

Measuring the Efficacy of Competition Policy: Identification using an RDD Approach

Ali Musali

Advisor: Raquel Carrasco

21 September, 2023

Outline

- 1 Introduction & Novelty
- 2 Data
- 3 Methodology & Identification
- 4 Results

Competition Policy in the U.S.

- Hart-Scott-Rodino (HSR) Act, enacted in 1976, requires mergers and acquisitions to be reported to Federal Trade Commission (FTC) and/or Department of Justice (DOJ).
- The primary objective of the HSR Act is to block anti-competitive deals before they can be consummated.
- Previously there was a \$ 10 million threshold below which deals were exempt from notification. In 2001, the Act was amended and deals with transaction size less than \$ 50 million were made exempt from notification. We study the impact of merger policy on innovation at this \$ 50 million threshold, where innovation is measured via patenting activity.

Objective

- The notification threshold captures anti-competitive mergers if they are reported, hence fostering innovation between reported deals as harmful mergers are deterred.
- Moreover, notification is costly as the parties have to hire lawyers, collaborate with economic consulting firms to prove that their deal is anti-competitive, pay the filing fees, etc., all of which may divert resources away from R&D.
- Hence, the effect of notification on post-merger innovation at the reporting threshold is ambiguous. We use Sharp "Donut" Regression Discontinuity Design (RDD) to estimate this effect by comparing the deals that were reported as they fall just above the threshold with the ones that fall just below it.

- The increase in the notification threshold led to a rise in anti-competitive mergers between competitors (Wollmann, 2019), and led to a reduction in post-merger innovation as shown in Morzenti (2022), as a reaction to reduced pre-merger scrutiny. By pooling pre and post-amendment periods, these studies use Diff-in-Diff to measure the impact of the amendment to the Act in 2001, not the threshold choice per se.
- This paper, on the other hand, checks the impact of notification at the threshold by using data from 2001 to as recent as 2018.
- Moreover, to the best of our knowledge, this is the first paper to use RDD to measure the impact of mandatory notification at the threshold.

- We generate three different measures of patenting activity and use 16 different year windows around the deal date for each measure, presenting a more robust and comprehensive analysis.
- Moreover, we are able to distinguish the impact between high-patent producers and low-patent producers by bounding above the number of patents. This allows for a more nuanced understanding of the overall average effect's composition.

- **SDC Platinum:** the most used and reliable database for M&A activity.
 - ① We retrieve deals in the U.S. between 2001-2018.
 - ② For the deals after 2005, we deflate transaction values by the growth in GNP as per the HSR Act.
 - ③ We drop those deals that are exempt from the HSR Act irrespective of their size, following Wollmann (2019).
 - ④ We choose \$ 15 million ¹ as the largest bandwidth and take the deals that fall within it.

¹This choice is arbitrary. Smaller and "optimal" bandwidths will be used later in the analysis.

- **PatentsView:** the database for patents which covers private companies together with public companies.
 - ① We match the company names in PatentsView with a loose string matching and Google Search API.
 - ② For each deal we combine the patents of the acquirer and target company and the ultimate parent company of the acquirer, before and after the deal date.
 - ③ For each patent, we retrieve the date of application, number of citations, and first-assigned technological field.
 - ④ For each patent, we define intensity as the number of citations it received divided by the average number of citations received by the patents in the same technological field and year.
- After all the cleaning, we end up with 1101 deals ², 630 technological fields, and around 1.8 million patents in total.

²This sample size is for the widest year window around the deal date

- There are high levels of heterogeneity in patenting activity across technological fields and years. It is also true that the older the patent, the higher its citations.
- Hence the number of citations and number of patents are imperfect measures of innovation. Patent intensity, on the other hand, corrects for this and enables us to compare patents in different fields and years.
- We define P_{dij} , C_{dij} , and S_{dij} for patent intensity, citation, and size, respectively, for each deal d , for i years before and for j years after, where $i, j \in \{2, 3, 4, 5\}$.

Definitions

- More formally, we define P_{dij} as:

$$P_{dij} = \log \left(\frac{1}{N_{dj}} \sum_{\substack{k=1 \\ k \in \text{After}_{dj}}}^{N_{dj}} \text{Intensity}_k \right) - \log \left(\frac{1}{N_{di}} \sum_{\substack{k=1 \\ k \in \text{Before}_{di}}}^{N_{di}} \text{Intensity}_k \right)$$

$\text{After}_{dj} = \{\text{Patents of deal } d \mid \text{Patent Date} \in [\text{Deal date}, \text{Deal date} + j \text{ years}]\}$,

$\text{Before}_{di} = \{\text{Patents of deal } d \mid \text{Patent Date} \in [\text{Deal date} - i \text{ years}, \text{Deal date}]\}$,

and N_{dj} and N_{di} are the cardinality of After_{dj} and Before_{di} , respectively.

