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Non-competes: a case of missing wages in Australia

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Abstract

Non-compete clauses have become a focal point in debates over fairness and efficiency in modern labour markets. There is growing academic and policy interest in non-competes, yet evidence on wage effects remains largely US-focused. Using new Australian survey data linked to administrative records, we find no systematic evidence of wage compensation for the mobility restrictions associated with non-competes. We test robustness across multiple samples and methodologies. Furthermore, our novel results show that there is substantial heterogeneity: high-productivity firms show a positive association with wages, while low-productivity firms use non-competes widely without clear justification. Smaller firms also appear to adopt non-competes without much justification. We document substantial heterogeneity in non-compete coverage and examine how it varies with firm size, industry, workforce skill composition, and occupational diversity. Our broader findings raise concerns over both efficiency and equity and underscore the case for policy scrutiny.

Key Points

- This paper provides a clear empirical and analytical foundation for government intervention in non-compete policy, establishing a strong case for targeted regulatory reform.
- It complements recent contributions by Andrews and Jarvis (2023) and Buckley, Rankin and Andrews (2024) in underscoring the case for intervention, and draws on evidence from Cowgill, Freiberg and Starr (2024), who experimentally show that including a non-compete in a job offer reduces worker mobility by 30–57 per cent.
- Non-compete clauses are contractual agreements that limit workers' ability to join competing firms or start competing businesses after leaving a job.
  - These clauses can restrict career opportunities and reduce the available talent pool.
  - However, they may also encourage companies to invest in employee training and innovation and can lead to increased compensation.
- While non-competes can support productivity by fostering skills and innovation, their restrictive nature can hinder labour market flexibility, leading to lower competition and productivity.
- Our framework shows how market failures (such as asymmetric bargaining power and incomplete information) can interact with NCs to make workers worse off, with non-competes particularly harming those with limited bargaining power or awareness of such clauses—raising concerns about fair use.
- Theoretically there could be both 'good' non-competes and 'harmful' non-competes. Hence, determining the impacts of NCs is an empirical question.
- Using novel data on restraint clauses (RCs) and linking it to microdata we find:
  - Prevalence and application: non-competes are common across industries and firm sizes, including sectors with lower wages and productivity. They are often used alongside other restraint clauses, such as non-disclosure agreements (NDAs) and non-solicitation clauses (NSs), which underscores the need to assess non-competes in combination with these clauses.
  - Usage of non-competes: Firms often use non-competes where their usage is not justified, for example, in low wage, low labour productivity and non-innovative sectors. This suggests that non-competes are more likely being used here to restrict competition rather than upskill workers, indicating that reform on how they are used could be essential.
  - Compensation for non-competes: While non-compete agreements restrict workers' mobility and career opportunities, we find no positive association with wages on average. This suggests that firms typically may not provide compensating wage benefits for mobility restrictions, diminishing worker wellbeing.

  - In our robustness checks analysing how firms implement RCs in combination, we find no systematic evidence of a positive wage association with non-competes. These results remain robust to a number of methodologies and sample tests.
  - Smaller firms are more likely to apply non-competes broadly across their workforce, while larger firms tend to be more selective. This suggests that blanket application may be driven by efforts to reduce HR costs from managing differentiated contracts rather than tailoring them to specific job needs — a practice likely to make workers worse off.
- The above results suggest that policy can restrict the occurrence of bad non-competes and help improve workers' welfare. Effective policy may lie in selectively restricting non-competes to deter misuse while preserving their benefits where justified.
- Our current data allows us to examine associations of RCs with firm and employee characteristics. Data on additional time periods and data on individuals would allow us to make more definitive causal statements.

1. Introduction

Non-compete clauses are employment contract terms that can limit a worker's ability to move to a new job or start a business in the same field for a certain period. Given this, do workers who face mobility restrictions — through non-compete clauses — receive compensation for these constraints? This question is at the heart of ongoing policy debates across several advanced economies. Growing access to data has revealed the widespread use of non-competes (such as Starr, Prescott, and Bishara (2021) in the US, Boeri, Garnero, and Luisetto (2024) in Italy and Alves et al (2024) in the UK, Australian Government Treasury & e61 Institute (2023) and Andrews and Jarvis (2023) in Australia) and prompted renewed attention to their implications for equity and efficiency in labour markets (Leigh, 2024). Workers face enormous constraints in the form of market failures, such as asymmetric bargaining power and incomplete information. If a firm does not fully internalise the cost of the non-competes that it imposes on workers, and if the workers are not able to properly negotiate for compensation, then the welfare of the workers may be lower. Against this backdrop, a central question emerges: is there a case for government intervention — and if so, what principles should guide it? To answer this question, the paper examines microdata on non-compete clauses and their relationship with the wages of workers employed at firms that use them, with a focus on Australia.

Importantly, while most studies concentrate on the U.S. (e.g. Starr, Prescott & Bishara 2021) and a growing strand examines European contexts (Boeri, Garnero & Luisetto 2024), this paper turns attention to Australia —an institutional middle ground for labour market regulations. Australia's employment protection legislation is often viewed as more rigid than that of the U.S. but less so than in many European nations (see Hermansen 2020). By exploring non-competes in this intermediate environment, the paper offers fresh evidence from a distinct institutional setup.

In Australia, non-compete clauses are governed primarily by common law, with relatively little variation across states. Under common law, such clauses are enforceable only if they are not considered contrary to the public interest, with the courts serving as the final arbiter. While workers could challenge a non-compete clause in court on the basis that it is unenforceable, the financial cost and uncertainty associated with legal action can be prohibitive. In a competitive labour market, restrictions on worker mobility such as non-compete clauses would be expected to be accompanied by compensating wage differentials. This idea aligns with a growing literature that shows non-competes result in substantially lower mobility; for instance, a forthcoming paper by Cowgill, Freiberg and Starr (2024), using an experiment, finds that a non-compete in a job offer lowers mobility by 30–57 per cent. However, market failures such as bargaining power asymmetry and incomplete information likely interact with non-competes to prevent compensation. Using novel microdata for Australia, this paper tests the hypothesis that a wage premium exists for signing non-competes.

The analysis draws on multiple samples and econometric methodologies, including exploiting how non-competes are used along with other restraint clauses (RCs) and the method used by Diegert, Masten, and Poirier (2022) to evaluate how stable the coefficient of interest is to unobservable factors. The paper's main results show that on average there is no positive wage association with non-competes, suggesting that workers likely give up the freedom to move but are not compensated for this restriction, which may be welfare-reducing. The results establish robust patterns between non-competes and wages. Despite controlling for a rich set of observable firm characteristics and incorporating multiple robustness checks, we interpret the estimates as descriptive. This finding of a lack of positive association is consistent with recent behavioural studies showing that workers are typically unaware of the presence of a non-compete at the time of entering an employment contract (Cowgill, Freiberg and Starr, 2024). The paper also finds that non-competes are not associated with wage growth.

An important, novel result is that there is marked heterogeneity in how firms deploy non-competes, and in their wage associations, with sharp differences across firm productivity. Firms with very high labour productivity and capital investment tend to be positively associated with wages when they use non-competes, whereas this association does not exist for low-productivity firms, suggesting non-compete usage may vary with firm-level characteristics.

If non-competes were primarily used to protect valuable knowledge, we would expect higher usage in firms with more high-skilled employees and greater occupational specialisation, consistent with the efficient contracting view (Starr 2025). Using additional novel person-level data, we examine how non-compete coverage relates to workforce composition and skill levels across firms. The data reveal no clear relationship between coverage and either the share of high-skilled employees or occupational diversity, undermining the view that non-competes are closely tied to the protection of specialised human capital.

One useful empirical contribution of the paper is to highlight a set of robustness tests to assess the stability of results when only single-period survey data are available. By combining clause-bundling comparisons, heterogeneity analyses, and formal sensitivity bounds, the approach provides a transparent way to assess the robustness of descriptive associations across empirical strategies. While focused on non-competes, this framework can be applied more broadly to other firm-level characteristics and practices, particularly where these are adopted in bundles. For example, it may be useful in analysing descriptive evidence on firms' adoption of organisational or innovation practices and their associated outcomes.

The paper builds on evidence that non-competes are common across industries and firm sizes, including sectors with lower wages and productivity. This suggests that in sectors with lower wages and productivity — where protecting high-value trade secrets or specialised investments is less likely to be necessary — the rationale for using non-competes is weaker. The results also show that smaller firms are more likely to apply non-competes broadly across their workforce, whereas larger firms tend to be more selective. This pattern suggests that blanket application may reflect an effort to reduce HR costs associated with managing differentiated contracts rather than tailoring them to specific job needs.

The paper also provides a taxonomy of how RCs are used in Australia. Firms typically use non-competes alongside other RCs, such as non-disclosure and non-solicitation of clients clauses (NSC), which underscores the need to assess non-competes in combination with these clauses. The paper also shows that firms with a single restraint clause differ markedly from those with four RCs, with the latter being significantly more productive and offering higher average wages.

The paper uses novel data, the 2023 Short Survey of Employment Conditions (SSEC), linked to administrative data using Business Longitudinal Analysis Data Environment (BLADE). It exploits the usage of non-competes along with the use of other RCs to provide a more comprehensive picture of how firms structure employment contracts and the potential implications for workers. The main limitation of this data is that it only provides one year of data, making it hard to establish a causal relationship. Thus, the results are best interpreted as associations. Regardless, the paper yields several important insights, which are consistent across various robustness tests.

