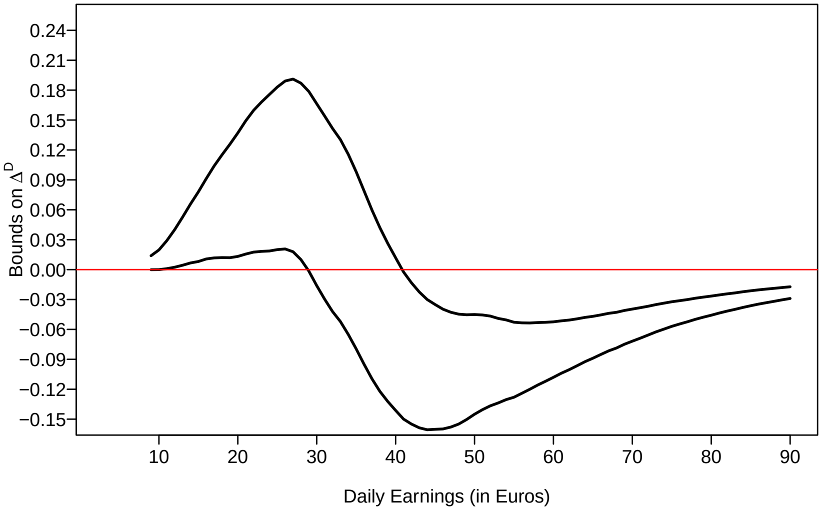
Non-mothers

	Overall Sample	Leavers $L=1$	Stayers $L=0$	Raw Difference
Personal Characteristics				
Age (Years)	27.27	24.66	27.47	−2.81†
No. of Children	0.54	0.33	0.56	−0.23†
Non-Austrian (Share)	0.04	0.03	0.04	0.01
Pre-Birth Labor Market Outcomes				
Daily Earnings (Euros)	29.82	27.48	30.00	−2.52†
Tenure (Days)	1,036.85	941.54	1,044.11	−102.57†
White Collar (Share)	0.57	0.53	0.57	−0.04†
University Degree (Share)	0.02	0.02	0.02	0.00
Pre-Birth Employer				
Firm Size (Median)	27.75	16.50	29.00	−12.50†
Share Females (Median)	0.70	0.75	0.70	0.06†
Log Pay Gap (Median)	−0.33	−0.34	−0.33	−0.01†
No. of Mothers	1,041,569	73,731	967,838	

Non-mothers



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Non-mothers (2)

- over 1mil obs.
- leavers: younger, fewer children, in smaller firms, larger inequality
- results very different - mirror image of mothers
- future fertility - sorting into lower paying jobs.

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Non-mothers (3)

Probability of having at least one more child in the next 10 years as function of job mobility.

	(1) Non-Mothers x 100	(2) Mothers x 100
$Y < 20$	-11.30	0.70
	(10.14)	(3.89)
$20 \leq Y < 40$	-2.44	-1.96
	(10.21)	(3.93)
$40 \leq Y < 60$	4.26	-0.64
	(10.01)	(4.04)
€€ $60 \leq Y < 80$	6.68	-2.52
	(10.13)	(3.79)
€€€ $80 \leq Y$	18.22	-8.10
	(9.97)	(3.66)

future mothers

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