The causal effect of UK firms' investment on their productivity

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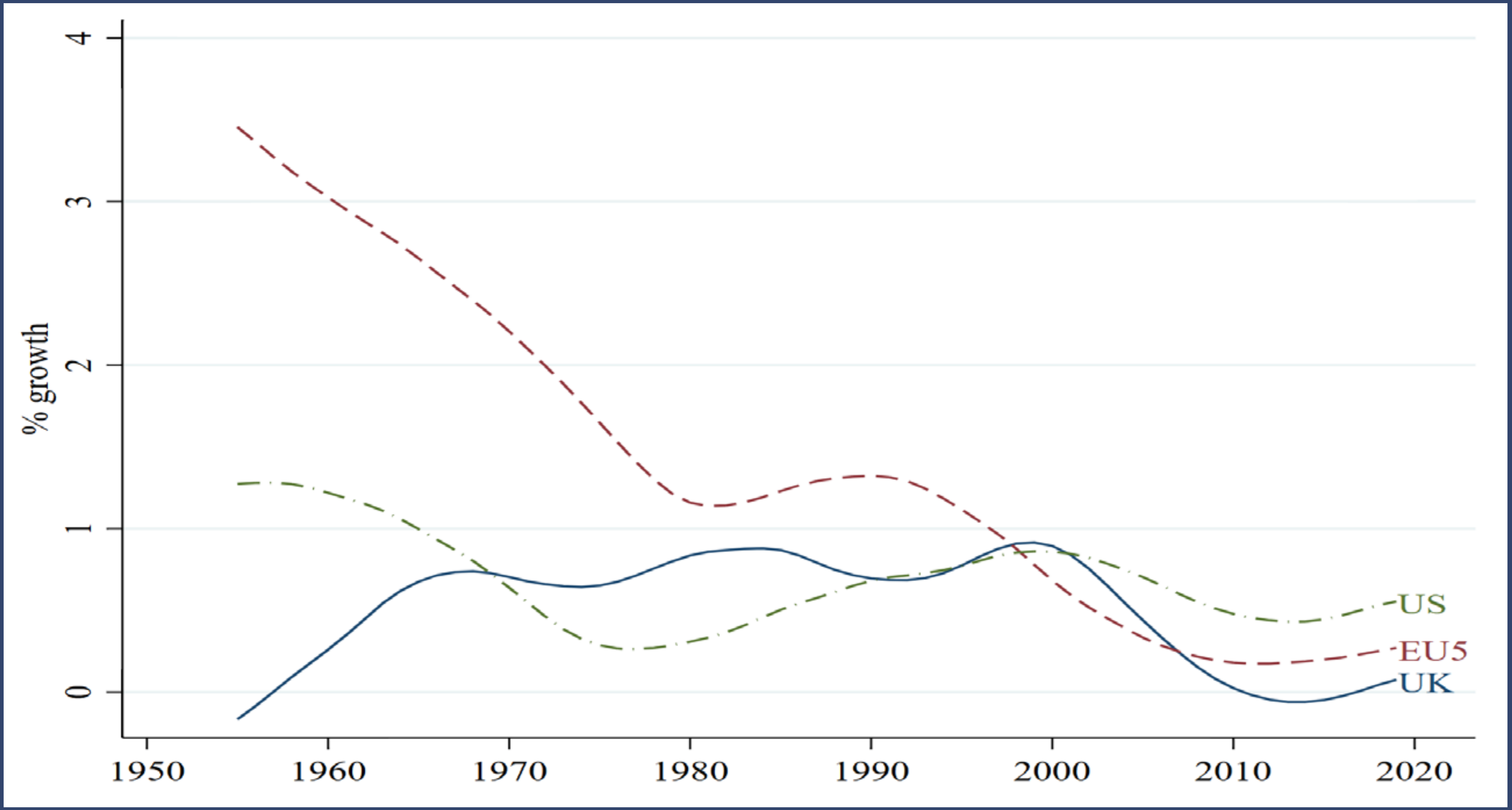
Motivation

