The Effect of Noncompete Enforceability on Productivity: Evidence from a New State-Level Manufacturing Dataset

By KATHERINE CHANG, MATTHEW JOHNSON, KURT LAVETTI, MICHAEL LIPSITZ, AND DEVESH RAVAL*

A substantial share of American workers are subject to non-compete agreements (NCAs), which contractually restrict them from accepting employment with competing firms (Starr, Prescott and Bishara, 2021). States vary widely in the extent to which such agreements are enforceable. In recent years, policymakers have expressed concern about the potential adverse effects of NCAs on workers and the economy, prompting both federal and state policy responses, including a proposed nationwide ban by the FTC in 2024 and a comprehensive state-level ban enacted in Minnesota in 2023.

The aggregate welfare effects of (enforceable) NCAs hinge on their effect on productivity. Stricter enforcement of NCAs (i.e., a greater willingness of courts to enforce NCAs) may reduce productivity by dampening worker effort and self-investment (Garmaise, 2011), impeding efficient worker–firm matching (Johnson, Lavetti and Lipsitz, 2025; Gottfries and Jarosch, 2023), and limiting employee spinoffs and knowledge spillovers that contribute to innovation (Marx, 2011; Johnson, Lipsitz and Pei, 2023; Lipsitz and Tremblay, 2024; Reinmuth and Rockall, 2023). On the other hand, stronger enforcement may increase productivity by strengthening firms' incentives to invest in workers' human capital and other intangible assets (Jeffers, 2024; Shi, 2023; Starr, 2019).

Existing empirical work finds that stricter NCA enforceability lowers wages (Johnson, Lavetti and Lipsitz, 2025; Lipsitz and Starr, 2022; Balasubramanian et al., 2022). These wage effects may reflect reduced productivity, but they could also arise from weaker worker bargaining power since NCAs reduce outside options. In that case, (enforceable) NCAs might lower the labor share without affecting output or productivity.

We examine these questions using a newly constructed state-level panel of manufacturing production from 1987 to 2021, compiled from historical Census records. These data allow us to estimate state-level productivity by industry and to study how productivity, output, and inputs respond to changes in NCA enforceability. We complement the Census data with state-level GDP and labor share measures from the Bureau of Economic Analysis and the Bureau of Labor Statistics, which enables us to assess whether the effects of NCAs extend beyond manufacturing to the broader economy.

I. Data Description

We construct a state-year panel of manufacturing production covering all U.S. states from 1987 to 2021 by harmonizing annual state-level Census manufacturing records drawn from multiple historical Annual Survey of Manufactures and Census of Manufactures archives. The most granular data are available at the 3-digit SIC level for 1987–1996 and the 4-digit NAICS level for 1997–2021, but we also include data at higher levels of aggregation, including the full manufacturing sector and 2-digit SIC / 3-digit NAICS industries. For each state-industry, the datasets includes measures of output—sales and value added—and inputs—capital investment, payroll, and employment, with employment and payroll separately reported for production and non-production workers. To facilitate estimation of total factor productivity, we construct capital stocks using the perpetual inventory method following Chirinko and Wilson (2009) and deflate all nominal variables to 1997 dollars.

* Chang: Federal Trade Commission (kchang@ftc.gov); Johnson: Duke University, NBER (matthew.johnson@duke.edu); Lavetti: Ohio State University, NBER (Lavetti.1@osu.edu); Lipsitz: University of Pennsylvania (lipsitzm@upenn.edu); Raval: Federal Trade Commission (draval@ftc.gov). We are grateful to audiences at the 2026 ASSA for helpful comments and suggestions. The views expressed in this paper are the authors' own and not necessarily those of the Federal Trade Commission or of any individual Commissioner.

To assess whether the effects of NCA enforceability extend beyond manufacturing, we supplement the Census data with a state-year panel of GDP, employment, and earnings from the BEA and BLS for broad industrial sectors from 1975 to 2023. These data do not include capital inputs so we only study output and labor shares. Additional details on data sources and construction are provided in the Supplemental Appendix.

NCA enforceability is determined by state law and varies over time, primarily due to changes in judicial precedent. We measure enforceability using the state-year index constructed by Johnson, Lavetti and Lipsitz (2025), which covers all U.S. states from 1991 to 2014 and aggregates seven legal dimensions into a single enforceability score. We rescale the index to lie between 0 (NCAs unenforceable) and 1 (most stringent enforcement). During this period, states experienced frequent within-state changes in enforceability, providing the variation used in our analysis.

