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The impact of labour mobility on innovation in Australia

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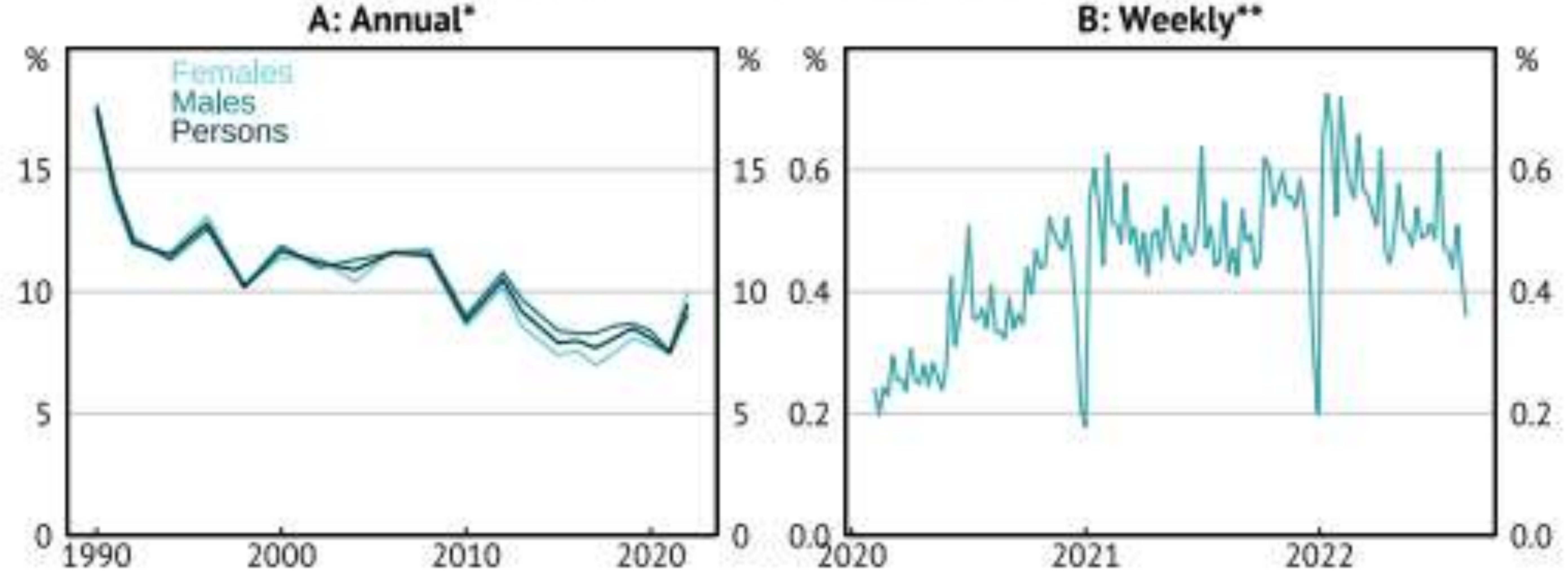
Declining Economic Dynamism

- Recent studies have highlighted declining economic dynamism in Australia, observed across many advanced economies, including reduced job switching rates and reduced competition for labour among established firms (Hambur, 2023)
- Higher rates of retention and lower in-bound employment transitions for workers in patent-holding firms compared to workers in non patent-holding firms.

Figure 1: Job-to-job Transition Rates



* Share of employed workers who changed jobs in the past year; data are from the ABS Participation, Job Search and Mobility (PJSM) survey.
** Share of employed workers who changed jobs in the past week; data are from Single-Touch Payroll.
Sources: ABS; e61 Institute

Responses to declining economic dynamism

"Reforming non-compete clauses is about encouraging aspiration, unlocking opportunity, lifting wages, and making Australia's economy more dynamic and competitive."

- Competition reform banning non-compete clauses from new employment contracts in the US was at least partially predicated on evidence for how labour mobility affects innovation.
  - -increased rates of business formation in high-tech industries (Johnson et al., 2023)
  - -increased employment among spinouts (Starr et al., 2018)
  - -increased quality-adjusted patenting rates (Johnson et al., 2023)

- Enabling innovation, particularly through patenting, is critical for productivity growth in Australia.

