

TTPI Working Paper Series

Tax and Transfer Policy Institute

The relationship between competitive restraints, R&D activity, productivity, and competition

Working Paper 20/2026
October 2026

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Abstract

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In this paper we empirically examine the effects of four types of competitive restraints (non-disclosure, non-compete, non-solicitation of clients, and non-solicitation of co-workers) on R&D activity, labour productivity, and industry competition. We use data from an experimental survey by the ABS, linked with administrative tax and business data. Because the survey measures restraint usage in a single year (2023), we impute usage in other periods; this is the central limitation of our design and restricts us to cross-sectional variation. To gauge robustness to omitted-variable bias, we apply the bounding method of Diegert et al. (2026), which is well suited to a setting with several correlated, potentially endogenous restraints. Our most robust findings concern industry competition: the use of non-disclosure agreements is estimated to raise market concentration, while non-competes and non-solicitation of clients lower it. Effects on R&D and productivity are smaller and more sensitive to selection assumptions. Overall, results are mixed in terms of significance, direction, and robustness.

1 Introduction

Competitive restraints, or non-compete clauses, are contractual arrangements that restrict employees from sharing information, joining a competitor, or engaging with clients or former colleagues after leaving their employer. These agreements aim to protect proprietary information and reduce talent attrition, especially in fields where intellectual property, trade secrets, and client relationships are crucial. However, policy-makers face a trade-off when regulating non-compete clauses. On one hand, they can safeguard companies' investments in employee human capital and in research and development (R&D), and prevent the rapid transfer of knowledge to competitors, which may incentivise businesses to invest in innovation. On the other hand, strict enforcement of non-competes can limit employee mobility, potentially harming knowledge spillovers and decreasing overall productivity in the economy. Ultimately, which effect dominates is an empirical question that depends on type of restraint and the competitive environment in which a firm operates. In this paper, we study the connection of competitive restraints to productivity, R&D activity, and competition in Australia.

Although theoretical research in this area is scarce, models of firm and worker behaviour emphasise the regulation of competitive restraints to improve social welfare (Lipsitz and Tremblay, 2024; Shi, 2023). Empirical studies on the effects of competitive restraints consistently find that strict enforcement of restraints reduces labour mobility.¹ Bartelsman et al. (2024) find that removing competitive restraints leads to higher wages and worker mobility. Although they find effects across industries and worker skills, the effect is larger for intangible-intensive firms. Moreover, Marx et al. (2015) document that jurisdictions with strong enforcement of competitive restraints experience a brain drain of inventors and the most collaborative workers. Those workers migrate to jurisdictions where competitive restraints are not enforced. The effects are found to be present across industries. Similarly, Belenzon and Schankerman (2013) find that strict enforcement of competitive restraints also restricts the geographic spread of knowledge generated through university research.

On the positive side, and in accordance with economic theory, Garmaise (2011) finds that stricter enforcement of competitive restraints encourages firms to invest in workers' human capital. Although, stricter enforcement also discourages workers from investing in their own human capital. That study also finds that increased enforceability shift executive compensation towards a larger use of salary.

Job mobility in Australia has been on the decline since the late 1980's (Australian Bureau of Statistics, 2023). At the same time, there is suggestive evidence revealing that the use of competitive restraints has seen a significant rise in recent years (Buckley et al., 2024). It is estimated that 50% of workers in Australia are subject to some form of competitive restraint (Andrews and Jarvis, 2023). Those restraints are concentrated among relatively younger workers, but across all income groups. This has resulted in government interest in examining the effects of competitive restraints in the economy (Leigh, 2024).

Our analysis faces one central limitation: the survey measures competitive restraints in a single year, so we impute firm-level usage in other periods. This rules out a firm fixed-effects strategy and means our estimates rely on cross-sectional variation. To assess how sensitive our conclusions are to unobserved confounders, we apply the omitted-variable-bias bounding method of Diegert et al. (2026), which is well suited to a setting in which several correlated restraints are used together and are potentially endogenous. Throughout, we report how far selection on unobservables would have to go before each result is overturned.

This paper is organized as follows: section 2 provides an overview of the mechanism through which competitive restraints affect R&D, productivity, and competition, section 3 describes the data used and its construction, and section 4 explains the econometric analysis performed. Section 5 presents results of the analysis, and section 6 concludes.

¹The literature on competitive restraints is scarce, but there are some reviews, see Starr (2023), Stam (2019), McAdams (2019), and Marx and Fleming (2012).

2 Restraints, R&D, productivity, and competition

This section outlines the theoretical impacts of competitive restraints on R&D, productivity, and competition.

Non-disclosure agreements protect confidential information, including trade secrets, proprietary technology, and strategic insights. Non-disclosures can enhance productivity by creating a secure environment that encourages internal information sharing. However, their impact on innovation is more complex. While non-disclosures promote firm-specific R&D investment by safeguarding intellectual property, they can impede the flow of knowledge between firms, which is essential for broader innovation. Employees and firms bound by non-disclosures may reduce engagement in knowledge-sharing networks or collaborative initiatives, potentially inhibiting the cross-pollination of ideas that drives industry-wide innovation. Thus, although non-disclosures safeguard productivity within firms, they may simultaneously constrain broader innovation by isolating knowledge and limiting collaboration.

Non-compete agreements also have mixed implications for productivity and innovation. By limiting employees' ability to join rival firms or start competing ventures, non-competes help firms protect intellectual assets and retain skilled labour, which contributes to productivity in the short term. This stability enables firms to invest in human capital without immediate concern over attrition. However, non-competes can suppress innovation by restricting labour mobility and limiting knowledge transfer across firms. Employees bound by non-competes have fewer opportunities to leverage their skills in new contexts, reducing knowledge spillovers. Jurisdictions with less stringent non-competes enforcement, exhibit higher levels of innovation and startup formation, indicating that increased labour mobility accelerates industry-wide productivity and innovation.