- P_{dij} measures, approximately, the percentage change in the average patent intensity from i years before to j years after the deal date.

Definitions contd.

- Similarly, we define C_{dij} as:

$$C_{dij} = \log \left(\frac{1}{N_{dj}} \sum_{\substack{k=1 \\ k \in \text{After}_{dj}}}^{N_{dj}} \text{Citation}_k \right) - \log \left(\frac{1}{N_{di}} \sum_{\substack{k=1 \\ k \in \text{Before}_{di}}}^{N_{di}} \text{Citation}_k \right);$$

- and S_{dij} as:

$$S_{dij} = \log \left(\frac{N_{dj}}{N_{di}} \right).$$

- C_{dij} measures the percentage change in the average patent citations from i years before the deal date to j years after it. Similarly, S_{dij} can simply be interpreted as the percentage change in the number of patents in the $i - j$ window around the deal date.

Empirical Framework & Assumptions

- **Running Variable:** "Adjusted" Transaction Value
- **Treatment:** Whether the deal is notified under the HSR act, or not.
- **Response Variable:** Change in patenting activity: P_{dij} , C_{dij} , and S_{dij} .

Assumptions:

- 1 The deals right above and below \$50 million (as adjusted) threshold are comparable: continuity in potential outcomes at the cutoff point
- 2 The density of transaction value is continuous around the threshold: no manipulation of running variable. This assumption is tested with local-polynomial density estimators described in Cattaneo et al. (2017) and we failed to reject the null of continuity for all estimations.
- 3 No discontinuity in other covariates at the cutoff: assumed due to unavailability of data for private companies.

Estimation

- Hence, $\forall i, j \in \{2, 3, 4, 5\}$, our baseline quadratic model is the following:

$$Y_{dij} = \beta_{0ij} + \beta_{1ij}Z_d + \beta_{2ij}Z_d^2 + \beta_{3ij}T_d \times Z_d + \\ + \beta_{4ij}T_d \times Z_d^2 + \theta_{ij}T_d + \sum_{t=2001}^{2017} \gamma_{tij} \times Year_{td} + \epsilon_{dij}$$

- Y_{dij} either one of the three measures, namely P_{dij} , C_{dij} or S_{dij} ; Z_d is the adjusted and centered transaction value; $T_d = \mathbb{I}(Z_d > 0)$; and $Year_{td}$ is the year dummy.
- Local Linear regression is equivalent to setting $\beta_{2ij} = \beta_{4ij} = 0$.
- The observations at the threshold are dropped because of non-random heaping - "Donut" RDD described in Barreca et al. (2011).
- Standard errors are clustered at running variable level as per in Card&Lee (2008), and weights are given by a triangular kernel.

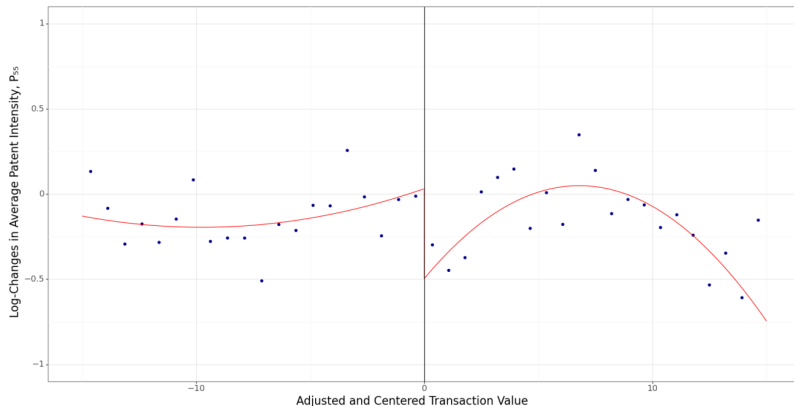


Figure 4.2: Regression Discontinuity plot for post-merger average patent intensity, P_{55} .

Notes: The figure is plotted with "rdplot" command developed by Calonico et al. (2014). A global quadratic relationship is assumed. The covariates are year dummies and weights are given by a triangular kernel where the bandwidth is 15. The bins are constructed with mimicking variance evenly-spaced method using spacings estimators described as in the aforementioned paper.