Knowledge spillovers

- Involve an entity benefiting from R&D of another entity.
  - FDI, Imports, Technology Transfer
  - Collaborations
  - Patents/ Scientific Publications
  - Human Capital Mobility
    - Spinouts
    - **Labour Mobility**

- A substantial body of literature highlights the positive role of knowledge spillovers in:
  - aggregate economic growth (e.g., Romer, 1986)
  - firms' R&D productivity (e.g., Jaffe)
  - technical efficiency (Lee et al., 2017)
  - product innovation (De Paris Caldas et al., 2021)
  - persistent innovation (Holl et al., 2022)
  - patent output (Myers and Lanahan, 2022)

Knowledge spillovers enhance the efficacy of public R&D investments.

- For every patent produced by firms receiving US government funding (Department of Energy), three more patents were produced by other firms that benefit from spillovers. (Myers and Lanahan, 2022)

- Firms receiving public R&D funding improve their performance and generate valuable productive knowledge. Firms which hired workers who directly participated in the funded program (through their previous firm) also benefited from an increase in firm performance (Castillo et al., 2019)

- Support the premise that the knowledge acquired through the exposure to innovation is embedded in human capital, has a recognizable market value, and is able to be transferred to other firms.

Research aims

- Assess impact of job switching on innovation protected by patents.
- Understand conditions where job switching can have stronger/weaker effects

Approach

- Quantitative analysis with linked employer-employee data on 1.6 million firms in Australia, between 2012 - 2021.
- Examine differences in firm-level patent applications dependent on the number of job switching employees, and variation across innovation capabilities and size of previous/future firm.

Employee mobility as a channel for knowledge transfer

- At a macro level, increased labour mobility generates better matching and extended networks, which increases knowledge flows between firms (Braunerhjelm et al. 2016, Drivas et al. 2020, Foster-Mcgregor & Pöschl 2016).

- At a firm level knowledge transfer can be facilitated by both the hiring of workers (the learning by hiring effect) and employee exits from the firm (the learning by diaspora effect).

The Learning by Hiring Effect

- New knowledge entering the firm can challenge existing processes, potentially providing new insights or business opportunities.
- New workers can also result in immediate transfers of technical knowledge – through either direct involvement or involvement via collaborators (Spender, 1996).
- Well documented outcomes across a number of countries and measures of innovation (Song et al. 2003, Kaiser et al. 2015, Braunerhjelm et al. 2018).
- Appears to be moderated by the innovation capabilities of the previous firm.
- Kaiser et al. (2015) and Braunerhjelm et al. (2018) find the effect is confined only to joiners from patenting firms, Foster-Mcgregor & Pöschl (2016) find a beneficial effect of labour mobility on industry productivity only when the worker is moving from high and medium-tech industries.

The Learning by Diaspora Effect

- Workers stay in contact with former co-workers, resulting in knowledge exchange among the firms' employees.
- Increased awareness of the worker's new employer as a source of knowledge - may result in closer attention to the firms' patents and other R&D activities.
- Corredoira and Rosenkopf (2010) and Agrawal et al. (2006) have shown an increase in bi-directional patent citations from both the firms losing workers and those gaining workers.
- Braunerhjelm et al. (2018) find no significant effect in Sweden of R&D workers leaving.
- Conversely, Kaiser et al. (2015) find a significant positive effect in Denmark of R&D workers leaving but only when the firm joined holds patents.