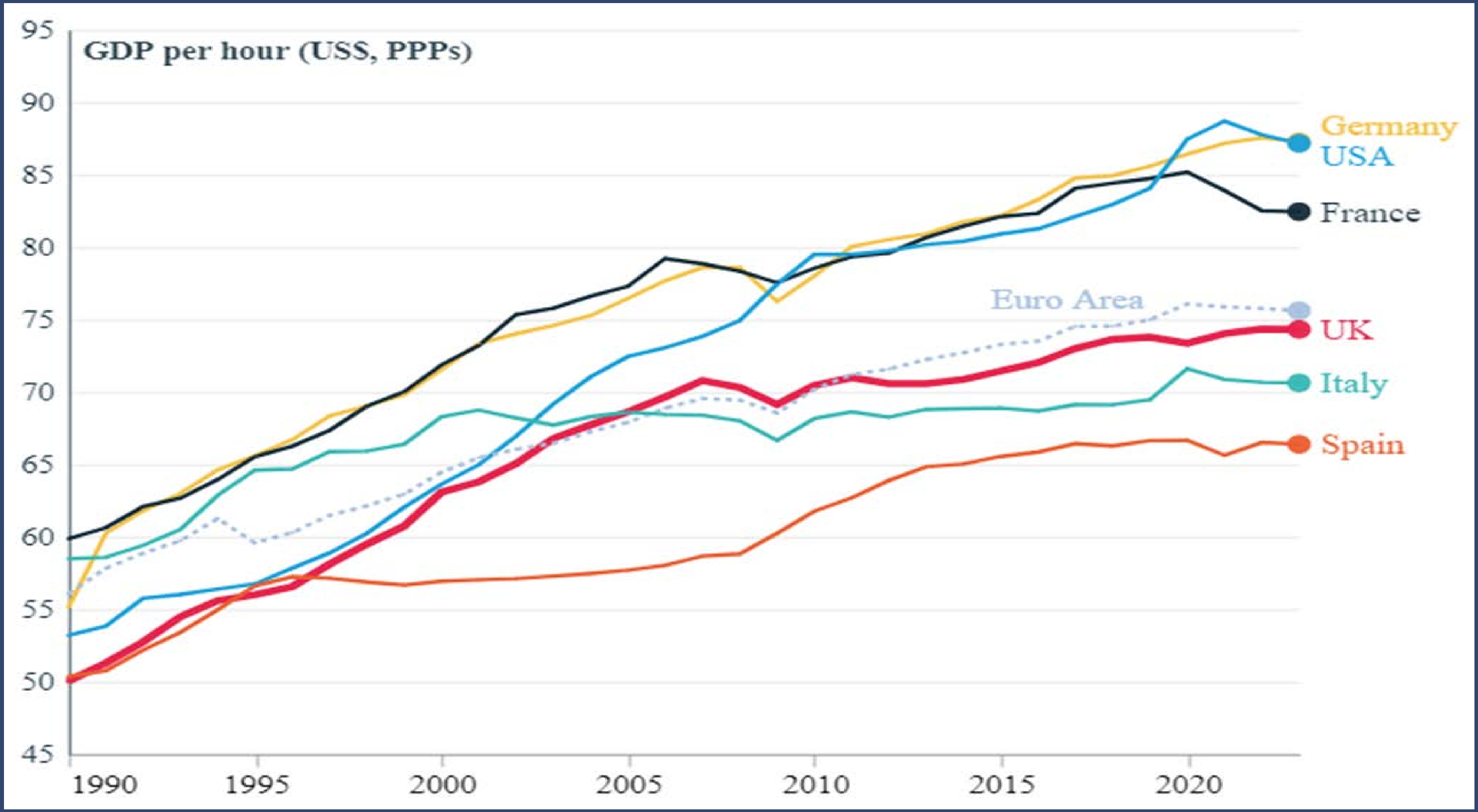
Trend TFP growth in the UK, Northern Europe, and U.S.



Source: J. Fernald, R. Inkaar (2022) The UK Productivity “Puzzle” in an International Comparative Perspective. Working Paper No. 020,The Productivity Institute.
The EU-5 group’s (Germany, France, the Netherlands, Belgium, and Finland, ranked by their 2010 GDP).

Motivation (cont.)

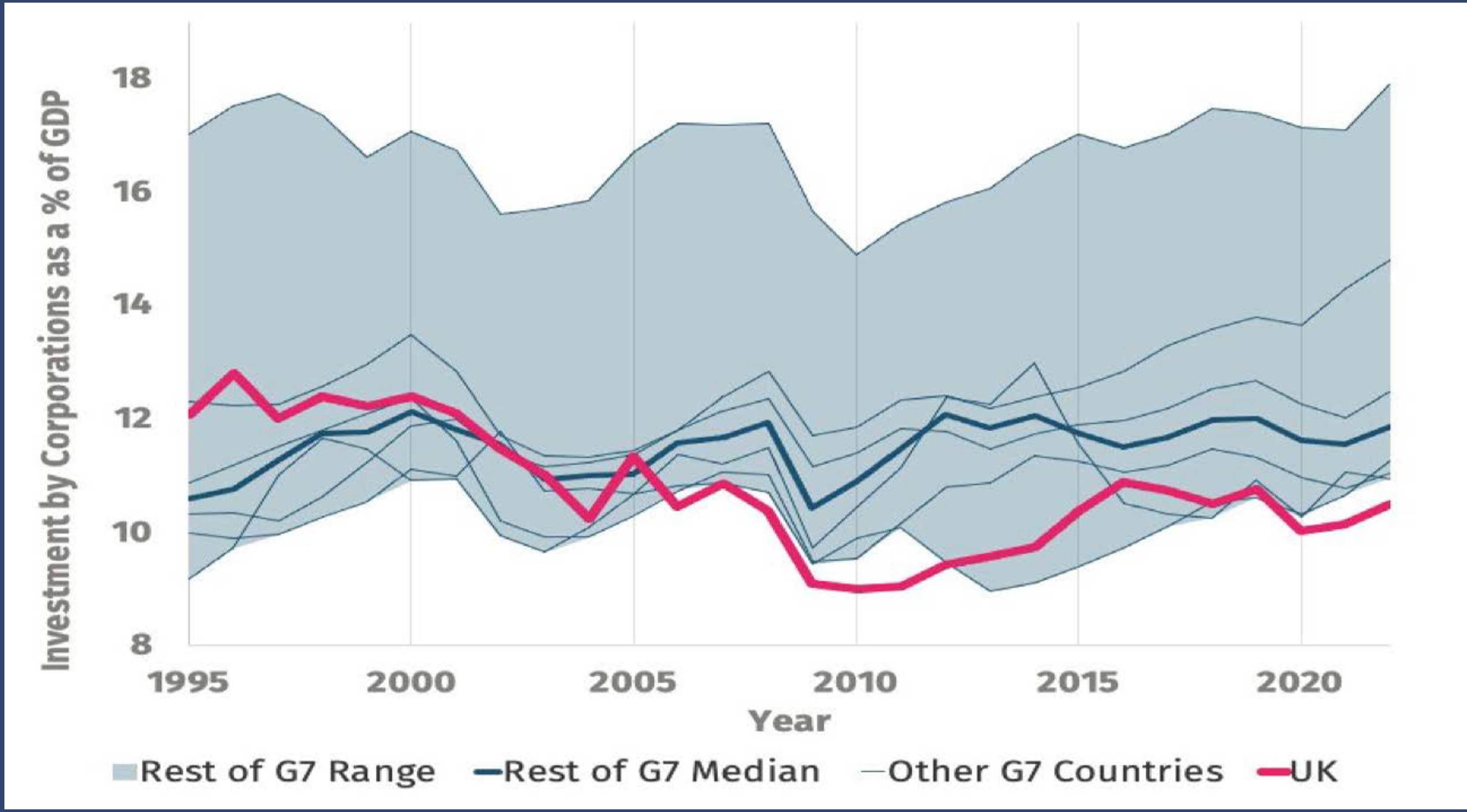
GDP per hour worked (in US$, PPP converted), 1990-2023