The lack of evidence of compensation for the average firm, along with concerns for market failures linked to bargaining power, incomplete information and management of contracts, raises the rationale for government intervention. Further, while non-competes may serve a legitimate role in certain high-productivity settings, their use in lower-productivity firms — where the economic rationale is less clear — raises concerns about potential misuse.

Importantly, to guide policy thinking about the wage effects of non-competes, the paper begins by developing a heuristic framework that illustrates why workers who give up freedom and mobility should, in principle, be compensated when bound by non-compete clauses. The framework is intentionally illustrative and is designed to guide policy intuition, generate priors, and aid in the interpretation of our empirical findings, rather than serve as a structural model.

The rest of the paper is as follows. Section 2 gives an overview of the existing literature on the effects of non-compete clauses, focusing on their relationship with wages and labour productivity. Section 3 summarises the relevant literature to motivate the conceptual framework. Section 4 describes the data sources, key variables, and descriptive statistics. Section 5 presents the empirical analysis. Section 6 gives policy implications. Section 7 concludes.

2. Literature Review

Recent literature examining non-compete clauses is growing, although most of the studies focus on the United States. A review of the literature shows that non-competes adversely affect worker mobility, innovation and competition. Some US studies use changes in enforceability rather than presence of non-competes as an explanatory variable, as that approach may better infer causal effects (Federal Trade Commission, 2024). However, non-competes are linked to decreased employee mobility, regardless of enforceability (Starr, Prescott, and Bishara 2020). Similarly, using Italian data Boeri, Garnero, and Luisetto (2024) show that unenforceable non-competes are still associated with lower wages, while Cowgill, Freiberg, and Starr (2024) use a large field experiment to conclude that non-competes lower workers' total earnings.

Traditionally, non-competes were justified in safeguarding trade secrets and client relationships among highly skilled professionals. However, Andrews and Jarvis (2023) reveal a troubling extension of these clauses into low-wage occupations—such as burger flippers and hairdressers (Lafontaine et al. , 2025) —roles that typically involve no transferable proprietary knowledge. This proliferation is particularly hard to reconcile with the classic rationale for non-competes.

This section reviews key empirical studies on the relationship between non-competes and two outcomes: wages and productivity, which are the focus of this paper. While some studies suggest that the signing of non-competes may be associated with an increase in wages for employees, others emphasise non-competes' role in restricting labour market competition and suppressing wage growth.

Studies document a range of associations between non-competes and wages, depending on firm characteristics and enforcement conditions. Table 1 summarises the results from individual studies.

Table 1: Literature findings on the relationship between non-competes and wages.

Study	Relationship with wages	Data	Type of claim
Cowgill, Freiberg, and Starr (2024)	12%-16% lower total earnings	Field experiment	Causal

Gopal, Li, and Rawling (forthcoming)	9% higher wage from non-competes within one year, with effect persisting at least six years	US National Longitudinal Survey of Youth 1997	Causal
Buckley, Rankin and Andrews (2025)	Workers at firms that use non-competes extensively are paid 4% less on average than similar workers at similar firms that only use NDAs.	Australian Bureau of Statistics (ABS) survey data	Correlation
Balasubramanian, Starr, and Yamaguchi (2024)	Employees with all four restrictions earn 5.4% less than employees with only non-disclosures.	US employee-level survey complemented with a firm-level survey, bargaining power question from National Longitudinal Survey of Youth 1997	Correlation
Johnson, Lavetti, and Lipsitz (2023)	3.2% to 14.2% increase in average earnings for all workers if non-compete were rendered unenforceable.	US individual-level data on earnings and employment from 1991 to 2014, Job-to-Job Flows	Causal
Rothstein and Starr (2022)	Positive association	US National Longitudinal Survey of Youth 1997	Correlation
Balasubramanian et al (2022)	4.6% lower cumulative earnings over 8 years for technology workers in states with average enforceability relative to a nonenforcing state.	Employer-employee matched data for workers from 30 US states for 1991-2008	Correlation
Lipsitz and Starr (2022)	2-3% increase in hourly wages for hourly workers on average after a non-compete ban	Current Population Survey looking at hourly workers in Oregon, US	Causal
Young (2021)	No impact on overall earnings growth detected	Austrian Social Security Database	Causal
Lavetti, Simon and White (2020)	8 percentage points increase on average annual earnings growth in each of the first 4 years of a job, with a cumulative effect of 35 percentage points after 10 years on the job.	Physician Perspectives on Patient Care Survey from five US states	Causal
Starr, Prescott, and Bishara (2021)	9.7% higher earnings for those who learnt of non-compete before accepting job offer.	US large-scale survey administered in 2014 to a panel of verified respondents	Correlation

Some evidence suggests that employees are compensated for signing non-competes. For example, studying physicians in the US, Lavetti, Simon and White (2020) find non-competes increase the annual rate of earnings growth by an average of 8 percentage points in each of the first four years of a job, with a cumulative effect of 35 percentage points after 10 years on the job. Similarly, Starr, Prescott, and Bishara (2021) report that workers who are informed about non-competes before accepting a job tend to earn higher wages.

However, other studies find wage growth for those who sign non-competes appears to be reduced, suggesting that non-competes function as a labour market restriction and limit options. Shi (2023) notes that while executives may start with higher wages due to non-competes, their long-term wage growth is constrained. Balasubramanian et al. (2022) estimate that higher non-competes enforceability is associated with a 4.6 per cent decline in cumulative earnings over eight years for technology workers. Similarly, Lipsitz and Starr (2022) find that non-competes bans increase wages by 2-3 per cent on average, with this effect more pronounced for women. These findings align with the monopsony power hypothesis, where non-competes restrict worker bargaining power, allowing firms to pay lower wages than they would in a competitive labour market (Krueger and Ashenfelter, 2018).

Labour productivity

Theoretically, non-competes can have offsetting impacts on productivity. On one hand, non-competes might incentivise firms to invest in productivity-enhancing activities, such as employee training, when they can restrict employee mobility. Garmaise (2011) provides empirical support for this argument, finding that stronger non-competes enforceability is associated with higher capital investment, greater R&D spending, and increased worker training.

On the other hand, non-competes might hinder productivity by reducing knowledge spillovers and slowing labour market dynamism resulting in poorer job matching. Across the literature, nearly all studies find that non-competes hinder worker mobility, even in jurisdictions with lax enforcement (Boeri, Garnero, and Luisetto, 2024). Balasubramanian et al. (2022) show that higher non-competes enforceability is associated with fewer job transitions, which can limit the diffusion of skills across firms, particularly in knowledge-intensive sectors. When employees circumvent non-competes by seeking employment in a new industry, their productivity declines by 30 per cent whereas those who move voluntarily are 16 per cent more productive (Mueller, 2022), indicating an inefficient reallocation of human capital from non-competes. Gopal and Li (2024) find labour market misallocation due to non-competes fosters inefficiencies, and Shi (2023) finds that non-competes lower competition by limiting mobility and inhibiting new firm entry.

3. Conceptual framework

We present a simple, illustrative heuristic framework to organise how non-compete clauses may influence wages. Rather than developing a fully formalised model, the framework is intended to guide policy thinking, generate priors, and aid interpretation of the empirical findings. While a broad range of channels is discussed, the empirical analysis focuses on a subset of key mechanisms.

Non-Competes: Balancing Utility, Profits, and Economic Dynamism

Non-competes can impact the welfare of employees, firms, and the broader economy. Below we discuss how various stakeholders can be impacted by non-competes.

Employees

The paper assumes that workers seek to maximize utility, a function of both consumption (c) and freedom (f):

$$Utility = U_i(c, f)$$

Non-competes reduce employees' freedom to pursue opportunities compared to an unrestricted contract ($f_{NC} < f_{UR}$). Thus, rational employees require higher compensation ($\widetilde{w}$) (or a wage premium), which enables them to have higher consumption ($c + \widetilde{w}$), to offset these restrictions on mobility.

So, for employees to accept a contract which includes a non-compete clause, the utility they gain from increased wage and increased consumption must at least compensate the workers for the disutility of giving up the freedom to move:

$$U_i(c + \widetilde{w}, f_{NC}) \geq U_i(c, f_{UR})$$

This means that when employees negotiate with the firm over their compensation and conditions, employees seek higher wages if a non-compete clause is present in their contract.

Firms

The paper assumes that firms aim to maximise profits:

$$\pi = pq - wL - rk - OC$$

Where profits are reduced by costs of labour (w), capital (r), and additional outlays (OC) like training (including onboarding of new employees) and legal enforcement of non-competes (Varian, 2009). Firms value workforce stability, protection from competitors (which allows them to restrict quantities and raise prices), and protection of intellectual property.

This means that when firms write employment contracts for employees, including for compensation and conditions, firms will seek to minimise costs (wages, additional outlays) associated with imposing a non-compete. As such we assume that firms will prefer not to pay a wage compensation for non-competes wherever possible.

The Economy

At the macro level, growth depends on productivity, human capital development, competition, and dynamism.

Non-competes can undermine allocative efficiency by restricting the free movement of talent and preventing optimal reallocation of labour across firms and sectors (He, 2025), further explored in Box 1.

However, non-competes may have ambiguous effects on dynamic efficiency. Non-competes may increase human capital development and incentives for innovation, which is productivity enhancing and therefore improves long-term growth. However, non-competes may limit knowledge diffusion by reducing labour mobility and may reduce firm level incentives to innovate by undermining competitive pressures. These frictions may slow innovation and suppress long-term growth (see Box 1).