II. Methodology

We estimate the effects of NCA enforceability using a stacked difference-in-differences design (Cengiz et al., 2019). Each subexperiment corresponds to a single state-year change in enforceability and compares treated states to states that do not experience any enforceability changes over the sample period. To ensure clean pre- and post-treatment dynamics, we restrict attention to state-years with no other enforceability changes in the four years before or after the event.

Observations are at the state-year-granular industry (3-digit SIC or 4-digit NAICS)-subexperiment level, where granular industries belong to broad industries (2-digit SIC) in order to create a consistent time series across years.[1] We exclude observations with missing or implausible values for wages or value added; details are provided in the Supplemental Appendix.

Formally:

$$Y_{s,t,n,b} = \beta\, Enforceability_{s,t} + \rho_{s,b} + \gamma_{t,N(n),b} + \alpha_{n,b} + \varepsilon_{s,t,n,b}, \tag{1}$$

where $Y_{s,t,n,b}$ denotes the outcome in state s, year t, granular industry n in broad industry $N(n)$, and subexperiment b. The specification includes state-by-subexperiment fixed effects, year-by-broad industry-by-subexperiment fixed effects, and granular industry-by-subexperiment fixed effects, absorbing permanent differences across states, common shocks within broad industries over time, and permanent differences across granular industries. We cluster standard errors at the state-subexperiment level and weight observations by pre-period employment.

III. Results

A. *Results from New Manufacturing Dataset*

Table 1 displays results from eight regressions comparable to Equation 1 using the Census manufacturing dataset. Each is a stacked Poisson pseudo-maximum likelihood model, except for the regression on the labor share of income (Column 7), which is a stacked OLS model.

The coefficient in Column 1 implies that making NCAs easier to enforce reduces manufacturing workers' earnings. An enforceability increase equal to 10% of the observed variation in the NCA Score dataset results in an earnings decline of about 0.7% (calculated as $exp(-0.0713*10\%)-1$), though the coefficient is not statistically significant. This is quantitatively smaller than but qualitatively in line with previous findings for the economy as a whole.[2] Figure 1, Panel (a), contains event

[1]We categorize broad industries as follows: apparel, chemical, electrical, fabricated metal, food, furniture, machinery, primary metal, miscellaneous, motor and transportation, nonmetal, paper, petroleum and coal, printing, rubber, textile, and wood. One could alternatively specify a model with state-by-subexperiment and granular industry-by-year-by-subexperiment fixed effects. However, due to the switch from SIC to NAICS that occurs in 1997 and the lack of a reasonable crosswalk between SIC and NAICS at the granular industry level, doing so eliminates the ability to use data from years prior to 1997—and therefore NCA law changes prior to 2002. We opt instead to use the full suite of data and control for permanent differences across granular industries.

[2]Johnson, Lavetti and Lipsitz (2025) find that the identical change in NCA score yields a 1.2% decline in earnings across all sectors.

Table 1—: The Effects of NCA Enforceability on Worker and Firm Outcomes in Manufacturing Data

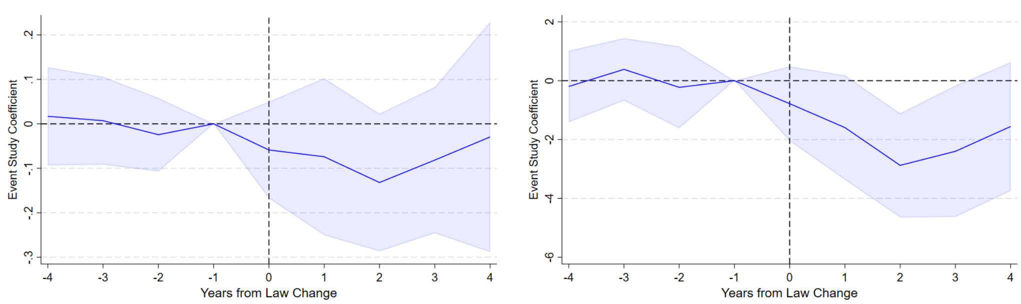
	(1) Average Earnings	(2) Manufacturing Value Added	(3) Value Added Per Worker	(4) Sales	(5) Capital	(6) Capital Per Worker	(7) Labor Share of Income	(8) Employment
NCA Score	-.0713	-1.69***	-.85***	-.794*	.128	.129	.0407	-.0434
	(.0763)	(.597)	(.309)	(.451)	(.256)	(.172)	(.051)	(.358)
N	252,774	252,987	252,774	252,987	248,425	248,214	249,965	252,987
Mean DV	37,218	3.35†	151,466	5.22†	1.50†	75,729	0.36	20,096

Note: This table reports estimates from the industry-by-state-level Poisson stacked regression model described in Equation 1 for all columns but Column 7, which reports estimates from a comparable industry-by-state-level OLS stacked regression model. Different sample sizes result from small amounts of data missingness. Each regression includes fixed effects for year × broad industry × subexperiment, state × subexperiment, and four-digit NAICS or three-digit SIC × subexperiment. Standard errors clustered at state × subexperiment level in parentheses. *** p <.01, ** p <.05, * p <.1.
†The mean dependent variables in Columns 2, 4, and 5 are in billions of dollars.

study estimates demonstrating wage dynamics over time in response to NCA enforceability increases centered at time zero.