Source: Ark, Bart van & O'Mahony, Mary, 2024, What explains the UK's productivity problem? Insights Blog, The Productivity Institute, Retrieved from https://www.productivity.ac.uk/news/what-explains-the-uks-productivity-problem/

Motivation (cont.)

Corporate investment as a % of GDP



Source: IPPR, 2024, Rock bottom: Low investment in the UK economy

The link between investment and productivity

- Labor productivity (LP):
  - more capital generally makes workers more productive
  - feature of all standard production functions

- Total factor productivity(TFP):
  - not as easy to reason about as LP because TFP is unobservable and a residual
  - embodied technical change in more recent capital vintages allows management and workers to be more productive for any given amount of capital – could an issue regarding the measurement of capital services
  - increased output, facilitated by increased investment, could lead to accelerated learning by doing
  - investment in physical capital can lead to larger TFP when combined with investment in intangibles and/or organizational change

Causality

- Causal statements are very difficult to make in our context:

  - investment is an endogenous decision: firms that invest more could also be on average, better run, or have better (expected) profit opportunities – systematically different

  - anticipated productivity gains could affect current investment

Causality (cont.)

- Panel data: cannot deal with time-varying unobservables affecting both investment and productivity (e.g., management quality, profit opportunities, new export markets). Panel data also require strict exogeneity

- IV: exogenous instruments very hard to find, LATE interpretation

- Diff-in-diff: high investment firms likely have different future productivity trajectories from low investment firms due, for example, to differences in management quality, profit opportunities even under low investment – violation of parallel trends assumption. Estimates ATT, not ATE

Contribution

- We derive informative identification regions for the average treatment effect (ATE) of UK firms' investment on their productivity using partial identification (PI) methods in an observational data context

- PI results are robust to endogeneity

- PI relies on weak, and thus credible assumptions

Literature

- Numerous papers document positive associations between investment (often measured in spikes) and productivity using panel data methods (e.g., Nilssen, 2009)

- Gradzewicz (2021), using Polish data and a diff-in-diff methodology, finds that LP increases by ≈3% after a spike, driven by capital deepening

- Karmakar et al. (2024), using UK firms and panel data methods, find that intangible investment raises TFP (≈ 9.7 % for firms in the top quartile of intangibles); tangible investment has no effect on TFP

Data

- FAME database – standard source of firm data for the UK
- Data from 2001 to 2023 – we stop at 2019 to exclude the labor hoarding effects of the pandemic period
- Balance sheet and profit loss statements available
- Output: gross value added
- Labor input: number of employees (not hours)
- TFP is calculated using the methodology in Ackeberg et al (2015, a modification of Olley and Pakes, 1996)

Data (cont.)

- We examine tangible investment (lagged, scaled by lagged capital)

- Since firms can dispose of capital, investment is net of disposals and thus can be negative (about 10% of our sample has negative investmnet)

- Crucially, disinvestment can be rational – downsizing of firms can lead to productivity gains and better performance