Box 1: How economic factors affect compensation for non-competes

Incomplete and Asymmetric Information

- Many employees may not realise a non-competes exists in their contract until they attempt to leave. This lack of awareness tends to disadvantage employees, who face unexpected restrictions (Cowgill, Freiberg and Starr, 2024).

Bargaining Asymmetry

- Workers with higher productivity, education, and specialised skills typically possess greater bargaining power (Becker, 1964), enabling them to negotiate compensation in exchange for accepting a non-competes. Conversely, workers with lower bargaining power — such as those with lower levels of education or in occupations characterised by weaker union representation — are less able to secure this compensation. They are more likely to experience adverse outcomes that they are not fully compensated for, including wage suppression and reduced labour mobility.

Transaction Costs

- To reduce administrative complexity, firms may default to using standardised contracts with non-competes across all employees, even when such clauses are unnecessary. Smaller firms without dedicated HR support are especially likely to rely on this one-size-fits-all approach, whereas larger firms are more likely to be selective.

Human Capital

- Non-competes can incentivise firms to invest in employee training and skill development by reducing the risk of immediate post-training turnover. By limiting the ability of workers to join competing firms, non-competes create conditions under which employers may perceive a higher likelihood of recouping training costs. In certain contexts, non-competes are associated with increased employer-sponsored human capital investment, particularly when training is industry-specific and costly (Starr, 2019).

Externalities

- Firms may view non-competes as a way to protect their investment in employee training. However, as they also limit competition, they can suppress overall investment, reduce talent circulation, and distort markets (Marx and Fleming, 2012).

Diverse Employee Preferences

- Not all workers oppose non-competes, some may accept them in exchange for financial security in the form of gardening leave or valuable learning opportunities. For certain employees, non-competes can align with their personal career goals (Aydinliyim, 2020).

Time Preferences and Decision Bias

- Employees may undervalue future risks when signing non-competes, focusing on immediate benefits like a job offer, without fully considering the long-term career restrictions these clauses impose (Aydinliyim, 2020). This present bias can increase the prevalence of non-competes in the labour market.

4. Data

Data sources

We utilise Australian Bureau of Statistics Short Survey of Employment Conditions (SSEC), which captures information on the use of non-compete clauses, non-disclosure agreements, non-solicitation of clients and non-solicitation of co-workers clauses in Australian firms. SSEC, conducted in 2023, has 3,757 firms in the survey.

To assess the economic implications of these restraint clauses, we link the SSEC data to BLADE, a series of integrated longitudinal datasets linking survey and administrative data from the Australian Taxation Office (ATO) and ABS. The data cover all Australian Business Numbers registered for the goods and services tax (GST) at some point in time. For our analysis, we use tax data for the years 2017–2023.

The final dataset includes 3,757 firms for 2022–23 and 21,128 observations from 2017–18 onward, allowing us to examine restraint clause use and trends in associated firm outcomes.

To mitigate distortions introduced by COVID-19, our robustness tests include just 2021–22 and 2022-23 years. Additionally, non-employing businesses (that is, those with a full-time equivalent (FTE) of less than 1) and businesses lacking key characteristic data were excluded to maintain data quality. The data were weighted using survey weights for the SSEC sample to ensure representativeness of the broader Australian business population.

Table 2: List of key variables

Variables	Definitions and Source
Average wage per firm	Calculated as the total salary, wages, and other payments reported in the firm's Business Activity Statement (BAS), divided by the firm's full-time equivalent (FTE) workers, as derived from Pay-As-You-Go (PAYG) tax data.
NC, NDA, NSW, NSC	Binary variables for whether a firm reported that it used one of these restraint clauses (1 = used, 0 = did not use).
Restraint clause bundles	Binary variables identifying firms that used a specific combination of restraint clauses (see Table 4 for details).
Clause coverage (NC, NDA, NSC, NSW)	The extent of usage of a particular clause – low (up to 30% of employees) medium (31-75%) and high (more than 75%).
Capital Expenditure (log)	Defined as the log of firm-reported capital investment
Industry Classification	Based on Australian and New Zealand Standard Industrial Classification (ANZSIC) codes, allowing for industry fixed effects.
Labour Productivity (lagged)	A one-year lag of log labour productivity.
Time and Industry Fixed Effects	All models include financial year and industry fixed effects.
Capital Expenditure (log)	Defined as the log of firm-reported capital investment.

Variables	Definitions and Source
Industry Classification	Based on Australian and New Zealand Standard Industrial Classification (ANZSIC) codes, allowing for industry fixed effects.
Occupational diversity	Number of unique occupations reported by employees in the firm on their tax return, divided by the number of employees in the firm
High-skill share	Share of employees in the firm that reported their occupation as being one that was classified as being at skill level of 1 in Australian and New Zealand Standard Classification of Occupations (ANZSCO).

All monetary variables are expressed in real terms in Australian dollars (base year 2022).

Descriptive statistics

Table 3 provides summary statistics for key variables in our sample for 2023. Similar to other microdata datasets (such as Coad and Hölzl (2012) and Coad and Rao (2008)), the table highlights that there is significant diversity in firms in the sample. In particular, the sample exhibits considerable heterogeneity in terms of the average wage and labour productivity. Similar earlier work in Australia such as Majeed et al (2021) and Suresh et al (2020) find firm size, as measured by FTE, is highly skewed. The median firm in the sample employs approximately 44 FTEs 1, while the mean is substantially higher at 833 FTEs, reflecting the presence of a small number of very large firms in the sample. As such, controlling for size will be important in our regressions.

The dummy variables indicate the prevalence of various restraint clauses. Approximately 72 per cent of firms in the sample report using non-disclosure agreements, while 34 per cent report using non-compete clauses, 42 per cent of firms report using non-solicitation clauses that restrict client poaching, and 34 per cent impose restrictions on soliciting workers. These shares suggest that RCs are a common feature of the employment landscape, particularly NDAs.

Table 3: Summary statistics for key variables – 2023

	N	Mean	SD	p25	p50	p75
Labour productivity	3535	477,304	4,616,826	118,489	200,827	378,433
Average wage	3555	87,924	272,269	58,670	71,738	89,310
FTE	3555	833	4,327	7	44	372
Capital expenditure	3730	46,688,509	1,479,160,467	0	0	989,430
Log of capital expenditure	1376	15.05	2.76	13.21	15.25	16.99
Turnover	3730	484,042,650	7,925,420,942	1,141,227	7,675,117	64,854,640
Growth of labour productivity (%)	3,379	0.03	0.44	-0.10	0.01	0.13
Growth of turnover (%)	3,558	0.11	0.57	-0.03	0.09	0.24
NDA [Dummy variable]	3,358	0.72				
NC [Dummy variable]	3,253	0.34				

1 Where this sample has overrepresentation of large firms, as such, our robustness in the results section will employ weighted analysis.

	N	Mean	SD	p25	p50	p75
NSC [Dummy variable]	3,187	0.42				
NSW [Dummy variable]	3,118	0.34				

Firms often bundle other restraint clauses with non-competes

Australian businesses often bundle non-competes with other RCs, mirroring patterns observed in the US, as per Balasubramanian, Starr, and Yamaguchi (2024). Figure 1 presents a Venn diagram illustrating the overlap between three types of RC used in employment contracts. Note, for the purpose of studying how firms bundle clauses, observations are removed if they reported "Unsure" for any of the clauses, and so the proportion of use differs slightly from the summary statistics in Table 3. Most firms (71 per cent) in our data use at least one restraint clause, and while 33 per cent report using non-competes, fewer than 10 per cent of firms impose them as a standalone restriction, confirming that non-competes are almost never used in isolation.

Table 4 further highlights how firms use non-competes in conjunction with other clauses, in this table NSC refers to non-solicitation of clients and NSW refers to non-solicitation of co-workers. As such, to study their impacts, it is essential to understand how these clauses function together rather than analysing them separately.

Figure 1: How are non-competes bundled with other restraint clauses?