Hypotheses

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    - Greater importance of technical knowledge to innovation.
    - Soft skills of lower skill level workers are often highly firm-specific.
        - Even when complementary to innovation may not be transferrable between firms.
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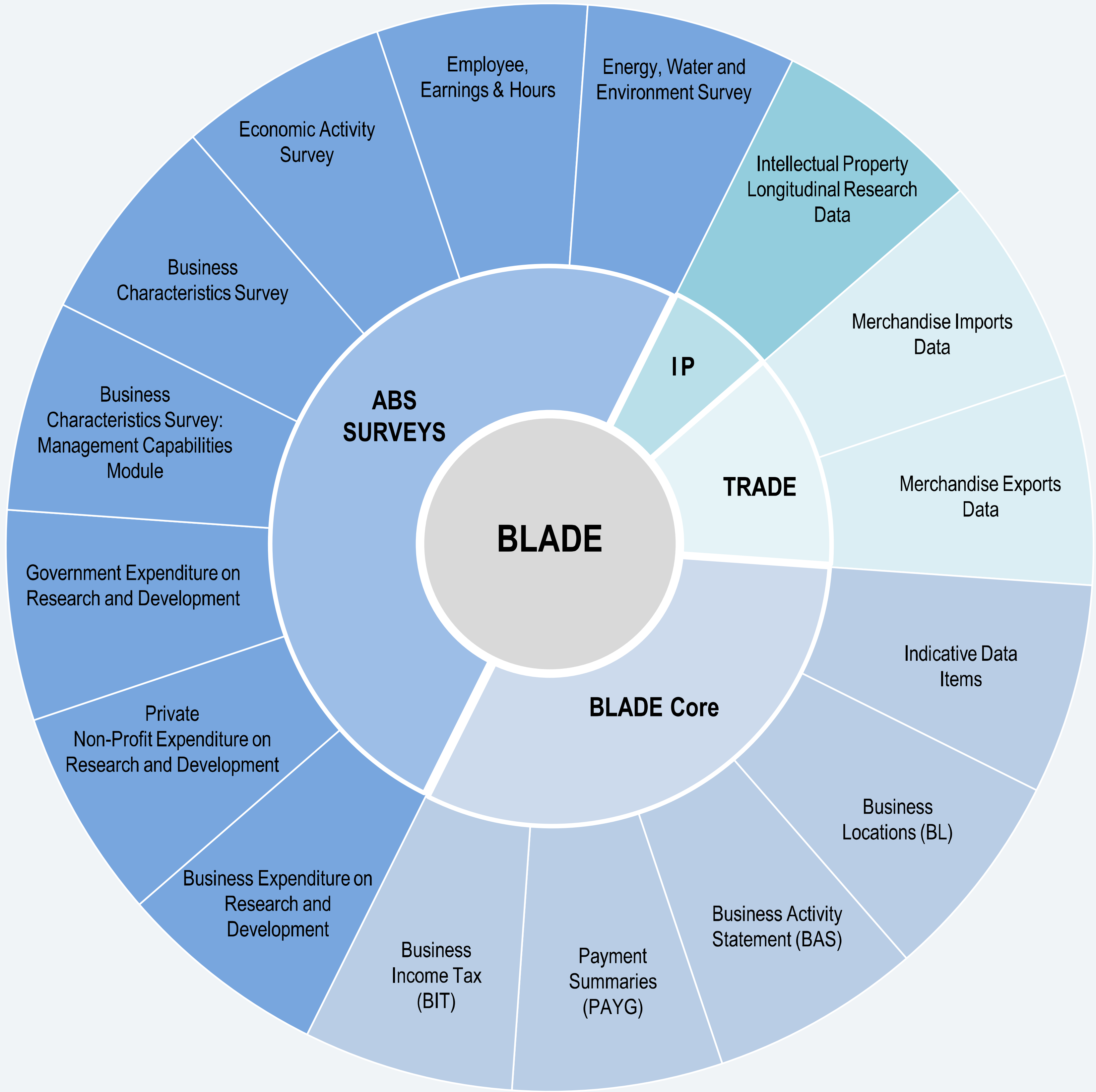
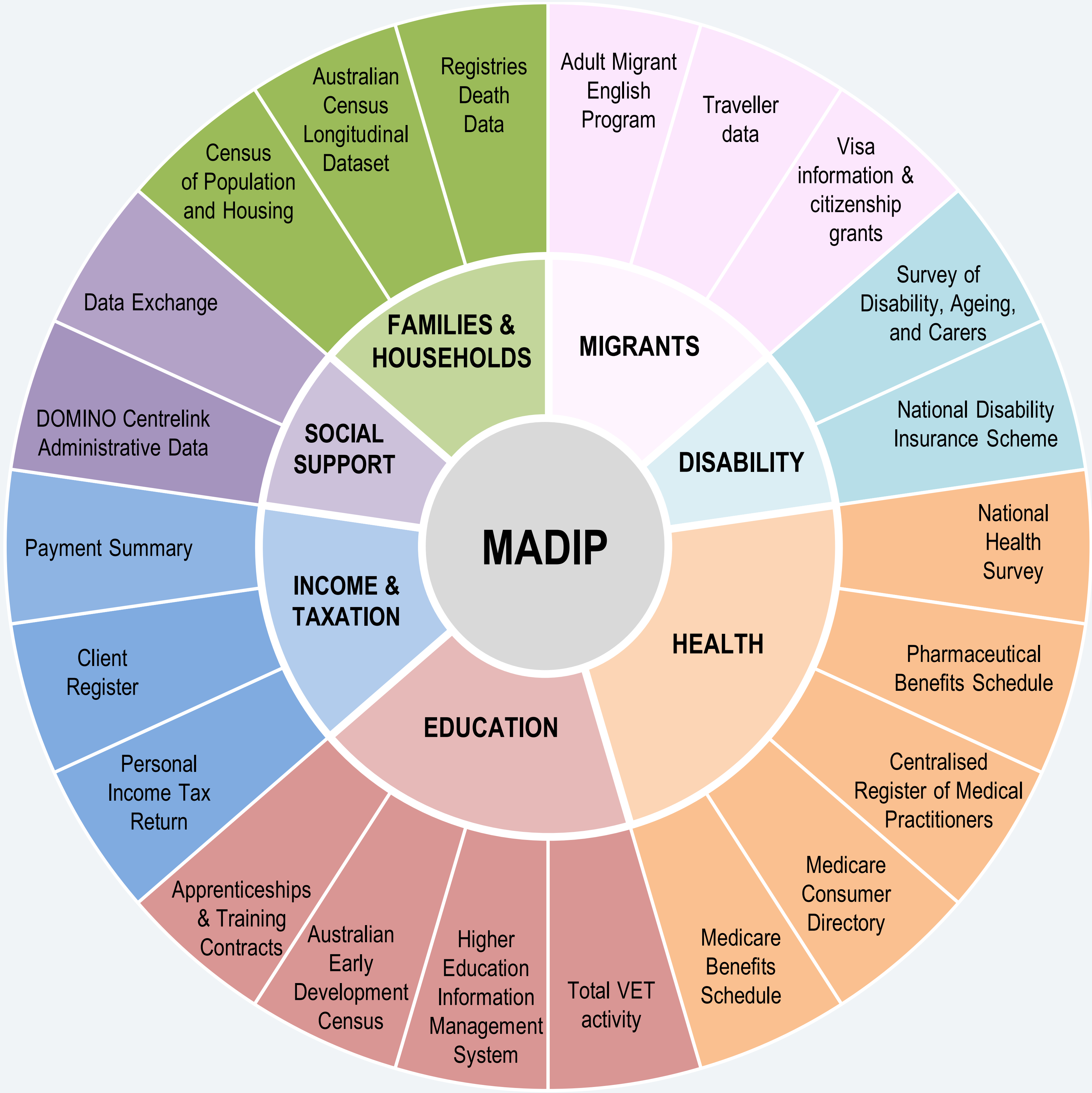
- Employee mobility by workers to/from SMEs will have more pronounced knowledge transfers.
  - Employees in small firms are likely to have a greater involvement with the firm’s innovation activities, either directly or indirectly, via their collaborators.
  - Small firms also have denser networks of collaboration. This increases the employee’s ability to transfer knowledge derived from their collaborators, or even other employees within the firm (Tzabbar & Seo, 2022).
  - Knowledge transfer to small firms may be increased by weaker enforcement of their intellectual property and trade secrecy laws.