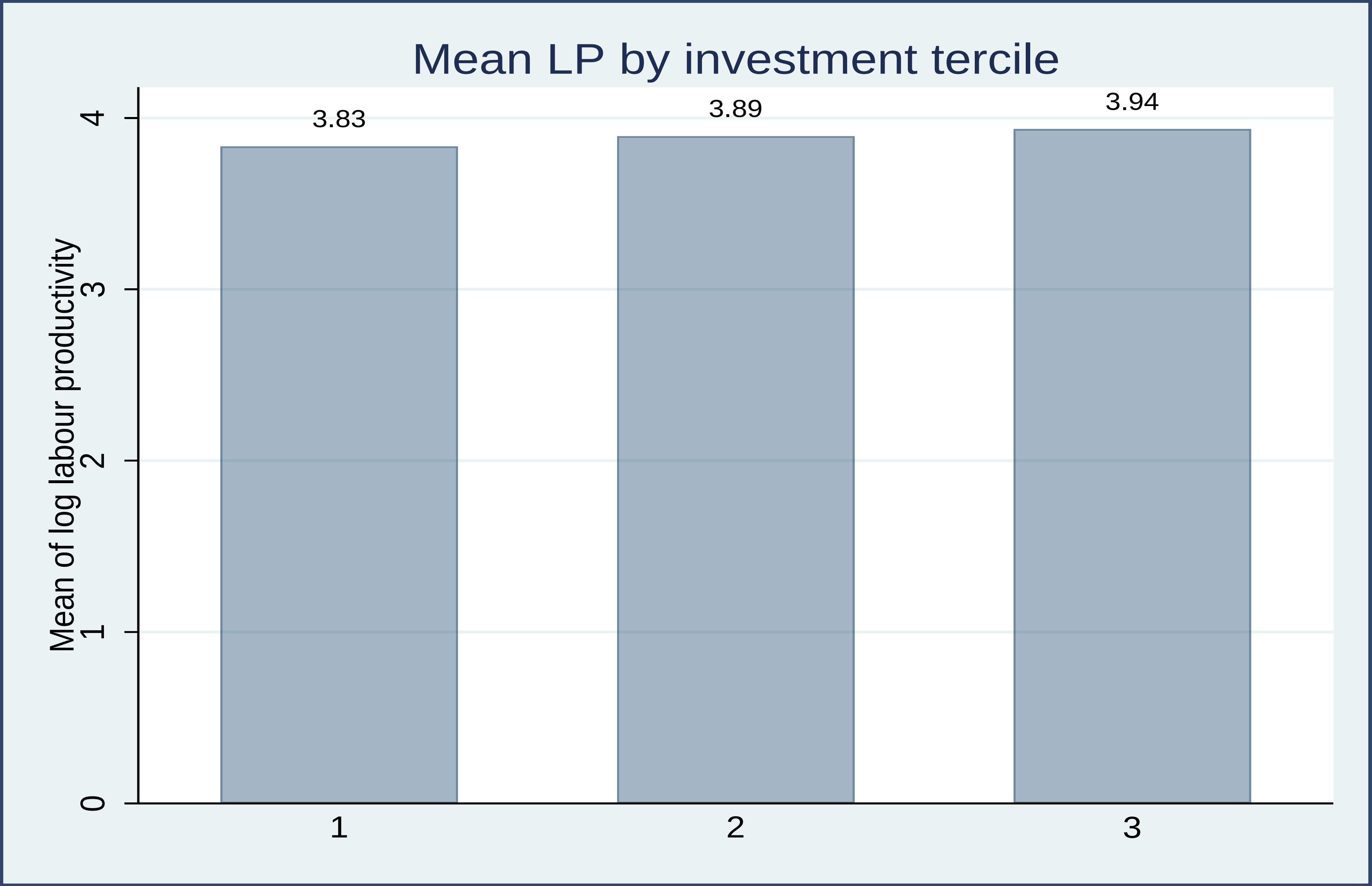
- We only look at firms with positive gross investment – can lead to further endogeneity, but PI accommodates endogeneity of any form

Data (cont.)

- We exclude agriculture, finance, public sector firms, and the household sector

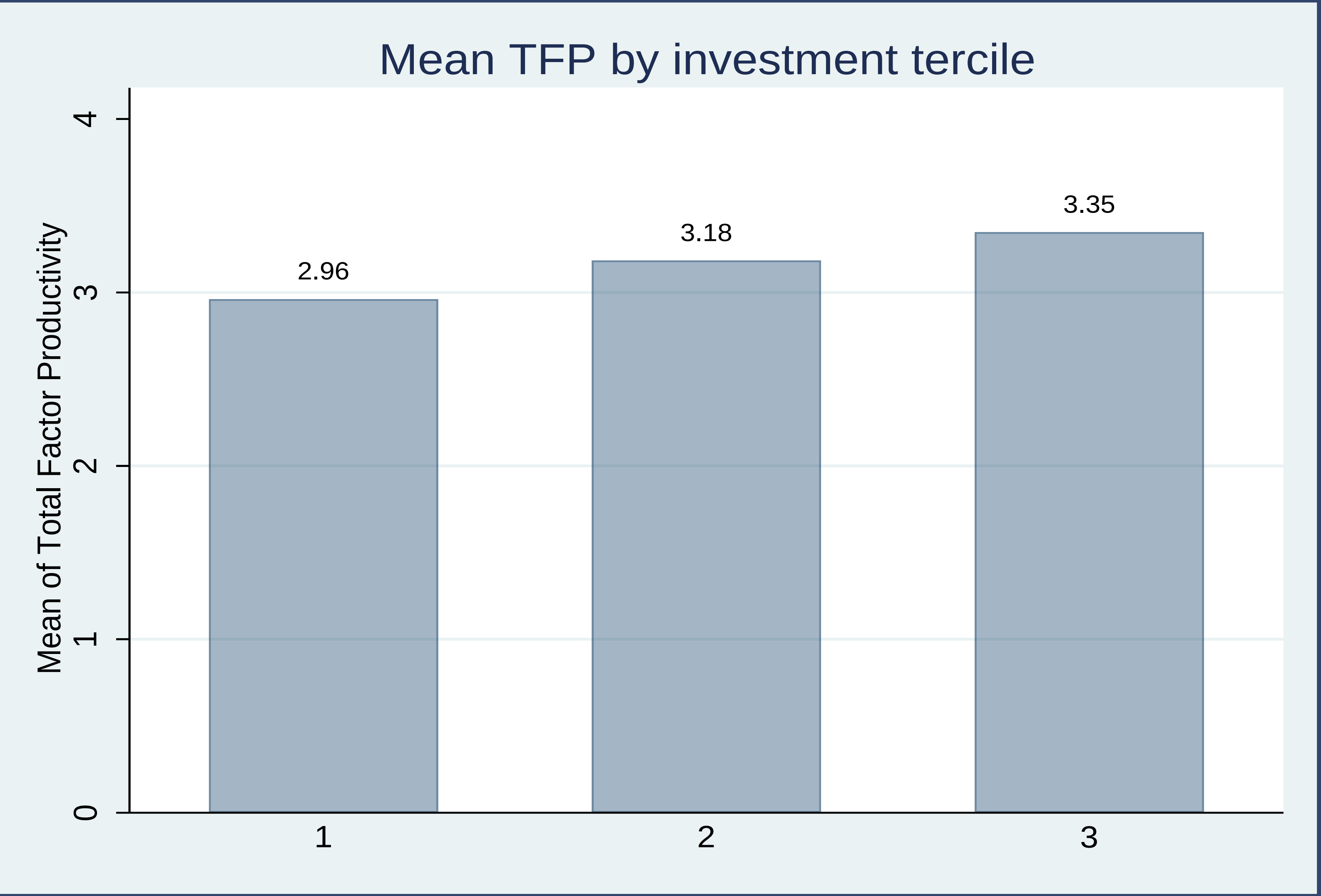
- Number of observations: about 358,400 for LP, about 205,450 for TFP

Data (cont.)