Non-solicitation of clients agreements prevent former employees from soliciting a firm's clients after departure. These agreements protect client relationships and prevent market share erosion, supporting productivity. However, they can also curtail innovation and competition. Former employees often possess insights into client needs and market demands, driving improvements in client engagement and fostering innovation. Restricting this exchange of insights may limit the advancement of strategies, potentially slowing industry progress in service delivery and innovation. While non-solicitation agreements protect firm-specific productivity, they may constrain the broader evolution of client services within markets.

Non-solicitation of co-workers agreements, which restrict former employees from recruiting their previous colleagues. These agreements aim to protect firms' human capital investments. These agreements stabilize productivity by reducing turnover and minimizing disruptions to team cohesion. Nonetheless, they may dampen innovation by curtailing

the mobility of cohesive, high-performing teams that could facilitate rapid advancements in new environments. Collective movement of employees to new settings can accelerate innovation by bringing established team dynamics and expertise into novel contexts, particularly in knowledge-intensive industries. By limiting these opportunities, non-solicitation agreements may reduce cross-firm talent circulation and dampen industry dynamism. Although they support workforce stability, the restrictions on team mobility may ultimately impede broader innovation across the industry.

3 Data

We draw on linked, firm-level data from the Australian Bureau of Statistics (ABS) Business Longitudinal Analysis Data Environment (BLADE). The data contains business characteristics and tax data from administrative sources. These data are linked to the Short Survey of Employment Conditions (SSEC), a cross-sectional survey about competitive restraints run by the ABS in 2023.

The SSEC considered four types of restraints, the same ones explained above:

1. Non-disclosure: to not share confidential information when employees leave the firm.
2. Non-compete: to not join or start a competitor when employees leave the firm.
3. Non-solicitation of clients: to not solicit or offer services to former clients or customers when employees leave the firm.
4. Non-solicitation of co-workers: to not solicit former co-workers when employees leave.

We construct a measure of R&D activity from information on claims on tax offset or tax incentives. Specifically, we define R&D activity with an indicator variable equal to 1 if the firm claims any of the following, and 0 otherwise:

1. Accounting expenditure in item 6 subject to R&D tax incentive.
2. Non-refundable R&D tax offset.
3. Non-refundable R&D tax offset carried forward from previous year.
4. Non-refundable R&D tax offset to be utilised in current year.
5. Non-refundable R&D tax offset carried forward to next year.
6. Refundable R&D tax offset.
7. R&D recoupment tax.

Other variables constructed include industry Herfindahl–Hirschman index, a measure of the degree of competition; labour productivity, as measured by revenue (turnover) over FTE employees, and capital expenditures. A table of descriptive statistics for the firm-level sample is included in the Appendix.

Figure 1 below displays the market share of firms reporting restraints by industry, defined by ANZSIC06 codes. A few patterns are worth noting. First, the use of competitive restraints is heterogeneous across industries. Second, by far, the most important restraint, in terms of market share, is non-disclosure. Third, although relative popularity of restraints has remained constant over time, overall use has been slowly increasing. This is most prominent in the public administration and safety, education and training, and other services industries.

Another important fact is that many firms bundle several competitive restraints in contracts offered to employees. That is, employees are often subject to more than one competitive restraint. For example, less than 1% of workers are subject to a competitive restraints but not subject to a non-disclosure agreement (Buckley et al., 2024).

Figure 1: Market share of firms reporting restraints.