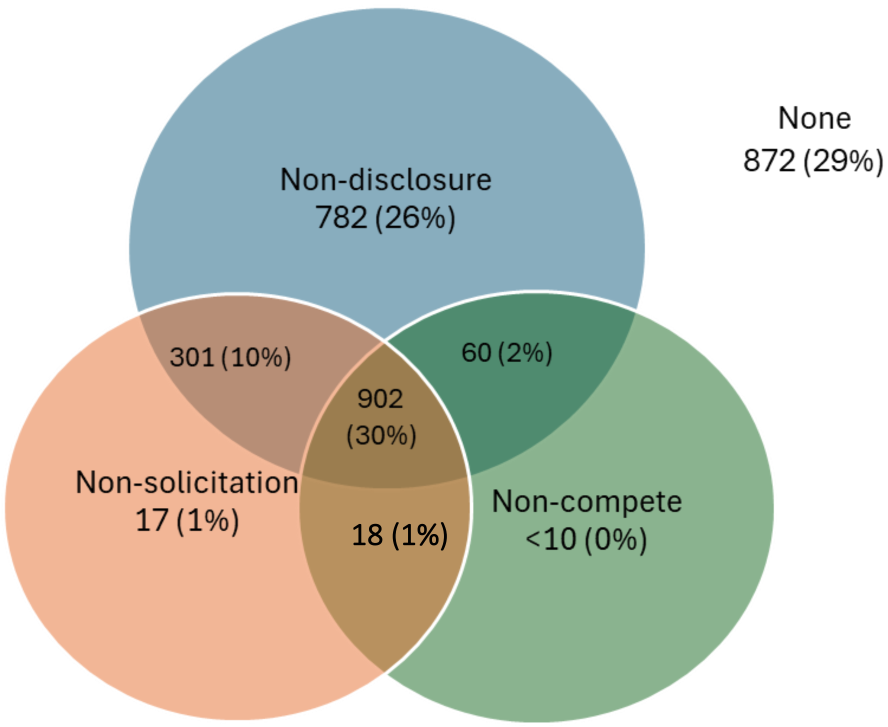


Table 4: Frequencies of combinations (2017-2023)

NDA	NC	NSC	NSW	N	Percent

×	×	×	×	4,884	28.97%
✓	×	×	×	4,552	27.01%
✓	×	✓	✓	955	5.67%
✓	×	✓	×	622	3.69%
✓	✓	✓	×	580	3.44%
✓	✓	×	×	337	2.00%
✓	×	×	✓	125	0.74%
×	✓	✓	✓	64	0.38%
×	✓	✓	×	44	0.26%
×	×	✓	×	40	0.24%
×	✓	×	×	43	0.26%
×	×	✓	✓	40	0.24%
✓	✓	×	✓	41	0.24%
✓	✓	✓	✓	4,529	26.87%
				16,856	100.00%

Note: The 2023 survey was linked to firms in the panel from 2017-2023.

Firm characteristics vary substantially based on the numbers of restraint clauses used. Table 5 summarises median wage, FTE, capital expenditure, and labour productivity across firms grouped by number of clauses. Firms with three or four restraint clauses tend to be larger, more productive, and offer higher wages compared to those with fewer clauses. Firms with three and four restraint clauses are the most similar. This suggests that different types of firms may implement restraint clauses for distinct strategic reasons.

Given these results, one approach to studying the association between non-competes and wages is to compare firms that use all four RCs with those that use all RCs except for non-competes. These firms are more similar in terms of size, labour productivity, and wages than other groups, making them more suitable for comparison. This comparison facilitates a clearer assessment of how wages differ between firms that include non-competes and those that do not, conditional on otherwise similar restraint-clause bundles. This analysis is undertaken in the Empirical Section.

We complement Table A 1 in the Appendix by comparing average wage, labour productivity and FTE workers between firms with all clauses except non-competes and firms who impose all clauses.

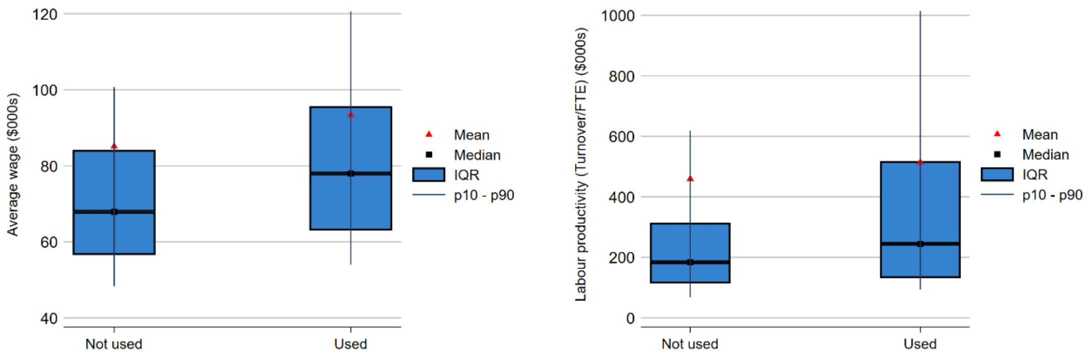
Table 5: Medians by number of clauses (unweighted) [2017-2023]

	0 Clause	1 Clause	2 Clauses	3 Clauses	4 Clauses
Average wage	66,282	74,410	71,572	75,135	82,354
Full-time equivalent	8	56	43	73	125
Log of capital expenditure	14.3	14.8	14.1	14.5	15.3
Labour productivity	180,770	185,823	197,059	203,418	273,055

Wage and labour productivity in firms using non-competes

On average, firms with non-competes tend to be associated with higher average wages and labour productivity. However, the data also show substantial variation. Figure 2 illustrates the distribution of wages (left panel) and labour productivity (right panel) across firms that do and do not use non-competes in 2023.

Figure 2. The distribution of average wage and labour productivity across firms that impose non-competes and those that do not.



From the figure, many firms with relatively low wages and low productivity impose non-competes. Such firms are less likely to be operating in high-value or skill-intensive industries and may offer limited opportunities for on-the-job learning. This brings into question why these firms use non-competes, especially if they are not contributing to the human capital of their employees in a substantial manner. Despite restricting worker mobility, non-compete clauses are not associated with providing workers in low-paying firms with a wage premium.

Studies document a range of associations between non-competes and wages, depending on firm characteristics and enforcement conditions. Table 1 summarises the results from individual studies.

Non-competes are being used in firms where there is poor justification

As discussed above, non-competes may be most defensible when accompanied by higher wages and/or firm-level productivity improvements consistent with investments in training or intellectual property development. Conversely, non-competes may be more difficult to justify in lower-wage, lower-productivity, and lower-growth firms.

Our analysis indicates that in Australia, non-competes are being used in firms where there is likely weaker economic justification to do so: 21 per cent of the sampled firms using non-competes experienced negative productivity growth over 2021–22 and 2022–23 (compared to 19 per cent in the sample of firms that did not use non-competes). We also observe that 20 per cent of the sampled firms that used non-competes were in the bottom quartile of productivity, and 17 per cent were in the bottom quartile of average wages. While this is consistent with firms that use non-competes being slightly higher-paying and higher-productivity on average (see Figure 2. The distribution of average wage and labour productivity across firms that impose non-competes and those that do not.Figure 2), it also highlights that a notable proportion of firms using non-competes are low-productivity and low-paying, settings in which it may be harder to justify non-competes.

5. Empirical analysis

In this section, we estimate the relationship between non-competes use and average wage using several regression approaches and samples. These results establish robust patterns between non-competes and wages. While the specifications control for a rich set of observable firm characteristics and incorporate multiple robustness checks, we interpret the findings as descriptive. We begin with a simple OLS regression where we estimate the relationship between firm's average wage and non-competes use while controlling for the use of other RCs and other firm characteristics observable in the data. Subsequently, we implement an alternative estimation strategy where we compare firms with all RCs with firms that use all clauses except for non-competes. We then test to see how stable the results are, when testing for omitted variable bias using the Diegert, Masten, and Poirier (2022) (DMP).

Linear regression estimates of restraint clauses on wage

Method

To examine the relationship between RCs and wages, we start by estimating an OLS regression model, following approaches used in Alves et al. (2024), Rothstein and Starr (2022), and Starr, Prescott, and Bishara (2021). As shown earlier, since restraint clauses are used in bundles, it is important to control for all RCs when examining the association of non-competes with wages. To this effect, we estimate:

$$\log w_{it} = \beta_0 + \beta_1 NC_i + \sum_{j=1}^{3} \beta_j RC_{ij} + X_{i,t-1}\Gamma + \gamma_s + \delta_t + \epsilon_{it} \qquad (1)$$

where $\log w_{it}$ is the log of the average wage per firm i in year t, NC_i is a binary indicator for whether the firm imposes non-competes, that is, whether any employee is subject to a non-compete, and RC_{ij} is a set of binary indicators for whether the firm imposes an NDA, NSW and/or NSC.

We also include a matrix of firm-level control variables X_{it} that include firm size (log of full-time equivalent workers), log of capital expenditure and lagged labour productivity. Γ is the vector of coefficients associated with the control variables. Firm control variables are lagged by one period to mitigate reverse causality. Results are qualitatively similar if contemporaneous firm controls are used instead. γ_s represents industry fixed effects at the ANZSIC 2-digit level, δ_t represents time fixed effects, and ϵ_{it} is the error term.

As highlighted in the descriptive section, controlling for all restraint clauses is essential, since firm wages and productivity differ systematically with the number of clauses adopted. Firms with one or two clauses diverge considerably from those with three or four clauses, while firms with three and four clauses display the most comparable characteristics, making them the most relevant for comparison. We exploit this similarity in our robustness analysis.

We are unable to eliminate firm-level fixed effects because RC data are only available for a single period. However, we can examine the association between non-competes and wages over several years by linking SSEC data with tax data for the years 2017 to 2023.

We differentiate firms by size, running separate regressions for large firms (200 or more FTE) and SMEs (fewer than 200 FTEs) to assess whether non-compete associations vary by firm size. Additionally, while the full sample covers financial years 2017–18 to 2022–23, we run separate regressions for 2021–23 to account for potential distortions introduced by COVID-19. Industry and time fixed effects are included to control for sectoral differences and broader economic conditions.

A key limitation of our empirical specification is that non-compete usage is measured at the firm level and is time-invariant in the data, meaning the estimated association may reflect unobserved firm characteristics—such as the use of trade secrets, business models, or managerial practices (discussed further in the "Time Invariant Nature of RCs" subsection)—rather than the independent effect of non-competes. As such, the results should be interpreted as descriptive associations rather than causal effects.