One explanation for workers' earnings declines is that increases in NCA enforceability cause firms to be less productive, generating less surplus to be shared with workers. We find (in Column 2) clear evidence of decreases in manufacturing output as measured by value added: an enforceability increase equal to 10% of observed variation generates a value added decrease of 15.5% $(= exp(-1.69 * 10\%) - 1)$. Figure 1, Panel (b), contains comparable event study estimates. We also find a decline in productivity, as measured by value added per worker, of 8.1% for the same enforceability increase (Column 3). It is also reflected in reductions in sales (Column 4), and does not appear to be driven by reductions in capital (Columns 5 and 6), though the estimated effects on capital are noisy.[3] We find zero effect on the labor share (Column 7), suggesting that any reductions in wages operate fully through the channel of productivity declines in the manufacturing sector, rather than changes in bargaining power. In Column 8, we do not find major changes in employment.

Figure 1. : Event Study Estimates for Average Wages and Manufacturing Value Added



(a) Average Earnings (b) Manufacturing Value Added

Note: Each figure contains coefficients and 95% confidence intervals from Poisson pseudo-likelihood stacked difference-in-difference regression models, weighted by average employment before the treatment year in each state in each industry. See Equation 1 for an analogous regression equation.

The estimated effects on output and productivity are large and difficult to reconcile with simple interpretations. Changes in aggregate productivity may arise from a range of factors, including

[3]We construct capital as described in the Supplemental Appendix. To generate a consistent time series, we combine estimates of capital for years up until 1996 based on SIC codes with estimates of capital for 1997 forward based on NAICS codes.

Table 2—: The Effects of NCA Enforceability on Worker and Firm Outcomes for All Sectors

Panel A: Manufacturing Only	(1) Average Wages	(2) Manufacturing Value Added	(3) Value Added Per Worker	(4) Labor Share of Income	(5) Employment
NCA Score	-.116	-1.05*	-.378	.0779	-.295
	(.122)	(.613)	(.476)	(.115)	(.263)
N	7,584	7,584	7,584	7,584	7,584
Mean Dep Var	44,652	77.8†	115,144	0.45	627,717
Panel B: All Sectors	(1) Average Wages	(2) Value Added	(3) Value Added Per Worker	(4) Labor Share of Income	(5) Employment
NCA Score	-.142**	.0114	-.119	.01	.145
	(.0603)	(.306)	(.149)	(.019)	(.218)
N	66,379	66,379	66,379	66,379	66,379
Mean Dep Var	35,243	72.5†	84,345	0.48	1,278,797

Note: Panel A reports estimates from state-level Poisson stacked regression models analogous to that described in Equation 1 for all columns but Column 4, which reports estimates from a comparable state-level OLS stacked regression model. Panel B is identical but is run at the broad sector-by-state level, where broad sectors correspond to 2-digit NAICS codes. Each regression in Panel A includes fixed effects for state × subexperiment, and year × subexperiment. Regressions in Panel B instead include state × subexperiment and year × broad sector × subexperiment fixed effects. Standard errors clustered at state × subexperiment level in parentheses. *** p <.01, ** p <.05, * p <.1.
†The mean dependent variables in Column 2 are in billions of dollars.

firm entry and exit, worker sorting, and within-plant changes. State-level estimates may be confounded by reallocation of production across states, changes in industry composition associated with the SIC–NAICS transition, or other confounding factors. In addition, the estimated effect of NCA enforceability on the labor share is counterintuitive: a back-of-the-envelope calculation using changes in earnings, employment, and value added would predict an increase in labor's share. Distinguishing among these explanations likely requires plant-level data, which we leave to future work.

B. Results for All Sectors

Table 2 displays results using the broader industry data for a subset of the outcomes in Table 1. Panel A focuses solely on manufacturing, while Panel B includes all sectors.[4]

The estimates in Column 1 further corroborate that increased NCA enforceability leads to lower average wages, both in manufacturing (Panel A) and overall (Panel B); the magnitudes are comparable, though the estimate is statistically significant only for the broader economy in Panel B.