Quadratic Regression

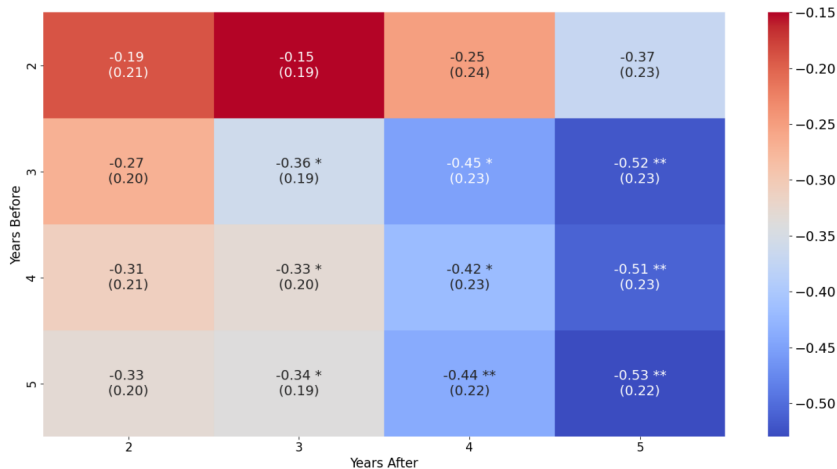


Figure 4.3: Estimated discontinuity in post-merger average patent intensity, P_{ij} .

Notes: The entry in row i and column j is the coefficient of θ_{ij} (estimated discontinuity) in Equation 1 where the dependent variable is P_{ij} and we use "Donut" RD estimation with a triangular kernel. The bandwidth is 15. The observations with the absolute value of the dependent variable higher than 3.5 are dropped. The standard errors are clustered at the running variable level and reported inside parentheses. (* ~ P-value < 10%, ** ~ P-value < 5%, *** ~ P-value < 1%)

Local Linear Regression

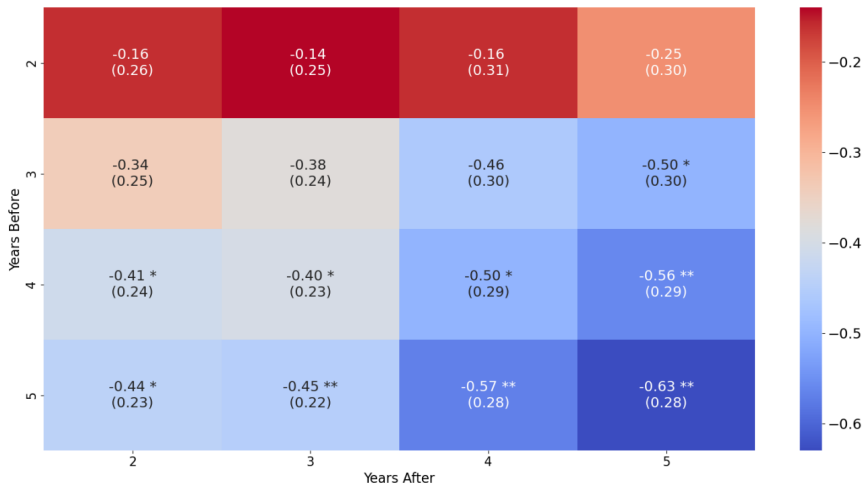


Figure 4.6: Estimated discontinuity in post-merger average patent intensity, P_{ij} .

Notes: The entry in row i and column j is the coefficient of θ_{ij} (estimated discontinuity) in Equation 1 where the dependent variable is P_{ij} and we use "Donut" RD estimation with an Epanechnikov kernel. Linearity is assumed, hence $\beta_{2ij} = \beta_{4ij} = 0$ is imposed on Equation 1. The bandwidth is 4 for both sides. The observations with an absolute value of the dependent variable higher than 3 are dropped. The standard errors are clustered at the running variable level and reported inside parentheses. (* ~ P-value < 10%, ** ~ P-value < 5%, *** ~ P-value < 1%)

Local Linear Regression contd.