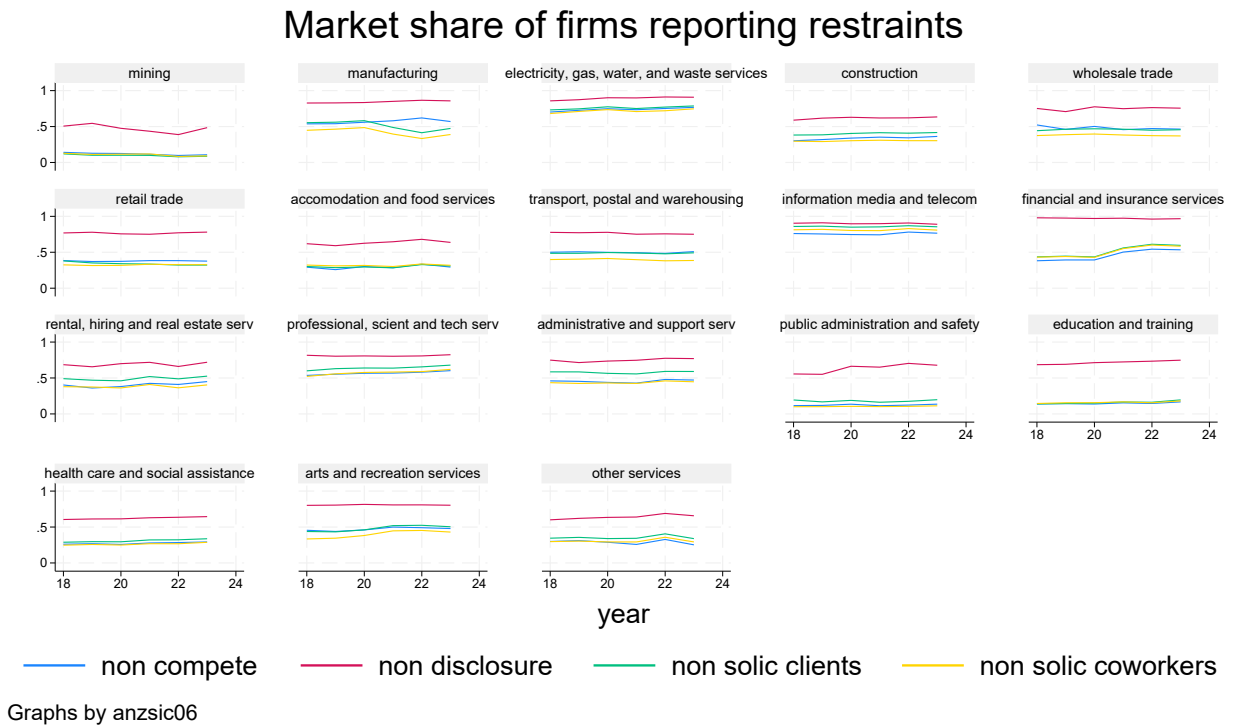
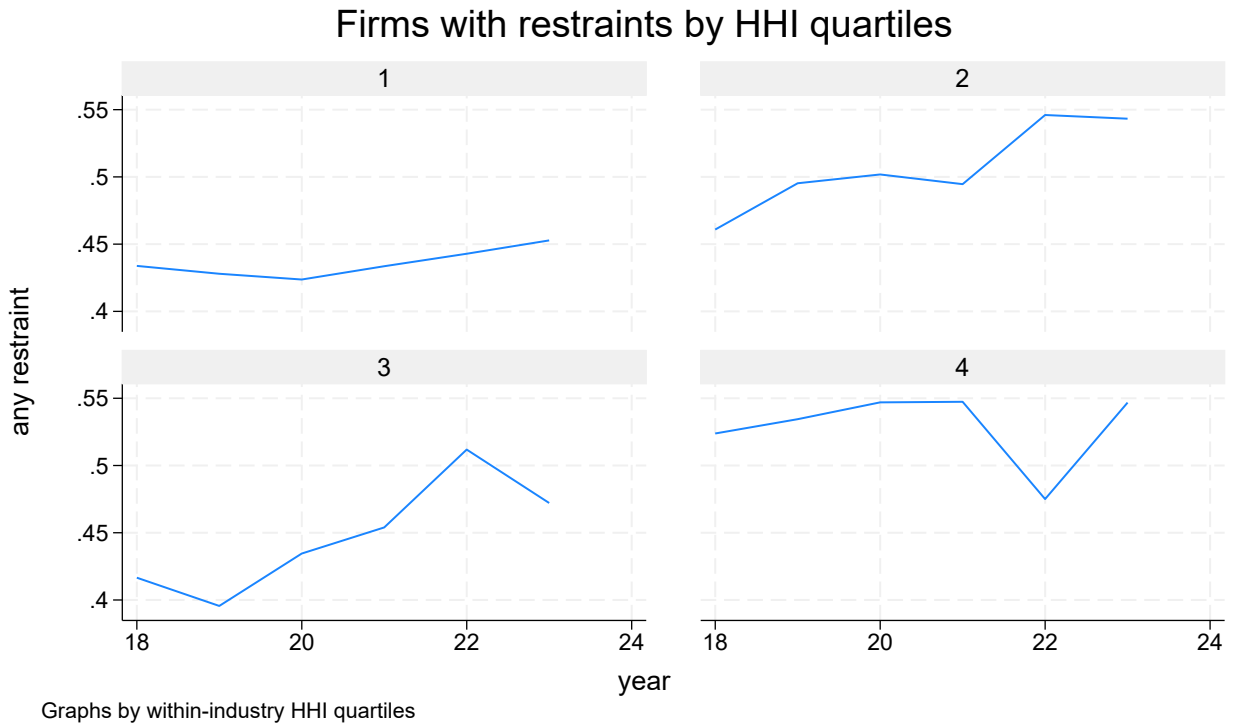


Figure 2 shows the frequency of restraints by labour productivity quartiles over time. The most productive firms report using competitive restraints most often. Figure 3 shows that firms in less competitive markets report using restraints more often. It also shows that usage of restraints has increased over time across all levels of HHI.

Figure 2: Firms with restraints by labour productivity quartiles.



Figure 3: Firms with restraints by HHI quartiles.



While the BLADE data provide a panel over time, the information on competitive restraints is only available for one year. To overcome that limitation, we impute use of restraints by firms in other periods with the information in 2023. Specifically, we assume

that firm-level usage of competitive restraints is the same in all periods. This imputation has important implications for the analysis in the next section.

4 Empirical strategy

The aim of the analysis is to estimate the influence of restraint usage on R&D activity and productivity. It is natural to attempt to regress our outcome variables (R&D activity and productivity) on indicators for restraints and control variables:²

$$y_{it} = \alpha + \sum_{r=1}^4 \beta_r \text{restr}_{ri} + \gamma \cdot x_{it} + \nu_{it}. \quad (1)$$

In panel settings, we also worry about time-invariant firm-specific characteristics that may be correlated with restraint usage (management ability/style, etc). In such cases, we can address those concerns by including firm-level fixed effects. This effectively decomposes the error term $\nu_{it} = \delta_i + \varepsilon_{it}$.³ The regression then becomes:

$$y_{it} = \alpha + \sum_{r=1}^4 \beta_r \text{restr}_{ri} + \gamma \cdot x_{it} + \delta_i + \varepsilon_{it}. \quad (2)$$

Regression (2) addresses the endogeneity concerns explained above. However, that regression is infeasible because the restraint indicators are invariant over time. Regression (1) is feasible but suffers from endogeneity and therefore would yield biased estimates of the coefficients of interest $\beta_1, \dots, \beta_4$.

We note two features of regression (2). First, usage of one restraint is correlated with usage of all others. Second, usage of restraints is also correlated with unobservable firm-specific characteristics. This implies that we are in the presence of a regression where we have endogenous treatments and at least three endogenous regressors regardless of what controls we include.

To fix ideas, suppose that we are interested in obtaining the coefficient of one particular restraint on an outcome. Because usage of one restraint is correlated with usage of all other restraints, we will need to include all restraints as controls in a regression. That means that we will have to consider controls as endogenous. In light of this, we employ a novel approach from Diegert et al. (2026) (DMP) to obtain bounds for the coefficients of interest under omitted variable bias and endogenous controls.⁴ The Appendix contains a brief exposition of that method.