Results

Table 6 presents the OLS results based on Equation 1. Columns (1) and (2) report results for all firms, covering all years and the subset years comprising 2022 and 2023, respectively. Columns (3) and (4) focus on SMEs over the same time periods, while Columns (5) and (6) present results for large firms.

Across all specifications, non-competes show a weak and inconsistent relationship with wages, with a non-compete being associated with an average 2-3 per cent wage premium. However, the estimated premium is imprecisely estimated and is statistically significant at the 10 per cent level in only a small subset of specifications (Columns 1 and 3). This suggests that, on average, there is no strong evidence of compensation for non-competes.

In contrast, NDAs are positively associated with wages for SMEs. Yet for large firms, NDAs are negatively associated with wages. Similarly, NSCs consistently show a negative association with wages across all firm sizes, with a stronger and highly significant negative association for large firms. Conversely, NSWs exhibit a positive association with wages, though the magnitude and statistical significance of this association vary across firm sizes and time periods. For a discussion of the potential effects of NDAs on wages, see Sockin, Sojourner, and Starr (2022).

Overall, the findings indicate that non-competes are not systematically associated with meaningful wage compensation, and that the relationship between restraint clauses and wages varies by firm size and clause type.

Table 6: Relationship between firms' log average wage and RCs

	All firms All years	All firms 2022 & 23	SME All years	SME 2022 & 23	Large All years	Large 2022 & 23
NDA	0.03***	0.04***	0.03***	0.04**	-0.10***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)
NC	0.03*	0.03	0.03*	0.03	0.02	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
NSC	-0.03**	-0.04*	-0.03**	-0.04*	-0.06***	-0.11***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.04)
NSW	0.04**	0.05*	0.04**	0.05*	0.04	0.09*
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.05)

Log of full-time equivalent hours (lagged)	0.03***	0.03***	0.03***	0.03***	0.04***	0.03***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Log of capital expenditure (lagged)	0.00	0.00	0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log of labour productivity (lagged)	0.07***	0.06***	0.07***	0.06***	0.09***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Constant	10.85***	11.00***	10.86***	11.01***	10.58***	10.74***
	(0.11)	(0.16)	(0.01)	(0.17)	(0.14)	(0.23)
Observations	12,359	5,302	8,486	3,696	3,873	1,606
R-squared	0.35	0.36	0.34	0.36	0.46	0.43
Industry FE at 2 digits	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Combined effect of RC1	0.07	0.05	0.07	0.05	-0.12	-0.10

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Combined effect (last row) includes all results that were significant at the 10 per cent or above. Source: BLADE analysis by Treasury.

Margins analysis

As we saw in the descriptive statistics, firms with various levels of productivity and investments use non-competes. It is thus possible that different types of firms use non-competes for various reasons and therefore the association between non-competes and wages is likely to vary.

Boeri, Garnero, and Luisetto (2024) employ interaction terms to analyse how non-competes affect labour market outcomes in different contexts. By interacting non-compete clauses with firm characteristics linked to productivity, this methodology seeks to capture heterogeneity in the relationship between non-competes and wages. We apply their method and modify equation (1) to estimate

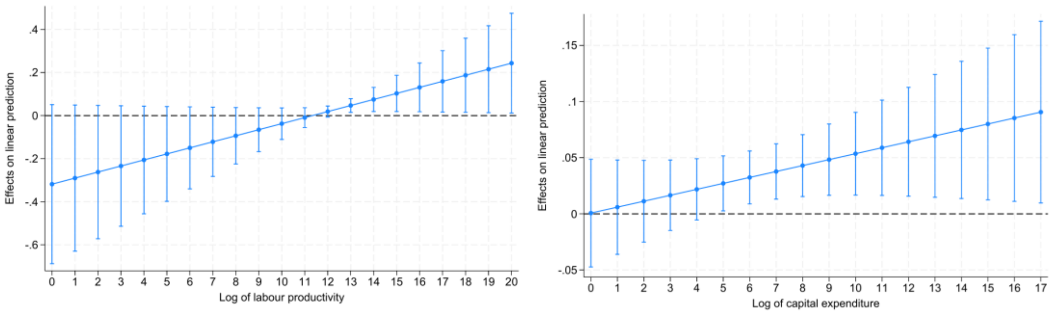
$$\log w_{it} = \beta_0 + \sum_{k=1}^{3} \beta_k RC_i^k + \beta_j NC_i \times Z_{it-1} + \beta_l NC_i + \beta_m Z_{it-1} + X_{i,t-1}\Gamma + \gamma_s + \delta_t + \epsilon_{it} \qquad (2)$$

where $RC_{it} \in \{NDA, NSC, NSW\}$ and, Z ∈{Labour productivity, Capital investment} is included one at a time in interaction with NC. In each specification, the corresponding variable is excluded from the control vector $\boldsymbol{X}$, such that $\boldsymbol{X}$ contains the remaining variables only. Again, to mitigate concerns about reverse causality, firm control variables are lagged by one period. Our findings remain qualitatively unchanged when contemporaneous controls are employed.

Figure 3 presents the marginal effect of non-competes use on firm's average wage at different -levels of labour productivity (left-panel) and capital expenditure (right-panel). At lower productivity levels, non-competes are associated with lower wages, though the estimates are statistically insignificant. However, as productivity increases, the association between non-competes and wages becomes positive and grows in magnitude. This result is significant at the 90 per cent level and is therefore interpreted as suggestive evidence of a wage premium[2].

Given that labour productivity is typically clustered at the lower end, its influence on wage differentials remains minimal for most firms when non-compete clauses are in effect. Further, the labour productivity distribution is heavily skewed — even at the 75th percentile (with log productivity around 8) this effect is not evident, meaning most firms do not demonstrate this positive association between average wages and labour productivity in the presence of a non-compete.

Figure 3. Average marginal effect of using non-competes on wage by labour productivity and investment.



Note: The dots plot the average marginal effect. The horizontal bars give the 95% confidence interval around the marginal effect.

Relationship between non-competes coverage and wage

We now examine whether the wage relationship differs by the breadth of non-competes use within a firm. To do so, we replace the binary non-competes variable in equation (1) with a categorical variable “NC coverage”[3] that groups firms based on the proportion of employees who have non-competes in their employment contracts. Because coverage is reported in uneven percentage ranges rather than as a continuous measure, we consolidate these into low, medium and high categories to create more comparable groupings and maintain a parsimonious specification. The updated specification is given by:

2 We explored the use of binsreg for nonparametric estimation; however, the small number of underlying observations, combined with ABS DataLab confidentiality rules (which restrict the display of scatterplots and raw data points), made it infeasible to implement this approach in compliance with data access conditions.

3 As the coverage of non-compete clauses is reported in uneven bins, we reorganise them into more intuitive categories: up to 30 per cent, 31–75 per cent, and more than 75 per cent.

$$\log w_{it} = \beta_0 + \beta_1 NC\ coverage_i + \sum_{j=1}^{3} \beta_j RC_{ji} + X_{it}\Gamma + \gamma_s + \delta_t + \epsilon_{it} \qquad (3)$$

Table 7 presents the results of this regression. The results show a statistically significant wage premium of 4 per cent for firms with high coverage, which is largely driven by SMEs with high non-competes coverage. This association is consistent across both the full SME sample and the 2022–23 subsample. All other categories, including large firms with high coverage, yield null or statistically insignificant results. These findings suggest that wage compensation for non-competes is not widespread but may arise in specific contexts.

Table 7: Firms' log average wage and non-competes coverage.

	All firms All years	All firms 2022 & 23	SME All years	SME 2022 & 23	Large All years	Large 2022 & 23
NC coverage (base = no NC use)						
- Low (<=30%)	-0.01	-0.02	-0.00	-0.00	-0.02	-0.02
	(0.011)	(0.016)	(0.018)	(0.027)	(0.012)	(0.017)
- Medium (31-75%)	0.02	0.01	0.04	0.03	-0.00	0.01
	(0.014)	(0.020)	(0.022)	(0.029)	(0.019)	(0.024)
- High (>75%)	0.04***	0.04*	0.04**	0.04*	0.01	0.02
	(0.010)	(0.016)	(0.013)	(0.020)	(0.015)	(0.023)
NDA	-0.01	0.00	0.00	0.01	-0.09***	-0.09***
	(0.007)	(0.011)	(0.009)	(0.014)	(0.014)	(0.020)
NSC	-0.03***	-0.04**	-0.03**	-0.04*	-0.03	-0.04
	(0.009)	(0.014)	(0.011)	(0.017)	(0.014)	(0.022)
NSW	0.04***	0.05**	0.06***	0.06**	0.01	0.04
	(0.009)	(0.015)	(0.013)	(0.019)	(0.014)	(0.023)
Log of full-time equivalent hours (lagged)	0.03***	0.03***	0.04***	0.05***	0.03***	0.03***
	(0.002)	(0.003)	(0.004)	(0.006)	(0.005)	(0.007)
Log of capital expenditure (lagged)	0.00***	0.00**	0.00**	0.01*	0.00**	0.00
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Log of labour productivity (lagged)	0.07***	0.07***	0.08***	0.07***	0.07***	0.06***
	(0.005)	(0.007)	(0.008)	(0.010)	(0.006)	(0.009)
Constant	10.74***	10.80***	10.72***	10.80***	10.89***	10.94***
	(0.072)	(0.101)	(0.097)	(0.137)	(0.095)	(0.141)
Observations	12,078	5,189	8,408	3,661	3,670	1,528
R-squared	0.37	0.37	0.31	0.31	0.50	0.48
Industry FE at 2 digits	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Combined effect (last row) includes all results that were significant at the 10 per cent or above. Source: BLADE analysis by Treasury. Each column incorporates industry and time fixed effects

Comparing firms with all RCs to firms with all RCs except for non-competes

Method

As discussed in Section 4, it is hard to establish causality in terms of the impact of non-competes on wages. A key limitation is that our RC data provide only a single point in time, making it challenging to account for reverse causality. This section exploits variation in how firms employ RCs to undertake an additional robustness exercise aimed at limiting this endogeneity. We nonetheless interpret the evidence as suggestive.