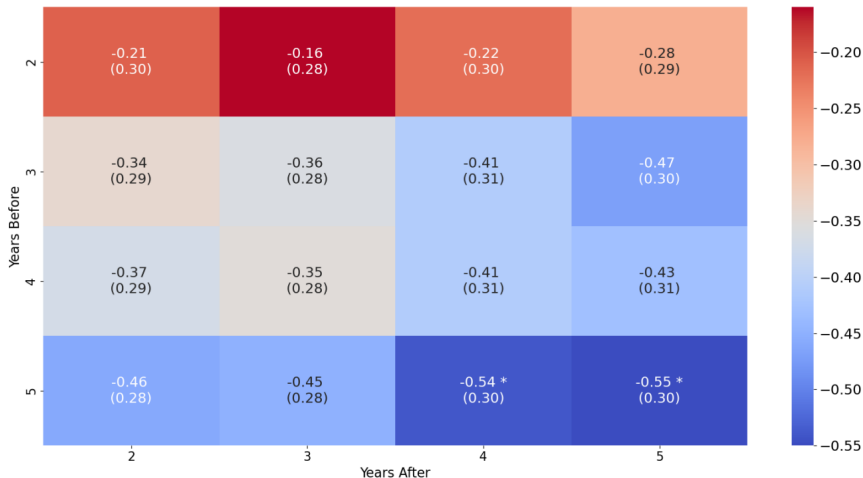


Figure 4.7: Estimated discontinuity in post-merger average patent citation, C_{ij} .

Notes: The entry in row i and column j is the coefficient of θ_{ij} (estimated discontinuity) in Equation 1 where the dependent variable is C_{ij} and we use "Donut" RD estimation with an Epanechnikov kernel. Linearity is assumed, hence $\beta_{2ij} = \beta_{4ij} = 0$ is imposed on Equation 1. The bandwidth is 4 for both sides. The observations with a value of the dependent variable higher than 3.5 are dropped. The standard errors are clustered at the running variable level and reported inside parentheses. (* ~ P-value < 10%, ** ~ P-value < 5%, *** ~ P-value < 1%)

Local Linear Regression contd.

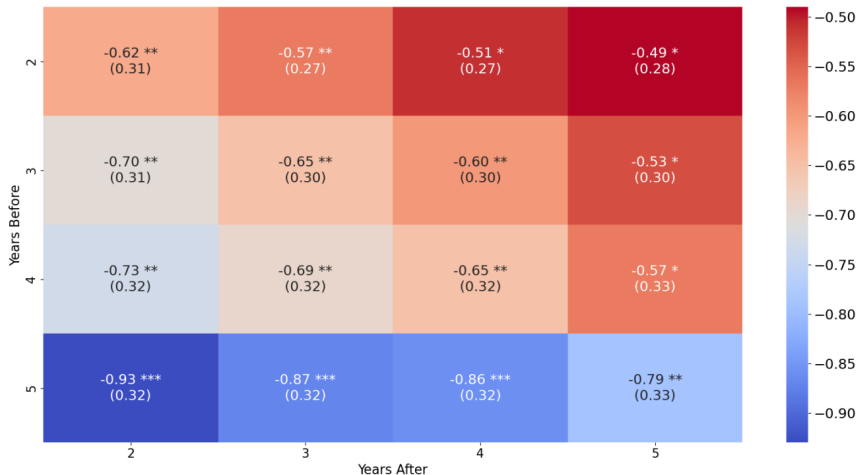


Figure 4.8: Estimated discontinuity in post-merger patent count, S_{ij} .

Notes: The entry in row i and column j is the coefficient of θ_{ij} (estimated discontinuity) in Equation 1 where the dependent variable is S_{ij} and we use "Donut" RD estimation with an Epanechnikov kernel. Linearity is assumed, hence $\beta_{2ij} = \beta_{4ij} = 0$ is imposed on Equation 1. The bandwidth is 4 for both sides. The observations with a value of the dependent variable higher than 3.5 are dropped. The standard errors are clustered at the running variable level and reported inside parentheses. (* ~ P-value < 10%, ** ~ P-value < 5%, *** ~ P-value < 1%)

Optimal Bandwidth & Bias Correction

- "rdrobust" command (Calonico et al., 2017) finds a bandwidth that is CER-optimal for each side of the cutoff for estimation, and higher auxiliary bandwidth to be used for bias correction.
- For each side of the cutoff, the former is used in local linear regression for point estimation while the latter is used in quadratic regression for bias correction.
- Calonico et al. (2019) argue that bias-corrected estimation with MSE-optimal bandwidth gives suboptimal confidence intervals in terms of coverage error. They develop a method to calculate the main and auxiliary bandwidth that is CER-optimal, in the sense that it has the fastest decaying coverage error rate.
- Weights are given by the Epanechnikov kernel and observations at the threshold are dropped as before.