²Because R&D activity is a binary indicator, equation (1) is a linear probability model. The Diegert et al. (2026) bounds we report below likewise rest on a linear specification.

³We could also worry about economy-wide shocks that affect all firms. Such cases can be accommodated by including time effects, which we consider to be included in x with the rest of the covariates.

⁴Other methods for obtaining causal estimates from regressions with endogenous treatments do not directly consider endogenous regressors. For example, Oster (2019) can accommodate endogenous regressors using a “residualization” approach, but Diegert et al. (2026) show that this approach can be misleading.

Because restraints are typically bundled, with fewer than 1% of workers subject to any restraint without also being subject to a non-disclosure agreement (Buckley et al., 2024), separately identifying the effect of each individual restraint is inherently fragile, and part of the mixed pattern of signs and significance we report below likely reflects this collinearity. As a complementary summary that sidesteps the problem, Appendix B reports regressions on an indicator for using any restraint.

5 Results

This section is divided into three subsections. Subsection 5.1 presents results on R&D, subsection 5.2 presents results on productivity, while subsection 5.3 shows results for competition. The Appendix contains supplementary analysis.

Table 1 summarises the twelve restraint-by-outcome results against the predictions of section 2. Two patterns stand out. First, our results for industry competition are the most robust: the effects of non-disclosure, non-compete, and non-solicitation of clients all survive substantial selection on unobservables (breakdown values of $\bar{r}_X$ up to 1.39). Second, several estimates run against the incumbent-protection prior: in particular, non-competes and non-solicitation of clients are estimated to increase competition, not reduce it. Estimates for R&D and productivity are, for the most part, statistically weaker and less robust.

Table 1: Predicted versus estimated effects of restraints, by outcome.

Restraint	Outcome	Predicted	Estimated	Breakdown $\bar{r}_X^{bp}$	Consistent
Non-disclosure	R&D activity	+	+**	0.12	Yes
	Productivity	+	—**	0.15	No
	Competition (HHI)	+	+***	1.39	Yes
Non-compete	R&D activity	+	+	0.29	—
	Productivity	+	—	0.10	—
	Competition (HHI)	+	—***	0.95	No
Non-sol. clients	R&D activity	?	+	0.27	—
	Productivity	+	—***	0.81	No
	Competition (HHI)	+	—***	0.71	No
Non-sol. co-workers	R&D activity	?	—	0.97	—
	Productivity	+	+	0.49	—
	Competition (HHI)	+	—	0.04	—

Notes: Predicted signs are taken from section 2; competition predictions follow an incumbent-protection prior and are not sharply derived. A higher HHI denotes less competition. Significance of the point estimate: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. $\bar{r}_X^{bp}$ is the breakdown value: the smallest ratio of selection on unobservables to selection on observables at which the sign of the effect is overturned (larger is more robust). The last column, “Consistent”, is blank when the estimate is not statistically significant.

5.1 Regression of restraints on R&D

Table 2 shows the results of regressing our measure of R&D activity on the four competitive restraints. The only restraint that is statistically significant in affecting R&D activity is non-disclosure of information. For that restraint, we estimate that firms that employ non-disclosures are about 0.6 percentage points more likely to engage in R&D activity than those who do not. Because the baseline rate of R&D activity in the sample is only about 1%, this is a large effect in relative terms. This is consistent with economic theory, and with the predicted sign in Table 1. Firms have more incentive to invest in R&D if they can safeguard new knowledge or technology and therefore reap private benefits from such investments.

Although we are interested in obtaining causal estimates of the effect of restraints on R&D, the coefficients on the restraint variables are likely biased. To mitigate that bias, we perform the DMP analysis below in order to obtain bounds for the effects of interest.

Table 2: Regression of R&D activity on restraints.

Variables	Coefficient	Robust std. err.	t	p-value
non-disclosure	0.0059077	0.0029566	2	0.046
non-compete	0.0071583	0.0049065	1.46	0.145
non-sol. clients	0.0058933	0.005144	1.15	0.252
non-sol. co-workers	-0.0099174	0.0082933	-1.2	0.232
labour productivity	-6.22E-10	7.32E-10	-0.85	0.395
avg capex	4.12E-09	6.96E-09	0.59	0.553
avg wage	1.71E-08	8.3E-09	2.06	0.039
log(turnover)	0.00466	0.0009991	4.66	0
HHI quant 2	0.0041502	0.0043917	0.95	0.345
HHI quant 3	-0.0045167	0.0032053	-1.41	0.159
HHI quant 4	0.005959	0.0076244	0.78	0.434
constant	0.0654846	0.036583	1.79	0.073
Observations	15382			
R-squared	0.03364739			
Industry dummies	Yes			
Time FE	Yes			

Tables 3 to 6 show results of performing a DMP analysis on the restraint variables from the regression in Table 2. In all those tables, we impose a hypothetical bound of correlation between controls and unobservables of 50%.⁵ In our DMP analysis of R&D activity we exclude industry dummies and time effects as comparison controls. In other words, we consider those groups of variables to be always observable.

Table 3 shows the effect bounds of non-disclosure on R&D activity as a function of $\bar{r}_X$, the magnitude of the effect of omitted variables on non-disclosure restraints relative to comparison controls. We can see how the bounds on the coefficient of interest change

⁵This corresponds to a value of $\bar{c} = 0.5$, see the Appendix for details.

as we vary $\bar{r}_X$. We note the breakdown value of $\bar{r}_X$ (the value of $\bar{r}_X$ for which the hypothesis $\beta_r > 0$ is overturned) is about 0.12. That breakdown value implies that if selection on observables is at least 8.6 times larger than selection on unobservables, the estimated effect disappears. Alternatively, the effect has the correct sign up to selection on observables being 8.6 times selection on unobservables. In that case, we estimate the effect of non-disclosure on R&D activity to be between 0 and 0.012.