Columns 2 and 3 of Panel A report negative effects on value added and value added per worker in the manufacturing sector. The coefficients are meaningfully smaller than those reported in Section III.A. Interestingly, in Panel B, we show that these results do not hold for the economy as a whole: we estimate no effect of NCA enforceability on value added across all industries, and a much smaller effect on productivity. This may be due to differential use of NCAs across industries, differential effects of NCAs on worker motivation or firm investment, differential importance of worker reallocation for aggregate productivity, or other factors. Exploring this finding is a leading avenue for future work.

[4]In order to create a consistent time series, we focus attention on sectors for which SIC and NAICS codes are easily comparable, excluding those for which a straightforward cross-walk at the sectoral level is not available. We group sectors as follows: Agriculture, Forestry, Fishing, and Hunting (NAICS 11; SIC 01-09); Mining, Oil, and Gas (NAICS 21; SIC 10-14); Utilities (NAICS 22; SIC 49); Construction (NAICS 23; SIC 15-17); Manufacturing (NAICS 31-33; SIC 20-39); Wholesale Trade (NAICS 42; SIC 50-51); Retail Trade and Services (NAICS 44-45, 56, 61, 62, 71, and 72; SIC 52-59 and 70-89); Transportation and Warehousing (NAICS 48-49; SIC 40-42 and 44-47); Finance, Insurance, and Real Estate (NAICS 52-53; SIC 60-67). Note that the crosswalks are imperfect, and some sub-industries may cross industrial lines between NAICS and SIC years.

Column 4 reports estimates of the effect of NCA enforceability on the labor share. We find noisy null effects for both manufacturing and all sectors together. In Column 5, we estimate a negative effect of NCA enforceability on manufacturing employment but a positive effect for all sectors. Neither result is statistically significant.

IV. Conclusion

We assembled a novel dataset on state-level manufacturing production to analyze the effect of NCA enforceability on productivity. We find that NCA enforceability strongly decreases output and value added per worker, but does not affect the labor share of income.The manufacturing production dataset may be useful for other researchers studying how other forms of state-level policy variation affect productivity, such as investment taxation or environmental regulation.

REFERENCES

Balasubramanian, Natarajan, Jin Woo Chang, Mariko Sakakibara, Jagadeesh Sivadasan, and Evan Starr. 2022. “Locked in? The enforceability of covenants not to compete and the careers of high-tech workers.” *Journal of Human Resources*, 57(S): S349–S396.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. “The effect of minimum wages on low-wage jobs.” *The Quarterly Journal of Economics*, 134(3): 1405–1454.

Chirinko, Robert S., and Daniel J. Wilson. 2009. “A State Level Database For The Manufacturing Sector: Construction And Sources.”

Garmaise, Mark J. 2011. “Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment.” *The Journal of Law, Economics, & Organization*, 27(2): 376–425.

Gottfries, Axel, and Gregor Jarosch. 2023. *Dynamic monopsony with large firms and noncompetes.*

Jeffers, Jessica S. 2024. “The impact of restricting labor mobility on corporate investment and entrepreneurship.” *The Review of Financial Studies*, 37(1): 1–44.

Johnson, Matthew S., Kurt Lavetti, and Michael Lipsitz. 2025. “The Labor Market Effects of Legal Restrictions on Worker Mobility.” *Journal of Political Economy*, 133(9): 2735–93.

Johnson, Matthew S, Michael Lipsitz, and Alison Pei. 2023. *Innovation and the enforceability of noncompete agreements.* National Bureau of Economic Research.

Lipsitz, Michael, and Evan Starr. 2022. “Low-wage workers and the enforceability of noncompete agreements.” *Management Science*, 68(1): 143–170.

Lipsitz, Michael, and Mark J. Tremblay. 2024. “Noncompete agreements and the welfare of consumers.” *American Economic Journal: Microeconomics*, 16(4): 112–153.

Marx, Matt. 2011. “The firm strikes back: Non-compete agreements and the mobility of technical professionals.” *American Sociological Review*, 76(5): 695–712.

Reinmuth, Kate, and Emma Rockall. 2023. “Innovation through Inventor Mobility: Evidence from Non-Compete Agreements.” *Available at SSRN 4459683*.

Shi, Liyan. 2023. “Optimal regulation of noncompete contracts.” *Econometrica*, 91(2): 425–463.

Starr, Evan. 2019. “Consider this: Training, wages, and the enforceability of covenants not to compete.” *ILR Review*, 72(4): 783–817.

Starr, Evan P, James J Prescott, and Norman D Bishara. 2021. “Noncompete agreements in the US labor force.” *The Journal of Law and Economics*, 64(1): 53–84.