

# Time to Innovate

by Hwang and Kim

Discussion by Ryan Kim

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- Timely question: shorter-workweek debates worldwide, AI era

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- Weekly hours ↓ 2–3 hrs, mostly weekend work
- Capitalized IPs ↑ in light mfg. (where labor matters most for innovation)
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⇒ Very important and interesting paper!

- New angle on innovation drivers: time, not just R&D
- Multiple identification (sharp RDD, fuzzy RDD, DiD) with careful and thorough robustness tests (bandwidths, polynomials, placebos, McCrary, ...)

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2. Why would workers innovate?
  - capitalized IPs belong to the firm; wages unchanged (Table B5)
3. Google analogy doesn't fit this context
  - Google's 20% time: engineers, working hours, patent ownership/equity stake
  - Korean light m fg. (food, textiles, apparel, leather)  $\neq$  Silicon Valley tech

## Comment 1: Mechanism - A More Natural Story

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**Suggestions:** Embrace firm-side story, or directly measure worker channel:

- Korean Time Use Survey: what did affected workers do with the extra leisure?
- Employee invention claims (KIPO): did production workers' inventions rise?
- Patent inventors (KIPRIS): production workers as inventors — ever?

## Comment 2: Identification - Paper's Placebo Check

Panel B. Innovation output across sectors

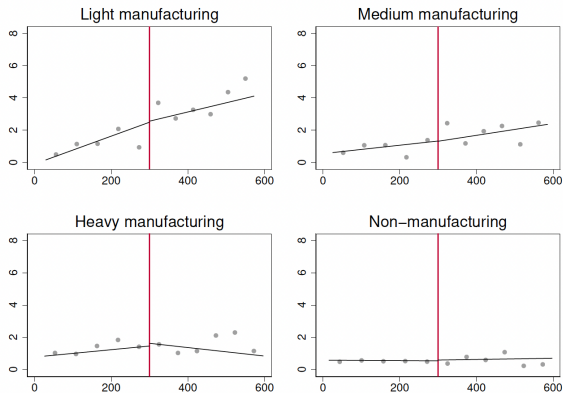


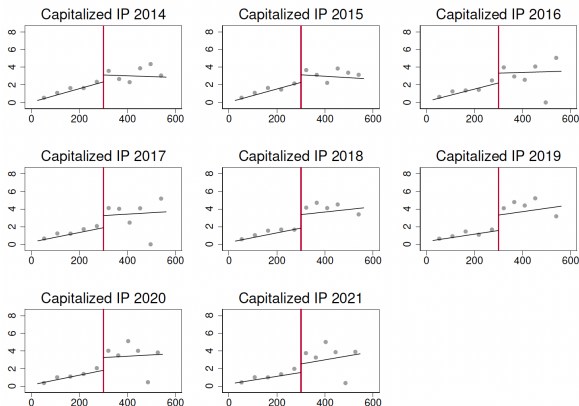
Figure 7 Panel B:  
Pre-law continuity check

- Outcome: capitalized IPs at 2015 FY-end
- Forcing: **2015 employment**
- No clear jump at 300

Paper's conclusion:  
RDD assumption valid

# Comment 2: Identification - But with 2017 Employment...

Panel D. Impacts in light manufacturing across years (RD plots)

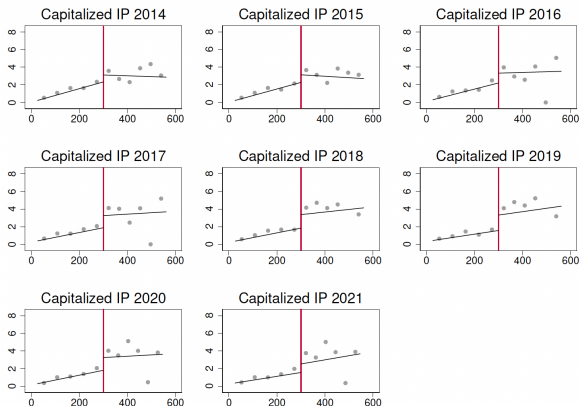


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**2017 employment**  
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- **Sorting:** 300+ firms (in 2017) are precisely those already investing in IP; regulation-averse firms split or stay below
- **Anticipation:** firms responded to the May 2016 proposal

## Comment 2: Identification - Implications

- $\beta_1^{2019}$  does not cleanly identify the law's effect:

$$\beta_1^{2019} = \underbrace{\text{anticipation}}_{2016-2018} + \underbrace{\text{sorting}}_{\text{type selection}} + \underbrace{\text{enforcement}}_{2018.7-2019.12}$$

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- Fuzzy RDD (2015 employment as IV) doesn't fix this completely
  - Exclusion: 2015 employment must affect 2019 IPs *only* via 2017 treatment
  - But large 2015 firms continue to innovate regardless of treatment:
    - persistent firm characteristics (R&D capacity, management)
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### Suggestions:

- Donut RDD: exclude firms crossing 300 between 2015 and 2017
- Reduced-form with 2015 employment as main forcing variable (+ robustness)
- Decompose: pre-enforcement (2017) vs. post-enforcement (2019)

## Comment 3: Light Manufacturing Specificity

- Paper attributes light mfg. specificity to  $\lambda$  (worker innovation sensitivity)
  - Figure 4: employment–innovation slope steepest in light mfg.
  - But  $\lambda$  from a cross-sectional slope is hardly identified

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  - But  $\lambda$  from a cross-sectional slope is hardly identified
- **Equally plausible alternatives:**
  - Short innovation cycles (food, cosmetics, apparel)
  - Pre-law hours longest in light mfg.  $\Rightarrow$  cap binds hardest
  - Low baseline R&D  $\Rightarrow$  small changes look large on log scale
  - Cheap, fast IP filings (Table B10: food, tobacco patents)

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  - Cheap, fast IP filings (Table B10: food, tobacco patents)
- $\lambda$  story is *one* possibility: not disciplined by the data

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  - Pre-law working hours (WPS, 2014/2016)
  - Baseline R&D intensity
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- Horse-race: does  $\lambda$  survive after controlling for these characteristics?

## Comment 4: What Does the Model Actually Do?

- The model assumes what it claims to show
  - $\lambda > 0$  (creative leisure  $\rightarrow$  firm innovation) *is* the mechanism
  - $\delta$  (fraction of leisure used creatively) unobserved, no connection to the data

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  - $\delta$  (fraction of leisure used creatively) unobserved, no connection to the data
- Silent on key empirical findings:
  - No prediction distinguishing alternative mechanisms (e.g., worker-leisure vs. firm-substitution)
  - Anticipation dynamics (static model)
  - Capital substitution ( $K$  fixed; ignores software  $\uparrow$ )
  - Sector heterogeneity ( $\lambda$  exogenous; cannot explain light mfg.)

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- **Suggestion:** extend the model to engage with these findings, or present results as clean reduced-form evidence

## Comment 5: Very Small and Concentrated Sample

- **Small Sample:** Only 27 establishments above 300 in light mfg. (Table 2)
  - Main spec relies on this small base:  $\pm 300$ : 129 obs,  $\pm 200$ : 72,  $\pm 100$ : 28
- Patents in light mfg. **concentrated** in few categories (Table B10)  
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### Suggestions:

- Which sub-sectors / establishments drive the effect?

# Final Comment

- Important question, ambitious paper
  - Rare quasi-experiment on work hours (Korea's 52-hour law)
  - Rich establishment-level data (WPS)
  - Connects time, labor, and innovation in a novel way
  
- Looking forward to seeing the final version!