Table 3: Effect bounds of non-disclosure on R&D activity.

$\bar{r}_X, \beta_r > 0$	lower bound	upper bound
0	0.00591	0.00591
0.05	0.00338	0.00844
0.1	0.00083	0.01098
0.15	-0.00176	0.01357
0.2	-0.00441	0.01623
0.25	-0.00715	0.01897
0.3	-0.01001	0.02183
0.35	-0.01302	0.02484
0.4	-0.01623	0.02804
0.45	-0.01969	0.03150
0.5	-0.02347	0.03529
Breakdown: 0.11615	0.0	0.01182

Tables 4, 5, and 6 show the DMP analysis for non-compete, non-solicitation of clients, and non-solicitation of co-workers. Although the breakdown values are larger than for non-disclosure, which imply that results are more robust to selection bias, caution must be exercised because those effects are not statistically significant. For the DMP analysis on non-solicitation of co-workers in Table 6, the breakdown analysis corresponds to the hypothesis $\beta_r < 0$, since the point estimate is negative to begin with.

Table 4: Effect bounds of non-compete on R&D activity.

$\bar{r}_X, \beta_r > 0$	lower bound	upper bound
0	0.00716	0.00716
0.05	0.00596	0.00836
0.1	0.00475	0.00956
0.15	0.00353	0.01079
0.2	0.00227	0.01205
0.25	0.00098	0.01334
0.3	-0.00037	0.01469
0.35	-0.00179	0.01611
0.4	-0.00329	0.01761
0.45	-0.00491	0.01923
0.5	-0.00667	0.02099
Breakdown: 0.28642	0.0	0.01432

Table 5: Effect bounds of non-solicitation of clients on R&D activity.

$\bar{r}_X, \beta_r > 0$	lower bound	upper bound
0	0.00589	0.00589
0.05	0.00485	0.00694
0.1	0.0038	0.00799
0.15	0.00273	0.00906
0.2	0.00164	0.01015
0.25	0.00051	0.01128
0.3	-0.00067	0.01245
0.35	-0.0019	0.01369
0.4	-0.00321	0.015
0.45	-0.00462	0.01641
0.5	-0.00616	0.01794
Breakdown: 0.27185	0.0	0.01179

Table 6: Effect bounds of non-solicitation of co-workers on R&D activity.

$\bar{r}_X, \beta_r < 0$	lower bound	upper bound
0	-0.00992	-0.00992
0.05	-0.01022	-0.00961
0.1	-0.01053	-0.00931
0.15	-0.01084	-0.009
0.2	-0.01115	-0.00868
0.25	-0.01148	-0.00835
0.3	-0.01182	-0.00801
0.35	-0.01218	-0.00766
0.4	-0.01256	-0.00727
0.45	-0.01297	-0.00687
0.5	-0.01341	-0.0064
Breakdown: 0.9719	-0.01983	0.0

5.2 Regression of restraints on productivity

Table 7 shows the results of the regression of (log) of labour productivity on competition restraints.⁶ In this case, non-disclosure and non-solicitation of clients are found to be significant on labour productivity. The use of non-disclosure results in a decrease of 5.1% in productivity, while the use of non-solicitation of clients results in a decrease of 13% in productivity. The negative sign on non-disclosure runs counter to the protective-investment prediction in Table 1. Again, these estimates are likely biased, so we perform the same DMP analysis as in the previous section. Those analyses are shown in tables 8 to 11.

⁶Labour productivity is measured as turnover per FTE employee. Because $\log(\text{turnover})$ is also included among the controls, the restraint coefficients should be read as effects holding firm size (turnover) fixed; average wage is likewise related to labour productivity through workforce composition. These conditioning choices should be kept in mind when interpreting the magnitudes.

As mentioned, non-disclosure and non-solicitation of clients are estimated to decrease labour productivity. The result on non-disclosure is robust up to selection on observables being 6.7 times selection on unobservables. For non-solicitation of clients, the result is robust up to selection on observables being 1.2 times selection on unobservables. The latter is our most robust firm-level result.

Table 7: Regression of labour productivity on restraints.

Variables	Coefficient	Robust std. err.	t	p-value
non-disclosure	-0.05099	0.02187	-2.33	0.02
non-compete	-0.0145	0.02835	-0.51	0.609
non-sol. clients	-0.12659	0.03095	-4.09	0.0
non-sol. co-workers	0.04088	0.03046	1.34	0.18
avg capex	1.39E-07	1.62E-07	0.86	0.392
R&D activity	-0.6294	0.09808	-6.42	0.0
avg wage	1.05E-06	3E-07	3.49	0.0
log(turnover)	0.41144	0.0149	27.61	0.0
HHI quant 2	0.07172	0.0873	0.82	0.411
HHI quant 3	0.09085	0.09109	1	0.319
HHI quant 4	0.16848	0.09256	1.82	0.069
constant	5.66436	0.25113	22.56	0.0
Observations	15382			
R-squared	0.51022			
Industry dummies	Yes			
Time FE	Yes			

Table 8: Effect bounds of non-disclosure on labour productivity.

$\bar{r}_X, \beta_r < 0$	lower bound	upper bound
0	-0.05099	-0.05099
0.05	-0.068	-0.03397
0.1	-0.08516	-0.01682
0.15	-0.10258	0.00061
0.2	-0.12044	0.01846
0.25	-0.13888	0.03691
0.3	-0.15812	0.05615
0.35	-0.17839	0.07642
0.4	-0.19998	0.09801
0.45	-0.22326	0.12129
0.5	-0.24873	0.1467
Breakdown: 0.14827	-0.10197	0.0

Table 9: Effect bounds of non-compete on labour productivity.