RD-Robust estimation

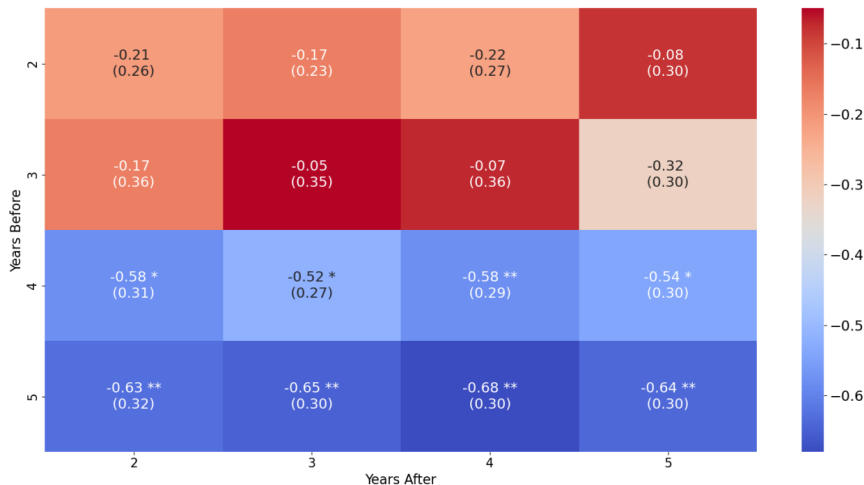


Figure 4.9: Estimated discontinuity in post-merger average patent intensity, P_{ij} .

Notes: The entry in row i and column j is the bias-corrected ATE for patent intensity estimated via user-written "rdrobust" command with Epanechnikov kernel. Linear regression is used for point estimation, while quadratic regression is used for bias correction. The bandwidth choice is CER-optimal and varies between 1.5 – 2.5 for the left side, whereas it is between 2.5 – 3.5 for the right side of the cutoff. The observations with an absolute value of the dependent variable higher than 3 are dropped. The standard errors are calculated with NN method with a minimum number of 3 neighbors and reported inside parentheses. (* ~ P-value < 10%, ** ~ P-value < 5%, *** ~ P-value < 1%)

High vs. Low patent producers

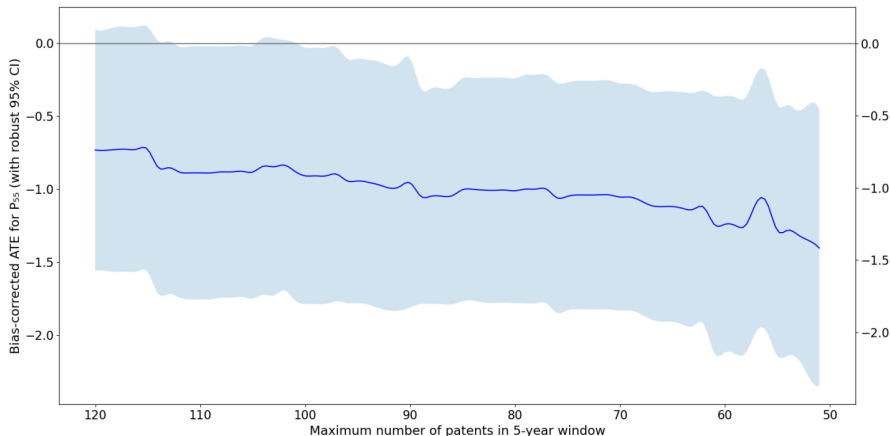


Figure 4.10: Estimated discontinuity in post-merger average patent intensity, P_{55} , for a given upper bound for the number of patents.

Notes: The value for a given level of the maximum number of patents in 5-year window around the deal date is the bias-corrected ATE (for the corresponding subsample) for patent intensity estimated via user-written "rdrobust" command with Epanechnikov kernel. Linear regression is used for point estimation, while quadratic regression is used for bias correction. The bandwidth choice is MSE-optimal and varies between 4 – 5 for the left side, whereas it is between 3 – 4 for the right side of the cutoff. Observations with an absolute value of the dependent variable higher than 3 are dropped. The robust 95% CI is depicted around a point estimate.

Summary of Results:

- ATE of notification on long-run patent intensity is -0.64 log-points, or 47% reduction, in the robust bias-corrected estimation.
- Moreover, the negative impact is more pronounced in long-term specifications, and for deals with relatively low patenting activity.

Discussion:

- Contrary to the objective of HSR Act, its impact on innovation at the threshold is negative, which hints that costs of notifying may outweigh the benefits of blocking anti-competitive deals. These costs most likely crowd out investment in R&D.
 - 1 Direct financial costs: Filing fees, seeking legal counsel, economic consultancy, hiring experts (Likely to increase as FTC prepares another package of newly designed requirements for documentation).
 - 2 Indirect costs: Time to arrange the submission in addition to 30-day waiting period, uncertainty in innovation strategy, strategic changes in the newly formed entity.

Thank You!

Thank you for listening. Any questions and/or comments?