As discussed earlier, RCs are often deployed in bundles. We exploit how firms bundle RCs to examine the association between non-compete clauses (non-competes) and wages. In effect, we compare firms that impose all four RCs with those that impose all but the non-competes. As shown in Table 5, these firms are more closely aligned on observable characteristics such as labour productivity, firm size, and turnover, suggesting a credible basis for comparison. Because the RC bundles are otherwise identical — with the key distinction being the presence or absence of non-competes — any observed differences in average wages between the two groups may offer suggestive evidence regarding how non-competes are related to wage outcomes.

We estimate the following regression model for this sub-sample of firms:

$$\log \boldsymbol{w_{it}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}(\text{"All RC including NC"}) + \boldsymbol{X_{it}}\boldsymbol{\Gamma} + \boldsymbol{\gamma_s} + \boldsymbol{\delta_t} + \boldsymbol{\epsilon_{it}} \qquad (4)$$

where “ALL RC including NC” is a binary variable that is equal to 1 if a firm uses all RCs and 0 if a firm uses all RCs except for non-competes. In this comparison, we only keep firms that either have all four RCs or firms that have all RCs except for non-competes.

If non-competes are associated with higher wages, we expect a positive coefficient on this variable, indicating that when firms go from three RCs (that do not include non-competes) to four RCs, employees exhibit higher wages alongside the use of non-competes. In other words, we expect the presence of a non-compete to be correlated with higher compensation, consistent with the idea that firms may offer higher wages in association with the mobility restrictions linked to non-competes.

The coefficient on the relevant variable “All RCs including NC” is positive but statistically insignificant across all columns, consistent with our previous results showing that employees are not systematically associated with higher wages when signing a non-compete clause.

Table 8: Difference in firms’ wage between firms with all RCs and those with all except non-competes

	All firms All years	All firms 2022 & 23	SME All years	SME 2022 & 23	Large All years	Large 2022 & 23
All RCs including NC	0.02	0.04	0.02	0.04	0.00	0.03

	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.03)
Full-time equivalent hours (lagged)	0.03***	0.03*	0.03**	0.03	0.04***	0.03**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Log of capital expenditure (lagged)	0.00	-0.01	0.00	-0.01	-0.01***	-0.01**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Log of labour productivity (lagged)	0.10***	0.08**	0.10***	0.08**	0.10***	0.06
	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.04)
Constant	10.86***	11.08***	10.88***	11.10***	10.30***	10.96***
	(0.24)	(0.33)	(0.24)	(0.34)	(0.32)	(0.51)
Observations	4,209	1,794	2,344	1,028	1,865	766
R-squared	0.33	0.38	0.33	0.38	0.47	0.46
Industry FE at 2 digits	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: BLADE analysis by Treasury. Each column incorporates industry and time fixed effects

Effect of omitted variable bias on the relationship between non-competes and wages

Another robustness that we undertake is to assess how sensitive our findings are to unobserved confounders, using the DMP method (Diegert, Masten, and Poirier, 2022), which is specifically designed to gauge how much omitted variables might affect our estimates. For more details on the methodology, refer to Diegert, Masten, and Poirier (2022).

The DMP approach creates bounds around our estimated effect, showing how the relationship between non-competes use and wages would change under different assumptions about unobserved influences. At the heart of the method is a sensitivity parameter r_X, which benchmarks how strong the selection on unobservables would need to be relative to the selection on observables (such as firm size, capital expenditure, or industry), to explain away the estimated association between non-competes and wages.

- If $r_X = 0$ this assumes no bias from unobserved confounders.
- As r_X increases, we assume unobservable factors are progressively more important.

A key output is the breakdown value, the r_X value at which the lower bound of the estimated positive association between non-competes and wages would cross zero, indicating a reversal of the observed relationship.

The value of r_X is used to calculate an upper and lower limit (a bias factor) for our coefficient of interest. If the relationship crosses zero (i.e. reverses signs) at r_X values very close to zero, then the estimated relationship is highly sensitive to omitted variables bias (that is, even when we assume that observable factors are not very important).

As shown in Table 9, the breakdown value for the association between non-competes and wages is low (0.04). This means that even a small influence from unobserved confounders could overturn the estimated positive association with non-competes. Similarly, we do not find a robust negative association.

Overall, this analysis suggests that the (partial) positive relationship between non-competes and wages is highly sensitive to unobserved confounding, and we cannot conclude that firms that use non-competes are systematically associated with a wage premium. We do not find any evidence of a negative association. This is consistent with our previous results, which indicate that there is no compelling evidence that wages are positively associated with non-competes.

Table 9: Treatment effect bounds of non-competes on firms' average wage (all years, all firms)

$\bar{r}_X, \beta_r > 0$	Lower bound	Upper bound
0.00	0.04	0.04
0.08	-0.04	0.13
0.15	-0.13	0.22
0.23	-0.23	0.32
0.30	-0.34	0.43
0.38	-0.48	0.57
0.46	-0.67	0.76
0.53	-0.99	1.08
0.61	-1.86	1.95
Breakdown: 0.04	0.000	0.088

Time invariant nature of RCs

To examine whether non-compete usage reflects underlying firm heterogeneity, this approach relates non-compete adoption to persistent firm-level wage premia obtained from a wage equation estimated with firm fixed effects. If RC adoption reflects deeper and persistent characteristics of firms—such as business models, organisational culture, or managerial strategy—then we would expect RC usage to be associated with time-invariant components of firm wage-setting that are absorbed by firm fixed effects. In other words, beyond observable firm characteristics such as productivity, growth, and size, some firms may systematically pay higher or lower wages due to stable, unobserved attributes (Table 10).

This subsection examines whether restraint clause adoption reflects persistent firm characteristics. To examine the relationship between time invariant firm characteristics and the presence of RC, we first estimate an FE regression using firm-level data. The dependent variable in this regression is the logarithm of average wages, which we regress on key firm characteristics: turnover growth, the lag of the logarithm of labour productivity (LP), and the lag of the logarithm of FTE. Additionally, we control for time-fixed effects and industry-fixed effects to account for macroeconomic fluctuations and industry-specific wage determinants. Where γ_t represents time-fixed effects, θ_i are firm fixed effects and ε_{it} is the error term. The regression specification is as follows:

$$\boldsymbol{log(wage)_{i,t} = \beta_1 Turnover.Growth_{i,t-1} + \beta_2 \log(LP)_{i,t-1} + \beta_3 \log(\mathrm{FTE})_{i,t-1} + \gamma_t + \theta_i + \varepsilon_{it}} \tag{5}$$

The firm fixed effect θ_i represents the firm's persistent wage premium (or discount) relative to other firms after controlling for observable characteristics and macroeconomic conditions.

In the second step, we regress the estimated firm fixed effects on indicators for contemporaneous RC usage:

$$\boldsymbol{\hat{\theta}_i = \alpha + \mu \sum Rc_i + J_i} \tag{6}$$

Where $\hat{\theta}_i$ is the estimated FE. $\mu \sum Rc_i$ control for all the RCs and J_i is an error term.

If RC usage is significantly associated with $\hat{\theta}_i$, this suggests that firms adopting RCs systematically differ in their persistent wage-setting behaviour from firms that do not. This would imply that RC adoption reflects deeper, time-invariant firm characteristics rather than merely short-run responses to observable conditions.

Table 10: Relationship between firms' time invariant characteristics and RCs

	Model 1	Model 2	Model 1	Model 2
Dependent variable in 1st stage	Log of average wage $\log w_{it}$	Log of average wage $\log w_{it}$	Log of full-time equivalent employees $\log fte_{it}$	Log of full-time equivalent employees $\log fte_{it}$
Control variables in 1st stage	All	Excluding $\Delta turnover_{it}$	Excluding $\log fte_{it-2}$	Excluding $\Delta turnover_{it}, \log fte_{t-2}$
NDA	0.01*	0.01	1.25***	1.29***
	(0.01)	(0.01)	(0.06)	(0.06)
NC	0.05***	0.02**	0.24***	0.31***
	(0.01)	(0.01)	(0.07)	(0.07)
NSC	-0.01	0.01	-0.52***	-0.53***
	(0.01)	(0.01)	(0.08)	(0.08)
NSW	0.05***	0.06***	0.98***	0.95***
	(0.01)	(0.01)	(0.08)	(0.08)
Observations	9,552	9,607	9,552	9,607
R-squared	0.02	0.01	0.11	0.11
Industry FE at 2 digits	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: BLADE analysis by Treasury. Each column incorporates industry and time fixed effects

The results indicate that RCs are statistically significant in explaining firm fixed effects. Therefore, it appears that RC usage is associated with the time-invariant characteristics of firms in Australia. One interpretation of this finding is that certain types of firms are inherently more likely to implement RCs, potentially due to their business models, workforce composition, or strategic considerations. An alternative interpretation is that RC usage is correlated with firm-level practices that persist over time.