$\bar{r}_X, \beta_r < 0$	lower bound	upper bound
0	-0.0145	-0.0145
0.05	-0.02182	-0.00718
0.1	-0.0292	0.0002
0.15	-0.03669	0.00769
0.2	-0.04435	0.01535
0.25	-0.05226	0.02326
0.3	-0.0605	0.0315
0.35	-0.06915	0.04015
0.4	-0.07835	0.04934
0.45	-0.08823	0.05922
0.5	-0.09899	0.06998
Breakdown: 0.09868	-0.029	0.0

Table 10: Effect bounds of non-solicitation of clients on labour productivity.

$\bar{r}_X, \beta_r < 0$	lower bound	upper bound
0	-0.12659	-0.12659
0.05	-0.13199	-0.12119
0.1	-0.13744	-0.11575
0.15	-0.14296	-0.11022
0.2	-0.14862	-0.10456
0.25	-0.15446	-0.09873
0.3	-0.16053	-0.09265
0.35	-0.16692	-0.08627
0.4	-0.1737	-0.07949
0.45	-0.18098	-0.0722
0.5	-0.18891	-0.06427
Breakdown: 0.80703	-0.25318	0.0

Table 11: Effect bounds of non-solicitation of co-workers on labour productivity.

$\bar{r}_X, \beta_r > 0$	lower bound	upper bound
0	0.04088	0.04088
0.05	0.03723	0.04454
0.1	0.03354	0.04822
0.15	0.0298	0.05196
0.2	0.02598	0.05579
0.25	0.02203	0.05974
0.3	0.01792	0.06385
0.35	0.01359	0.06817
0.4	0.00901	0.07276
0.45	0.00408	0.07769
0.5	-0.00129	0.08305
Breakdown: 0.48843	0.0	0.08177

5.3 Regression of restraints on competition

We now explore the influence of restraints on competition at the industry level. For that, we run similar regressions as above, where the outcome variable is the HH index of competition at the industry level,⁷ and the variable of interest on the right-hand-side is the share of firms in an industry that report using each restraint. It is worth emphasising that these regressions are run at the firm level, even though HHI is calculated at the industry level. Table 12 shows the results of that regression. In that case, we include industry and time dummies.⁸

The only restraint that is not significant is non-solicitation of co-workers. The effects of the other restraints are mixed. Non-disclosure is estimated to decrease the degree of competition: a 1 percentage-point increase in the share of firms that use non-disclosures raises HHI by about 0.005 (the estimated coefficient is 0.49 on a share measured as a proportion). The effects of non-compete and non-solicitation of clients go the opposite way: a 1 percentage-point increase in the share using non-compete (non-solicitation of clients) lowers HHI by about 0.0027 (0.0022), thereby increasing competition. These are sizeable effects relative to the sample-average HHI of about 0.028. As noted in Table 1, the last two run against the incumbent-protection prior.

Table 12: Regression of HHI on restraints.

Variables	Coefficient	Robust std. err.	t	p-value
non-disclosure	0.49485	0.04394	11.26	0.0
non-compete	-0.26535	0.03719	-7.14	0.0
non-sol. clients	-0.2221	0.06889	-3.22	0.001
non-sol. co-workers	-0.01003	0.07701	-0.13	0.896
Observations	4474			
R-squared	0.96229			
Industry dummies	Yes			
Time FE	Yes			

As before, we perform the same DMP analysis. The results are displayed in tables 13 to 16. It is interesting that for non-disclosure, the breakdown point of $\bar{r}_X$ is larger than 1, at 1.39. That means that the result is robust even when selection on unobservables is larger than selection on observables by almost 40%. In that case, the identified set for the coefficient is roughly $[0, 0.99]$, so a 1 percentage-point increase in the share of firms using non-disclosure raises HHI by at most about 0.01, although a null effect is also possible.

⁷We measure competition using the Herfindahl–Hirschman index. It consists of the summation of the squared market shares of firms in a market or industry. This index is a well-known measure of market competition, but we note that it is not a perfect measure, as it is sensitive to market dynamics. For example, the index can indicate concentration while not necessarily reflecting changes in competitive behaviour by firms.

⁸Both HHI and the restraint share enter in levels, with HHI regressed on the share of firms using the restraint (a proportion between 0 and 1), so each coefficient is a marginal effect: the change in HHI associated with a one-unit change in the share. Because both variables are defined at the industry level while the regression is estimated at the firm level, the reported robust standard errors may understate sampling variability; clustering at the industry level would be more conservative, so the very large t -statistics in Table 12 should be read with this in mind.

Table 13: Effect bounds of non-disclosure on HHI.

$\bar{r}_X, \beta_r > 0$	lower bound	upper bound
0	0.49485	0.49485
0.05	0.48998	0.49972
0.1	0.48507	0.50463
0.15	0.48008	0.50961
0.2	0.47498	0.51472
0.25	0.46971	0.51999
0.3	0.46421	0.52548
0.35	0.45843	0.53126
0.4	0.45228	0.53741
0.45	0.44566	0.54403
0.5	0.43843	0.55126
1	0.3194	0.6703
Breakdown: 1.38841	0.0	0.98969

Usage of non-competes and non-solicitation of clients also show remarkable robustness, although in this case the sign of the coefficient is the opposite of that of non-disclosures. For non-competes, the breakdown value of $\bar{r}_X$ is about 0.95, which implies robustness up to selection on observables being 5% higher than selection on unobservables. For non-solicitation of clients, the breakdown value is about 0.71, implying robustness up to selection on observables being 42% higher than selection on unobservables.

Table 14: Effect bounds of non-compete on HHI.

$\bar{r}_X, \beta_r < 0$	lower bound	upper bound
0	-0.26535	-0.26535
0.05	-0.27332	-0.25738
0.1	-0.28136	-0.24934
0.15	-0.28953	-0.24117
0.2	-0.29789	-0.23281
0.25	-0.30654	-0.22416
0.3	-0.31556	-0.21514
0.35	-0.32507	-0.20563
0.4	-0.33519	-0.19551
0.45	-0.34612	-0.18458
0.5	-0.35809	-0.17261
Breakdown: 0.94764	-0.5307	0.0

Table 15: Effect bounds of non-solicitation of clients on HHI.