Mean LP by investment tercile
Mean of log labour productivity
0
1
2
3
4
3.83
3.89
3.94
1
2
3

Data (cont.)



Mean TFP by investment tercile
Mean of Total Factor Productivity
0
1
2
3
4
2.96
3.18
3.35
1
2
3

Partial identification

- We use partial identification methods (Manski, 1990; Manski, 1997; Manski and Pepper, 2000)

- Starting premise:
  - the treatment is endogenous (any form of endogeneity can be accommodated) and there is no exogenous variation that can help point identify the ATE

- PI puts bounds around counterfactual outcomes, and thus around the average treatment effect (ATE), using credible assumptions

Partial identification

- Average treatment effect (outcome Y, observed treatment w, generic treatment value d, controls x) :

$$E[Y(d_2)|x] - E[Y(d_1)|x]$$

- Average potential outcome:

$$E[Y(d)|x] = E[Y(d)|x, w=d]P(w=d|x)$$
$$+ E[Y(d)|x, w\neq d]P(w\neq d|x)$$

Partial identification (cont.)

- Observed sample analogues of $E[Y(d)|x,w=d]$, $P(w=d|x)$, $P(w\neq d|x)$

- Unobserved counterfactual $E[Y(d)\,|\,x,w\neq d]$

- Exogeneity implies $E[Y(d)\,|\,x,w\neq d]=E[Y(d)|x,w=d]$. Thus

$$E[Y(d_2)|x]-E[Y(d_1)\,|x]=$$
$$E[Y(d_2)|x,w=d_2]-E[Y(d_1)|x,w=d_1]$$

Problem of the counterfactual

- Two approaches:
  - statistical models
  - models modelling explicitly decision-making

- Both approaches rely on exogeneity
  - error distributions are assumed to have no connection to observables or other parameters in the model
  - the same estimating equation/decision rule can be applied irrespective of actual treatment received
  - all that is left out of the model is unsystematic

- PI postulates that one cannot included all systematic factors in the model; hence exogeneity cannot be assumed, which leads to $E[Y(d) \mid x, w \neq d] = E[Y(d) \mid x, w = d]$

Partial identification

- PI, instead of assuming $E[Y(d)|x,w\neq d]=E[Y(d)|x,w=d]$, put bounds around $E[Y(d)|x,w\neq d]$. Endogeneity for any reason can be accommodated as all reasons lead to the same implication: $E[Y(d)|x,w\neq d]\neq E[Y(d)|x,w=d]$

- Bounds on $E[Y(d)|x,w\neq d]$ imply bounds on average potential outcomes, and bounds on the differences in average potential outcomes, that is, average treatment effects

- PI is non-parametric, relies on few and credible assumptions, and is absolutely transparent how each assumption affects results.

Partial Identification (cont.)

- For example,

$$2 \leq E[Y(d_1)|x] \leq 3$$
$$5 \leq E[Y(d_2)|x] \leq 7$$

Then,

$$5 - 3 = 2$$
$$\leq E[Y(d_2)|x] - E[Y(d_1)|x)] \leq$$
$$7 - 2 = 5$$

- To narrow identification regions, we need lower bounds that are as large as possible, and upper bounds that are as small as possible

Partial Identification (cont.)

- Without assumptions, the only credible bounds on the counterfactual terms are the minimum and maximum possible values, which typically produce uninformative identification regions

$$E[Y(d) \mid x, w=d] P(w=d|x) + y_{min} P(w \neq d|x)$$
$$\leq E[Y(d)|x] \leq$$
$$E[Y(d) \mid x, w=d] P(w=d|x) + y_{max} P(w \neq d|x)$$

- Using assumptions, we will replace y_{min} with something larger, and y_{max} with something smaller

Assumption 1: Monotone Treatment Response (Manski, 1997)

- Higher investment does not decrease productivity, ***on average***, ***keeping everything else constant.*** For $d_2 > d_1$ and $\forall d$

$$E[Y(d_2)|w = d] \geq E[Y(d_1)|w = d)]$$

- Weak monotonicity, thus equality allowed - not sufficient to exclude zero from the ATE identification region

- Plausible assumption – difficult to think why higher investment would reduce productivity, on average and conditional on investment being positive. Has strongest effect on ATE lower bounds

- How it works:

$$E[Y(d_1)|w = d_2)] \leq E[Y(d_2)|w = d_2]$$

Assumption 2: Monotone Treatment Selection (Manski and Pepper, 2000)

- Higher investment firms have weakly higher productivity than lower investment firms for any common level of investment, ***on average.*** For $d_2 > d_1$ and $\forall d$

$$E[Y(d)|w = d_2] \geq E[Y(d)|w = d_1)]$$

- Weak monotonicity, thus equality allowed. MTS characterises the direction of treatment endogeneity

- Plausible assumption – higher investment firms likely to have better investment opportunities and more far-sighted management – on average and conditional on positive investment. Has strongest effect on ATE upper bounds

- How it works:

$$E[Y(d_1)|w = d_2)] \geq E[Y(d_1)|w = d_1]$$

Joint test of MTR+MTS (Manski and Pepper, 2000)

- Very important to test as many assumptions as possible for the credibility of results

- Manski and Pepper (2000) show that MTR+MTS implies that

$$E[Y(d_2)|w=d_2] \geq E[Y(d_2)|w=d_1] \geq E[Y(d_1)|w=d_1)]$$

The first inequality holds due to MTS, and the second due to MTR.