Therefore, we can say that there is evidence consistent with a time-invariant nature of RC usage in Australia.

This analysis strengthens the policy relevance of our findings: it suggests that some firms — or segments within certain industries — may systematically rely on restrictive clauses as a core feature of their wage-setting architecture. This may be driven either by a strategic intent to limit competition in their market area, by management practices, firm level habits or by the routine inclusion of non-compete clauses in employment contracts, thereby being associated with reduced worker mobility by default. In either case, the findings point to a potential role for regulatory intervention, and suggest that policy design could consider these deeper, structural drivers of RC usage.

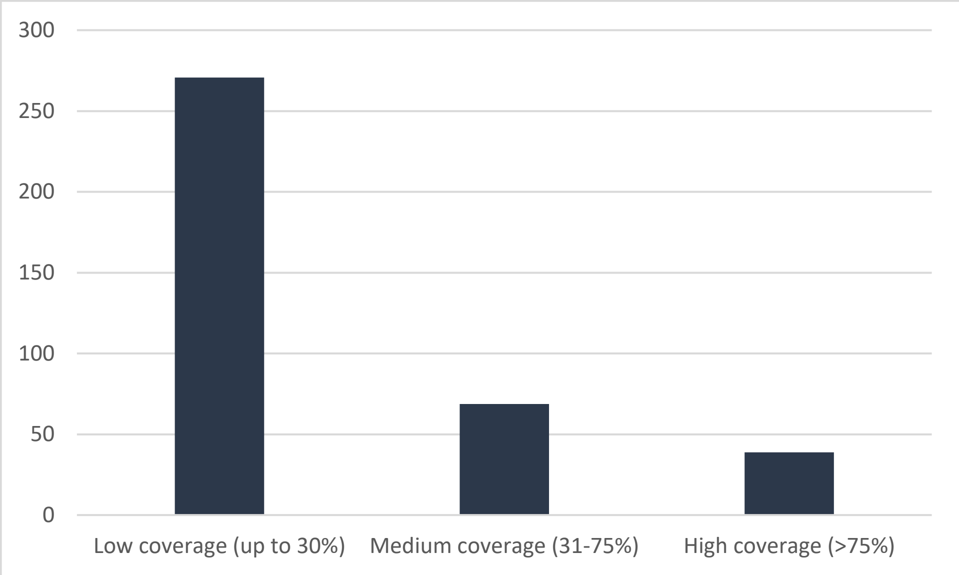
Coverage of non-competes by size

As there is heterogeneity in the coverage of non-competes, we can also explore the how the intensity of usage varies with different attributes of the firm. This can help us assess whether non-compete usage is more widespread in firms with features which better justify broad usage, such as a significant portion of the workforce in high-skilled, knowledge intensive roles.

To start, Figure 4 illustrates the relationship between the percentage of employees covered by non-competes and firm size. Firms that apply non-competes selectively, with lower coverage (up to 30 per cent) tend to be larger. In contrast, firms that implement non-competes more broadly tend to be smaller, as reflected in lower FTE counts across medium (31–75 per cent) and high non-competes coverage (more than 75 per cent)[4]. This pattern may be consistent with larger firms, with dedicated HR departments, being better equipped to apply non-competes selectively, while smaller firms may be more likely to adopt a blanket approach to minimise the administrative costs of negotiating individual contracts.

4 The survey reports non-compete coverage in uneven percentage bands; we therefore consolidate these into low, medium and high categories to obtain more comparable groupings.

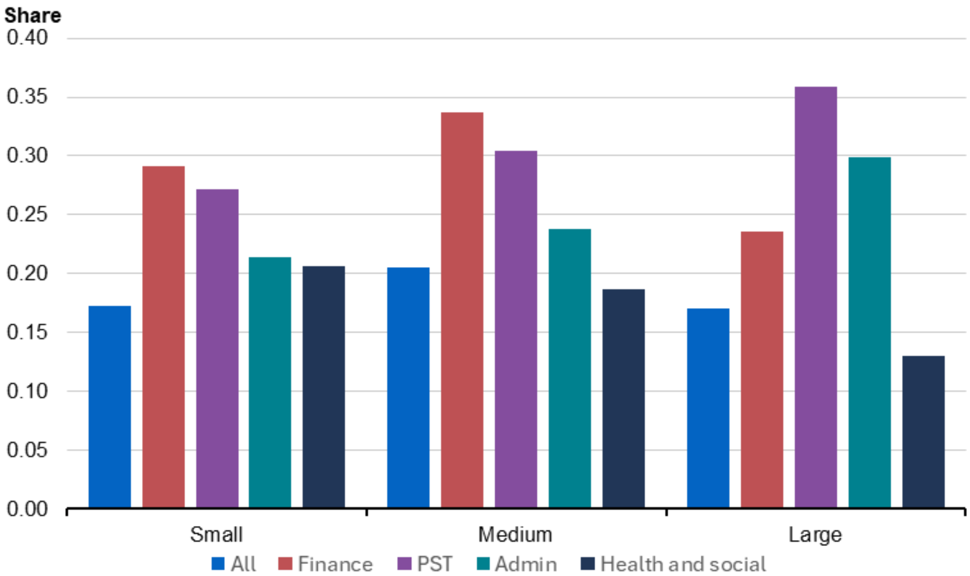
Figure 4: Firm size (FTE median) by coverage.



Note: Only firms with non-competes included

Usage of high coverage non-competes varies significantly by industry. From Figure 5 we can see that that high-coverage of non-competes is more common in finance and insurance services, professional scientific and technical services, administrative support services, and health care and social assistance. For all but health care, this is true across small, medium, and large firms. However, for health care and social assistance, it is less common for medium and large firms to have high coverage in non-competes.

Figure 5: Share of firms with a high-coverage (75%+) of non-competes



To further understand patterns in the coverage of non-compete clauses, we examined the occupations of employees in firms that responded to the SSEC survey. A plausible prior under efficient contracting is that non-compete coverage is higher in firms with more high-skilled and specialised workers, reflecting the greater need to protect firm specific human capital, training investments, and proprietary knowledge (Starr, 2026). We looked at two features: the occupational diversity within the firm (the ratio of distinct occupations to the number workers[5]), and the share of employees in occupations with the highest skill level under the ANZSCO system[6].

We regress the variable of interest (occupational diversity or high-skilled share) on interacted size and coverage categorical variables, in addition to industry fixed effects (Equation 7). This allows us to examine means by size and coverage cohorts, controlling for between-industry variation.

$$\boldsymbol{C_i = \beta_0 + \beta_1 NC\ coverage_i + \beta_2 size + \beta_3 NC\ coverage_i * size + \gamma_s + \epsilon_{it}} \tag{7}$$

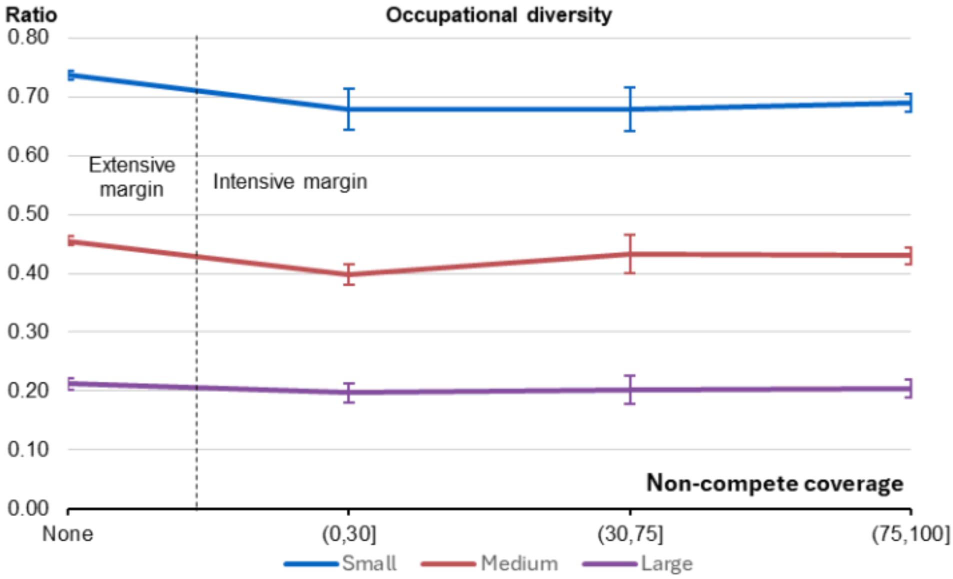
Here C_i is either occupational diversity or high-skilled share. The margins plots from these regressions are presented below.

A plausible prior is that higher usage of non-competes is likely to be associated with lower diversity, as a lack of diversity may signal greater specialization of knowledge and hence a stronger need to protect specialized training. However, in Figure 6, we find no meaningful relationship between occupational diversity and the level of non-compete coverage in the firm.

5 Using this measure, 1 represents the maximum possible diversity in occupations, with each person reporting a different occupation. The measure approaches zero in firms that have employees of only one occupation.

6 The skill level of an occupation is a function of the range and complexity of the set of tasks performed. Skill Level 1 occupations have a level of skill commensurate with a Bachelor Degree or higher qualification. At least five years of relevant experience may substitute for the formal qualification.