$\bar{r}_X, \beta_r < 0$	lower bound	upper bound
0	-0.2221	-0.2221
0.05	-0.23372	-0.21047
0.1	-0.24543	-0.19876
0.15	-0.25733	-0.18686
0.2	-0.26952	-0.17467
0.25	-0.28211	-0.16209
0.3	-0.29522	-0.14897
0.35	-0.30903	-0.13516
0.4	-0.32373	-0.12046
0.45	-0.33956	-0.10463
0.5	-0.35685	-0.08734
Breakdown: 0.70506	-0.44419	0.0

The results for non-solicitation of co-workers are less satisfactory. The breakdown value of $\bar{r}_X$ is less than 4%. Perhaps this is not surprising given that non-solicitation of co-workers is not significant in the estimated regression.

Table 16: Effect bounds of non-solicitation of co-workers on HHI.

$\bar{r}_X, \beta_r < 0$	lower bound	upper bound
0	-0.01003	-0.01003
0.05	-0.02385	0.00379
0.1	-0.03778	0.01771
0.15	-0.05193	0.03186
0.2	-0.06643	0.04636
0.25	-0.0814	0.06134
0.3	-0.09702	0.07695
0.35	-0.11347	0.0934
0.4	-0.13099	0.11092
0.45	-0.14987	0.12981
0.5	-0.17053	0.15046
Breakdown: 0.03632	-0.02007	0.0

6 Conclusion

In this paper we have empirically examined the effects of four types of competitive restraints on R&D activity, productivity, and competition. Results are mixed, both in magnitude and in the sign of coefficients. While some competitive restraints are found to have a null effect, others are robust to a wide range of selection assumptions.

Our most robust findings concern competition at the industry level, where non-disclosure, non-competes, and non-solicitation of clients all have effects that survive substantial selection on unobservables. The larger the usage of non-disclosures in an industry, the less competitive the industry tends to be. However, the effect runs in the opposite direction for non-competes and non-solicitation of clients: the larger their use in an industry, the

more competitive the industry tends to be. The latter two effects run against the naive prior that restraints entrench incumbents, and are, to us, the most striking result of the paper.

At the firm level, we analyse how competitive restraints fare in relation to R&D activity and labour productivity. Results here are less robust. Non-disclosures have a small and somewhat robust positive effect on R&D activity (consistent with the incentive to invest in innovation when new knowledge can be protected), while the other restraints do not significantly affect R&D activity. In terms of labour productivity, non-disclosures and non-solicitation of clients are found to have significant but opposite effects: the effect of non-solicitation of clients is negative and very robust to selection concerns, and is our most robust firm-level result.

In addition, we note that the relationships between restraints and all outcomes (R&D, productivity, and competition) are the end result of market equilibria (the interaction of supply and demand schedules), which in turn are shaped by the strategic interaction of firm decision-making. Despite our efforts to obtain results robust to endogeneity through the DMP method, our regressions may miss features of market structure that themselves determine firms' use of competitive restraints, and this should be borne in mind when interpreting the estimates.

We believe that these results, coming from analysing a one-time experimental survey conducted by the ABS, are promising but not final. Because restraint usage is observed in a single year and imputed to other periods, we cannot exploit within-firm variation over time; longitudinal data on restraints would support a deeper and more credibly causal understanding of their impacts on firms and markets. Balancing the need to protect business interests with the imperative of promoting a dynamic, innovative labour market remains a complex and highly debated issue among regulators, as both sides of this trade-off significantly impact economic growth and innovation.

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A Descriptive statistics

The table below shows descriptive statistics of the sample used.

Table 17: Descriptive statistics.

	Mean	SD	Min	Max	N
used non-disclosures	0.515883	0.499761	0	1	18888
used non-competes	0.234695	0.42382	0	1	18261
used non-solic clients	0.2956	0.456325	0	1	17892
used non-solic co-workers	0.21198	0.408723	0	1	17520
c_label_d	11635.04	355445.3	0	2E+08	21090
c_rdnfto	2213.176	143098.3	0	79038408	21090
c_rdnrfcfsyr	4098.378	402410.7	0	2.18E+08	21090
c_rdnftocy	2129.01	221322.8	0	2.52E+08	21090
c_rdnftocf	4179.23	392237.5	0	1.93E+08	21090
c_rdrto	3089.24	61530.59	0	5292204	21090
c_fedstk_adjstmt_adtnl_ai_amt	22.54373	3378.921	0	835626	21090
c_rdrft	0.73201	123.5897	0	56516.59	21090
R&D activity	0.010412	0.101508	0	1	21090
labour productivity	309135.9	1019728	0	6.54E+08	19589
avg capex	1765.993	46725.96	0	16759342	19589
avg wage	68404.67	165130.5	0	70267272	19651
turnover	7553169	9.93E+08	0	9.5E+11	20992
hhi	0.028446	0.049575	0.00736	0.322818	21090

B Additional regressions

Given that usage of one restraint is correlated with usage of other restraints, it may be difficult to separately identify the effects of individual restraints on outcomes. Still, we are interested in learning about those effects. We created an indicator variable that is equal to 1 if a firm uses any restraint, and zero otherwise. Running regressions on that variable would then yield the total influence of all restraints on outcomes. The tables below show such regressions for the same outcomes examined in the main text: R&D, productivity and competition.

Table 18: Regression of R&D on any restraint.