- Very easy to test this condition regarding weak monotonicity of observed conditional mean outcomes, which clearly holds in our data

Assumption 3: Monotone Instrumental Variable (Manski and Pepper, 2000)

- MIVs can be weakly monotonically associated with the outcome, and are thus much easier to find
- They do not identify the LATE but the ATE – nothing to do with compliers
- An instrument z is monotone if

$$z_1 < z_2 \Rightarrow E[Y(d)|Z = z_1] \leq E[Y(d)|Z = z_2]$$

- Assumption is about potential outcome $E[Y(d)]$, hence it is untestable. It also reflects a simple correlation, not a causal relationship

Monotone instrumental variable (MIV)

- MIV condition allows a directed search in the sample space, through conditioning on the MIV, for larger lower bounds and smaller upper bounds

- Our MIV: twice lagged GI/K
  - Assumption: given last year's GI/K, the higher GI/K was two years ago, the weakly higher current LP and TFP are
    - Weak assumption, denotes only a weakly positive association, on average, between GI/K and productivity two years apart

PI results – 3d vs 1st tercile of GI / K

Assumptions	Labor Productivity		Total Factor Productivity	
	Lower bound	Upper bound	Lower bound	Upper bound
Exogenous treatment selection	0.101		0.386	
No assumptions	-12.188	12.255	-11.907	12.165
MTR	0.000	12.255	0.000	12.165
MTS	-12.188	0.101	-11.907	0.386
MIV	-11.789	6.637	-10.953	6.638
MTR+MTS	0.000	0.101	0.000	0.386
MTR+MIV	0.014	6.637	0.074	6.638
MTS+MIV	-11.789	0.044	-10.953	0.239
MTR+MTS+MIV	0.014	0.044	0.074	0.239
Number of observations	358,393		205,449	

PI results– remaining ATEs under MTR+MTS+MIV

Assumptions	Labor Productivity		Total Factor Productivity	
	Lower bound	Upper bound	Lower bound	Upper bound
Panel A: second vs first tercile of I/K				
MTR+MTS+MIV	0.001	0.038	0.043	0.166
Panel B: third vs second tercile of I/K				
MTR+MTS+MIV	0.000	0.023	0.000	0.140
Number of observations	358,393		205,449	

Conclusions

- We find a positive and economically substantial causal effect of firm investment on both firm LP and firm TFP using micro data from FAME
- Results are obtained via PI methods using weak, and thus credible, assumptions
- Observational data (even cross-sectional ones) can be used to make causal statements, without the use of exogenous variation
- Future work: quantile treatment effects, the effect of intangible investment, incorporation of negative investment firms

THANK YOU!