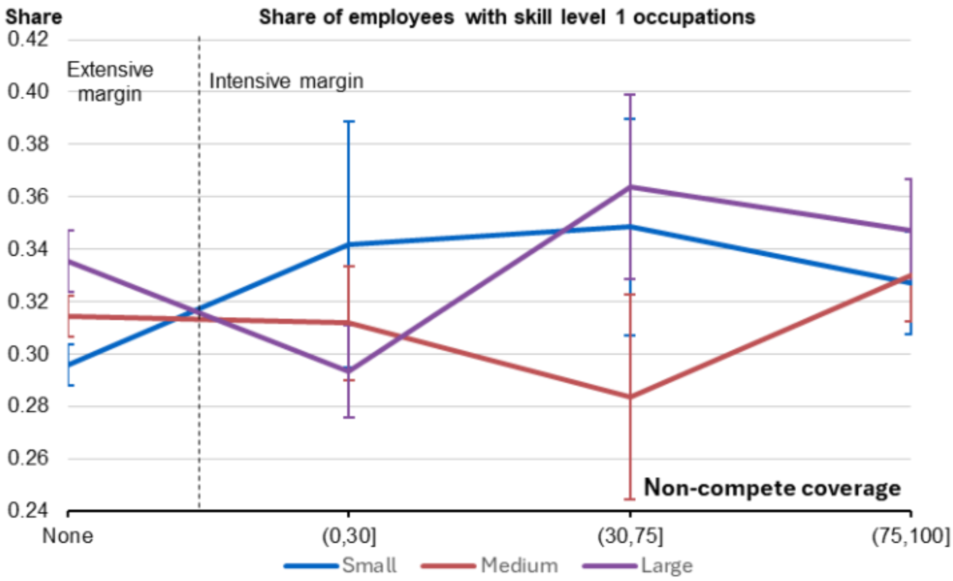
Figure 6: Occupational Diversity by non-compete coverage



Looking at the share of highest-skilled employees in Figure 7, we find that for small and medium-sized firms the share of high-skilled employees does not differ meaningfully across non-compete coverage ranges. That is, small and medium firms with a larger share of high-skilled employees do not appear to apply non-competes more broadly than those with lower shares of high-skilled employees.

However, for large firms, those that use non-competes more selectively—applying them to 30% or fewer of employees—exhibit a lower average share of high-skilled employees compared with other large firms. Taken together, these patterns suggest that non-compete coverage is not closely aligned with the concentration of the most highly skilled workers, calling into question whether broad or blanket use of non-competes is primarily motivated by the protection of specialised human capital.

Figure 7: High-skilled employee share and non-compete coverage



6. Policy implications based on the results

This paper provides robust evidence suggesting a clear rationale for government intervention on non-compete policy, based on several grounds. First, while the framework of the paper demonstrates that firms should compensate workers for the mobility restrictions imposed by non-competes, the empirical analysis finds no systematic associated evidence that such compensation occurs in practice.[7] This suggests that there may be a substantial gap in wage compensation for a large segment of workers.

Second, the framework highlights how market failures — particularly those stemming from bargaining power imbalances and information asymmetries — can be associated with welfare losses for large segments of the workforce, especially among more vulnerable workers.

Third, the prevalence of non-competes in non-innovative, low-productivity firms suggests that many clauses are not being used to protect trade secrets or firm-specific investments but may instead be associated with efforts to reduce staff turnover — often without corresponding compensation. In some of these cases, non-competes may be consistent with anti-competitive behaviour.

Further, we find some evidence that smaller firms may be applying non-competes in a blanket fashion — potentially to minimise contracting costs — rather than tailoring their use to specific roles.

Finally, we find that non-competes usage reflects persistent, time-invariant firm characteristics, suggesting that some employers embed non-competes into business models or organisational practices rather than designing the clause based on the specific features of the job. This blanket approach to non-compete usage within a firm weakens the case for relying solely on market discipline or private contracting to ensure efficient use. Taken together, these findings suggest scope for a targeted regulatory intervention.

7. Conclusion

How to regulate non-compete clauses has become a pressing policy question across OECD economies. In settings where non-competes are widespread but weakly justified, are workers adequately protected? And could governments play a more active role in regulating or restricting non-competes where their economic rationale is unclear? As several countries consider regulatory action, this paper provides timely evidence from Australia to inform that debate.

New data has revealed that non-competes are more pervasive than previously understood and have a high prevalence in sectors with little evidence of trade secrets or firm-specific capital. In parallel, a growing body of research has documented their potential to impact workers' welfare, limit mobility, and distort market competition.

7 This general finding is not inconsistent with compensation being paid for non-competes in some industry settings. For example, it is well documented that firms in the financial services sector expressly provide compensation for the non-compete lay-off periods in their employment contracts. See: Australian Financial Markets Association; Managed Funds Association, Submissions to the Competition Review's Issues Paper, 2024.

In a competitive labour market, mobility restrictions such as non-compete clauses would be expected to be accompanied by compensating wage differentials, reflecting workers' loss of outside options. However, market frictions — including asymmetric bargaining power, incomplete information, and administrative costs — are likely to limit workers' ability to secure such compensation for reduced mobility.

Empirically, we examine whether this benchmark prediction holds in Australian data. This paper explores the association between non-competes and Australian wages, using linked survey and administrative data. Across multiple samples and estimation strategies — including comparisons of firms with and without non-competes, coverage-based analyses, different samples and sensitivity checks — the paper finds no systematic evidence that non-competes are associated with a wage premium. While non-competes may be linked to higher wages in a subset of high-productivity firms, for most workers, these clauses appear to restrict labour market mobility without any clear positive association with wages.

We document substantial heterogeneity in non-compete coverage and examine how it varies with firm size, industry, workforce skill composition, and occupational diversity, with little evidence of alignment with skill-based explanations. The paper also contributes methodologically by demonstrating a set of robustness and sensitivity checks that can be applied when clause data are observed at only a single point in time, helping to assess the stability of descriptive associations in the absence of causal identification.

Data disclaimer: The following data disclaimer should be noted: the results of these studies are based, in part, on Australian Business Registry (ABR) data supplied by the Registrar to the ABS under A New Tax System (Australian Business Number) Act 1999 and tax data supplied by the Australian Taxation Office (ATO) to the ABS under the Taxation Administration Act 1953. These require that such data are only used for the purpose of carrying out functions of the ABS. No individual information collected under the Census and Statistics Act 1905 is provided back to the Registrar or ATO for administrative or regulatory purposes. Any discussion of data limitations or weaknesses is in the context of using the data for statistical purposes and is not related to the ability of the data to support the ABR's or the ATO's core operational requirements. Legislative requirements to ensure privacy and secrecy of these data have been followed. Only people authorised under the Australian Bureau of Statistics Act 1975 have been allowed to view data about any particular firm in conducting these analyses. In accordance with the Census and Statistics Act 1905, results have been confidentialised to ensure that they are not likely to enable identification of a particular person or organisation.

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Appendix

Firm's characteristics for key restraint clause bundles

Table A 1: Firm characteristics for key restraint clause bundles

	All RC except NC	All including NC
Count	170	791
Labour productivity ($AUD)		
Mean	378,811	559,274
Median	202,097	262,271
Standard deviation	479,798	1,096,855
Average wage ($AUD)		
Mean	165,778	98,328
Median	70,414	80,258
Standard deviation	1,112,811	163,946
Full-time equivalent workers		
Mean	678	1,098
Median	94	112
Standard deviation	1,947	3,179

Note: Table shows summary statistic for the sub-sample of firms who used all four clauses (col2) and those who used all except non-competes (col1). Firms using all restraint clauses exhibit higher median labour productivity ($262,271) than firms that exclude non-competes ($202,097). This suggests that firms implementing non-competes, alongside other restraint clauses, on average tend to be more productive than those that do not. Similarly, firms that impose all restraint clauses report a higher median wage ($80,258) than firms that impose the other restraint clauses excluding non-competes ($70,414). However, these labour productivity gains and wage premia are not uniform, as dispersion is high across all groups.

Restraint clauses and wage growth

To examine whether restraint clauses are associated with wage growth, we repeat the regression (1) with the one-year growth in firms' average wages as the independent variable instead of log average wages.

Table A2: Relationship between firms' wage growth and RCs

	All firms All years	All firms 2022 & 23	SME All years	SME 2022 & 23	Large All years	Large 2022 & 23
NDA	0.02	0.03*	0.02	0.03*	0.02	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
NC	0.01	0.02	0.01	0.02	-0.02	0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
NSC	-0.03	-0.07	-0.03	-0.07	0.01	-0.01

	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)	(0.02)
NSW	0.02	0.03	0.02	0.03	-0.01	0.01
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Log of full-time equivalent hours (lagged)	0.00	0.00	0.01	0.00	0.04**	-0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)
Log of capital expenditure (lagged)	-0.00	-0.00	-0.00	-0.01	-0.00	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log of labour productivity (lagged)	-0.02***	-0.01	-0.02***	-0.01	-0.05***	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Constant	0.25***	0.11	0.25***	0.12	0.47***	0.23
	(0.08)	(0.12)	(0.08)	(0.12)	(0.15)	(0.17)
Observations	12,358	5,302	8,486	3,696	3,872	1,606
R-squared	0.03	0.04	0.03	0.04	0.08	0.10
Industry FE at 2 digits	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Combined effect of RC1	0.07	0.05	0.07	0.05	-0.12	-0.10

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Except for NDA, we observe no significant association between wage growth and restraint clauses.