Variables	Coefficient	Robust std. err.	t	p-value
any restraint	0.009726	0.002147	4.53	0
labour productivity	-1.1E-09	8.27E-10	-1.33	0.184
avg capex	3.17E-08	2E-08	1.59	0.112
avg wage	4.05E-09	3.06E-09	1.32	0.186
log(turnover)	0.006714	0.001061	6.33	0
HHI quant 2	0.041222	0.023484	1.76	0.079
HHI quant 3	0.023396	0.021845	1.07	0.284
HHI quant 4	0.029546	0.021803	1.36	0.175
constant	-0.0040529	0.0377732	-0.11	0.915
Observations	19502			
R-squared	0.03679483			
Industry dummies	Yes			
Time FE	Yes			

Table 19: Regression of labour productivity on any restraint.

Variables	Coefficient	Robust std. err.	t	p-value
any restraint	-0.08235	0.016743	-4.92	0
avg capex	2.99E-07	9.48E-08	3.16	0.002
R&D activity	-0.53226	0.079404	-6.7	0
avg wage	1.91E-07	1.12E-07	1.71	0.088
log(turnover)	0.402967	0.012679	31.78	0
HHI quant 2	0.049317	0.077789	0.63	0.526
HHI quant 3	0.068564	0.081766	0.84	0.402
HHI quant 4	0.127752	0.082824	1.54	0.123
constant	5.866392	0.217	27.03	0
Observations	19502			
R-squared	0.49275615			
Industry dummies	Yes			
Time FE	Yes			

Table 20: Regression of HHI on any restraint.

Variables	Coefficient	Robust std. err.	t	p-value
any restraint	0.0000846	0.0002964	0.29	0.775
constant	0.0633976	0.0011573	54.78	0
Observations	21090			
R-squared	0.89099717			
Industry dummies	Yes			
Time FE	Yes			

C Robustness analysis using Diegert et al. (2026)

Diegert et al. (2026) provide a method for performing robustness analyses regarding selection bias on linear regressions. This method can be applied to situation in which

the treatment and control variables are endogenous. The analysis yields identification intervals for the coefficient of interest under different degrees of selection bias (or equivalently, different levels of hypothetical correlation between the treatment variable and unobserved variables). Because the method is very general, researchers can also specify different degrees of endogeneity between control variables and unobservables. The resulting identification intervals provide information on the sign of the coefficient of interest.

Here we provide a sketch of the main result in Diegert et al. (2026), see the paper for more details. Consider the regression

$$Y = \beta_{\text{long}}X + \gamma_1'W_1 + \gamma_2'W_2 + Y^{\perp X, W}. \quad (3)$$

Variable Y is the outcome of interest, X is the treatment variable. W_1 is a vector of observed covariates, while W_2 is a vector of unobserved covariates. $Y^{\perp X, W}$ includes the constant and the error term.

Consider also a model for the endogeneity of X :

$$X = \pi_1'W_1 + \pi_2'W_2 + X^{\perp W}. \quad (4)$$

Equation (3) is infeasible since it includes variables that are not observed. However, we can readily estimate a feasible regression:

$$Y = \beta_{\text{med}}X + \delta_1'W_1 + Y^{\perp X, W_1}. \quad (5)$$

That last regression would yield biased estimates of the true coefficient β_{long} since X is endogenous, and W_0, W_1 are potentially endogenous. Notice that if $\pi_2 = 0$, then $\beta_{\text{long}} = \beta_{\text{med}}$ and we would have no need for further analysis.

Diegert et al. (2026) propose measuring endogeneity with the expression

$$r_X = \frac{\sqrt{\text{Var}(\pi_2'W_2)}}{\sqrt{\text{Var}(\pi_1'W_1)}}.$$

That expression measures the degree of selection on unobservables relative to selection on observables W_1 . Different values of r_X , up to a maximum value of $\bar{r}_X$, yield different identification intervals for the coefficient of interest. Theorem 4 of Diegert et al. (2026) provides the identification interval of that coefficient.

Theorem. Diegert et al. (2026).

Suppose that:

1. The joint distribution of (Y, X, W_1) is known.
2. The variance matrix of (Y, X, W_1, W_2) is finite and positive definite.
3. $r_X \leq \bar{r}_X$ for a known value of $\bar{r}_X \geq 0$.
4. $\text{Cov}(W_1, Y) \neq \text{Cov}(W_1, X) \text{Cov}(X, Y)$ and $\text{Cov}(W_1, X) \neq 0$.

Normalize $\text{Var}(X) = 1$ and $\text{Var}(W_1) = I$. Let $R_{X \sim W_1}^2$ be the R-squared of a regression of X on W_1 . If $\bar{r}_X < \sqrt{1 - R_{X \sim W_1}^2}$. Then

$$\beta_{\text{long}} \in \left[\beta_{\text{med}} - \sqrt{\frac{\text{Var}(Y^\perp X, W_1)}{\text{Var}(X^\perp W_1)} \frac{\bar{r}_X^2 R_{X \sim W_1}^2}{1 - R_{X \sim W_1}^2 - \bar{r}_X^2}}, \beta_{\text{med}} + \sqrt{\frac{\text{Var}(Y^\perp X, W_1)}{\text{Var}(X^\perp W_1)} \frac{\bar{r}_X^2 R_{X \sim W_1}^2}{1 - R_{X \sim W_1}^2 - \bar{r}_X^2}} \right].$$

□

In this framework, an important parameter of interest is $\bar{r}_X^{\text{bp}}$, the minimum value of $\bar{r}_X$ for which the identification interval contains zero. This is a measure of robustness of the hypothesis that β_{long} has a specified sign. The larger the value of $\bar{r}_X^{\text{bp}}$ is, the more robust the results are to selection bias.

In addition to obtaining identification intervals for various values of $\bar{r}_X$, we can also impose restrictions on the degree of endogeneity of covariates W_1 . For a single unobservable variable W_2 , this effectively places restrictions on the R-squared of a regression of W_2 on W_1 .

The framework can be extended to allow for calibration on a subset of covariates. We can do that by considering two types of observable covariates W_0 and W_1 , where covariates W_0 are the “calibration” covariates, and W_1 are the specific covariates we have in mind when we say “selection on observables.”