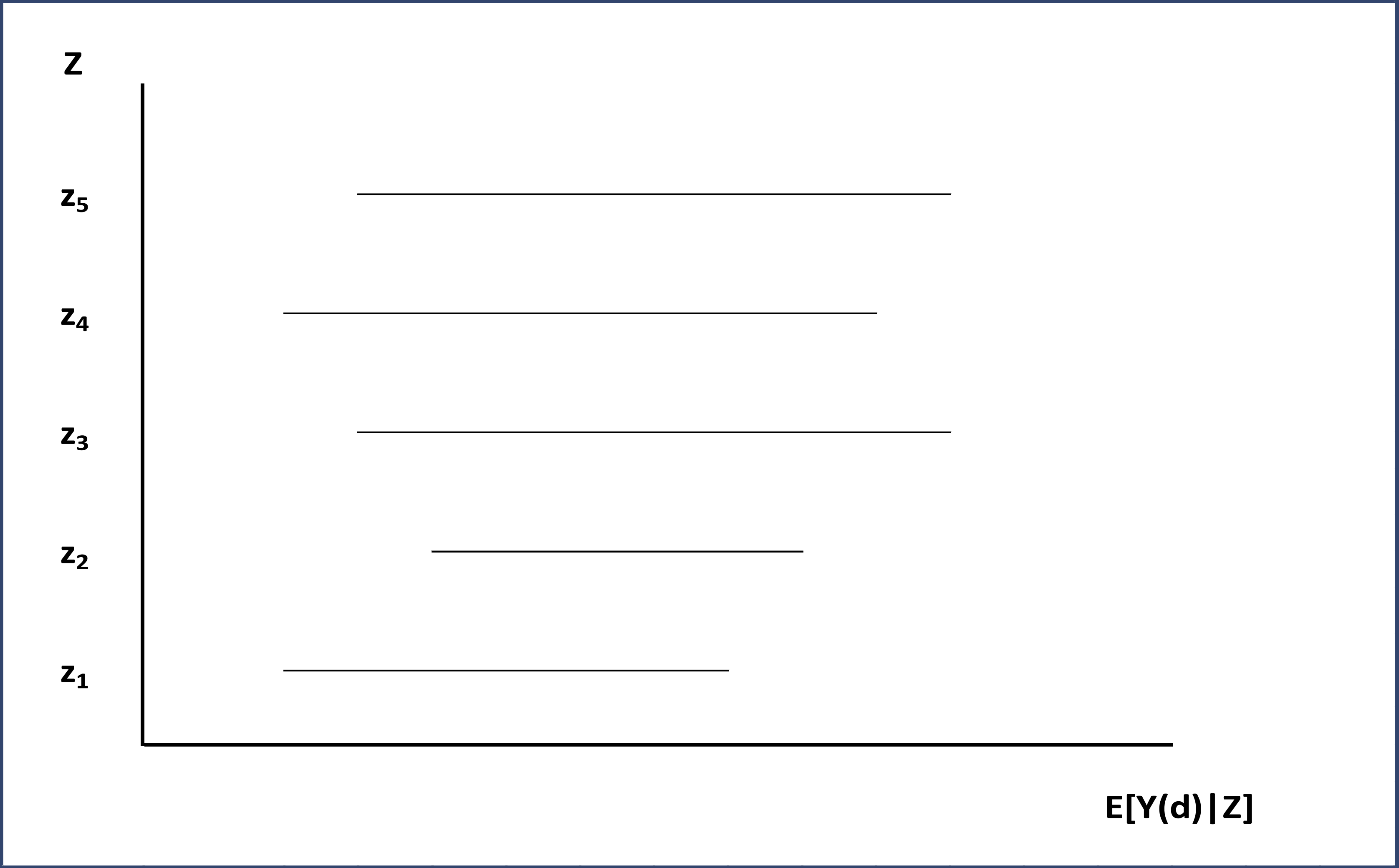
How do MIVs work? - XIVs

- Let us assume for the moment that the instrument is exogenous (XIV)

$$E[Y(d)|Z = z] = E[Y(d)], \forall z$$

- Need to narrow the identification region
  - LB example: $LB(d) = \sum_z LB(d|Z = z)P(Z = z)$
  - need to increase $LB(d|Z = z)$, as $P(Z = z)$ is given by the data
  - Correspondingly, need to decrease $UB(d|Z = z)$

How do MIVs work? - XIVs (cont.)



How do MIVs work? - XIVs (cont.)

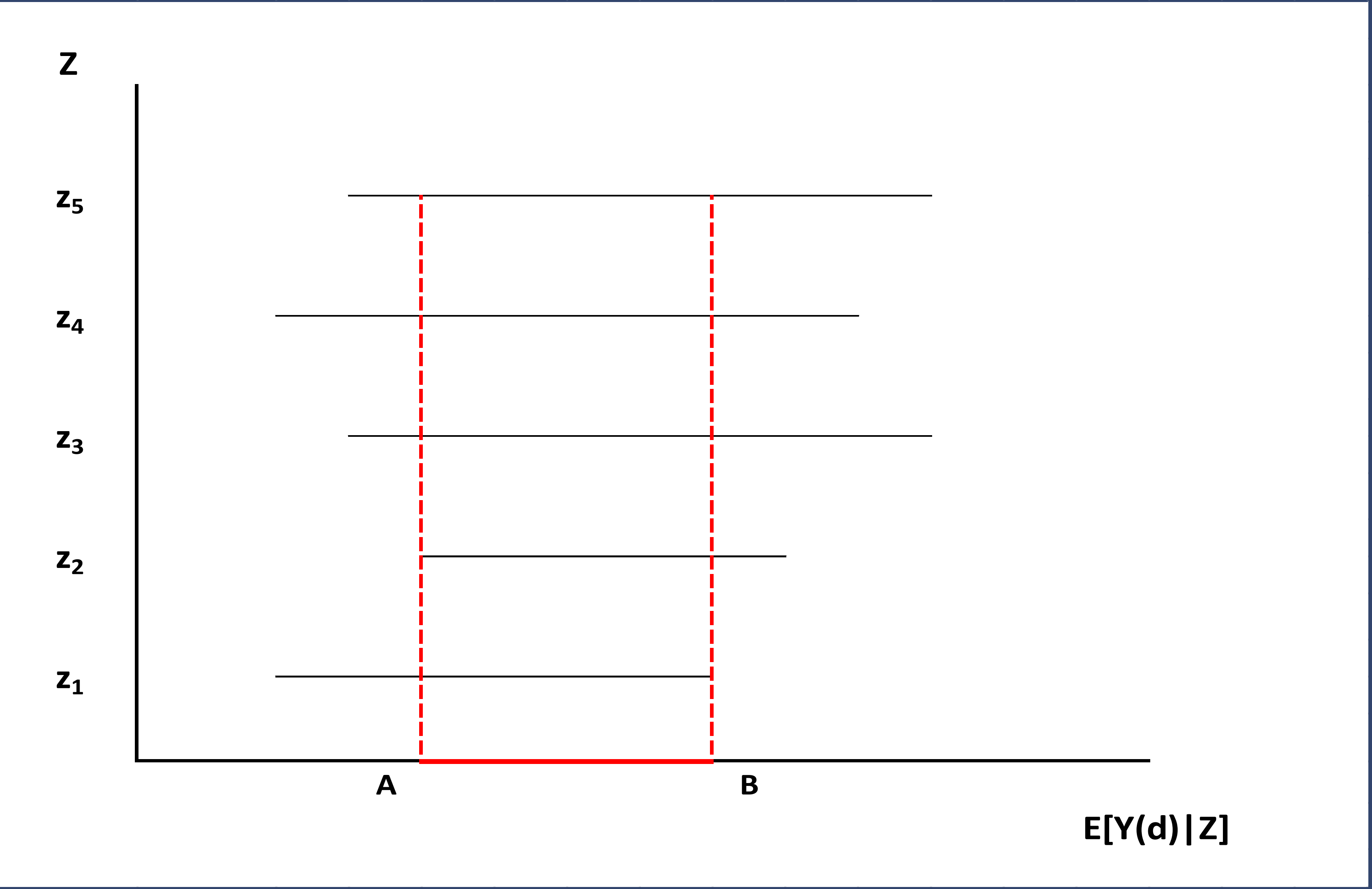
- Since the instrument is exogenous, results from all conditional identification regions are valid for the population

- All regions give valid answers → the intersection of all identification regions

- The intersection is given by the maximum lower bound and the minimum upper bound

$$\max_z LB[d|Z=z] \leq E[Y(d)] \leq \min_z UB[d|Z=m]$$

How do MIVs work? - XIVs (cont.)

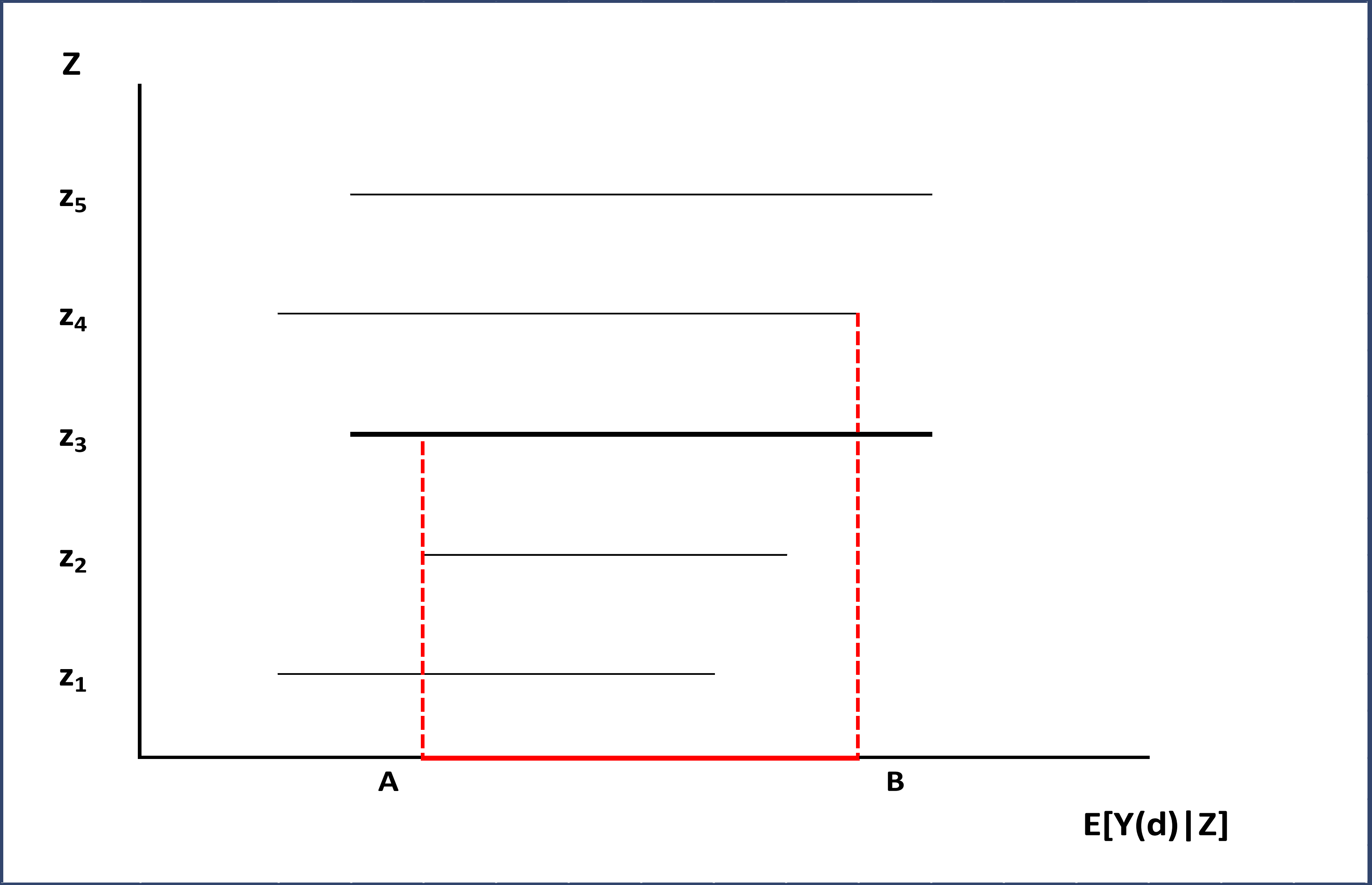


How do MIVs work?

$$z_1 \leq z_2 \rightarrow E[Y(d)|Z = z_1] \leq E[Y(d)|Z = z_2]$$

- For a given MIV value can examine only what happens to
  - lower bounds at lower instrument values
  - upper bounds of higher instrument values

How do MIVs work?



How do MIVs work? (cont.)

- Hence, the final bounds for the identification region conditional on MIV value z_3 are:
  - the maximum lower bound over z_1, z_2, z_3, which is the one corresponding to MIV value z_2
  - the minimum upper bound over z_3, z_4, z_5, which is the one corresponding to MIV value z_4

- Analogous calculations performed for identification regions conditional on MIV values other than z_3

- Finally, overall bounds are computed by integrating out the MIV

How do MIVs work? (cont.)

- Thus, optimization takes place only for a restricted range of values – identification regions less informative

- To be expected, as the MIV assumption is weaker than the XIV one

MIVs (cont.)

- MIVs partition the sample space into cells defined by instrument values and look for minima (maxima) of upper (lower) bounds
- In the case of MIVs, the search is directed
- Typically, the finer the partition (achieved, e.g., by using more than one MIVs) the narrower the identification regions
- Local minima and maxima are perfectly OK – they just lead to wider identification regions
- Different instruments possibly lead to different identification regions – this is fine, as the unobserved average potential outcomes do not change
- Constraint: number of observations