Linked employer-employee data from Australian Bureau of Statistics

- BLADE Dataset covering 1.6 million Australian businesses over the period 2002-2022 allowing the construction of pre-sample patenting activities.
- PLIDA Dataset includes complete information on 17.3 million individuals over 11 years (2012 – 2021).
- Build a linked employer-employer job-year level dataset, which enables identification of employees new to the firm and employees leaving the firm as well as the characteristics of their previous or future employer.

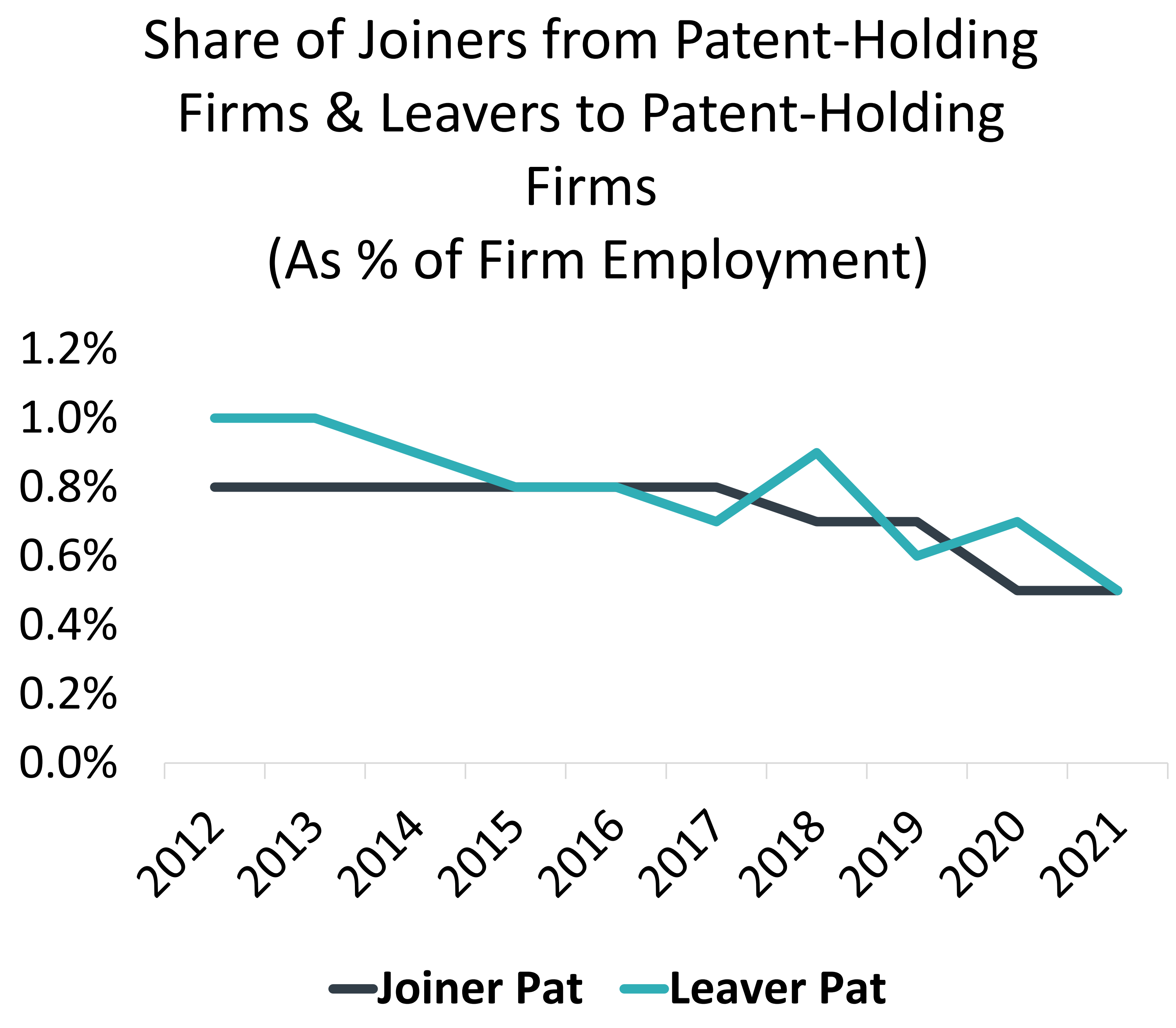


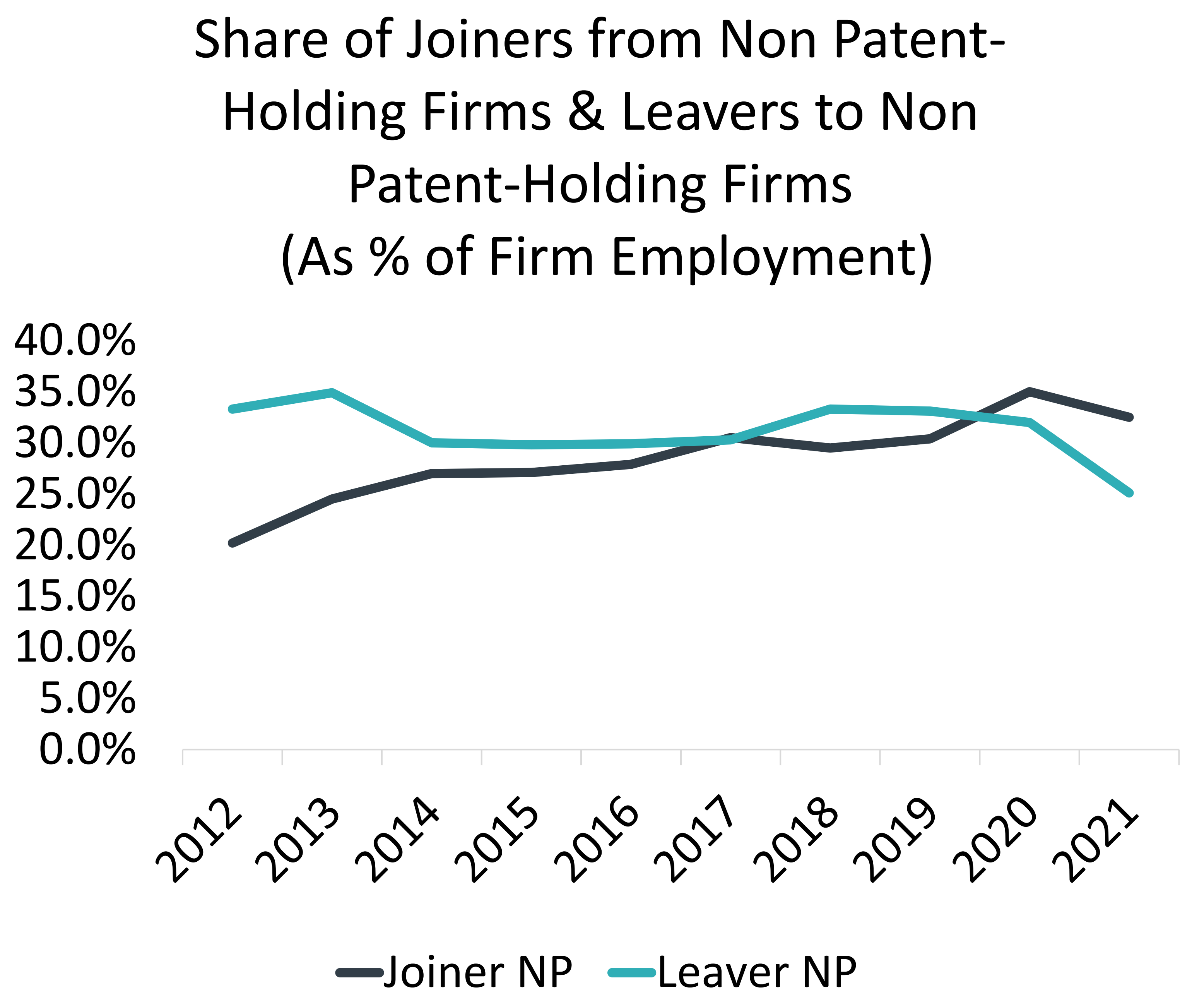


Firms Average Employment Dynamics

Stats	Employees	Stayers	Joiners	Leavers
Mean	20	13	7	7
Median	3	2	1	1

Firm Average Employment Dynamics by Year





Empirical Specification

- Follow Kaiser et al. (2015) and Braunerhjelm et al. (2018) building upon a Cobb-Douglas specification:

$$E(P) = exp\,(\,ln(A) + \alpha\, ln(QL) + \beta\, ln(K)$$

- Quality-adjusted labour is represented as an additive composite of different types of workers, and firm size acts as a proxy for capital stock, giving the base specification:

$$E(P) = \exp(\,\ln(A) + \alpha \ln(L) + \beta_{JP} \frac{L_{JP}}{L} + \beta_{JNP} \frac{L_{JNP}}{L} + \beta_{JN} \frac{L_{JN}}{L} + \beta_{LP} \frac{L_{LP}}{L} + \beta_{LNP} \frac{L_{LNP}}{L} + \beta_{LE} \frac{L_{LE}}{L}$$

- Approximate unobserved time-invariant heterogeneity using information on the firm's patenting behaviour prior to the start of the estimation period – dummy and count variables.
- Also include **year** and **industry** fixed effects

Selected Negative Binomial Regression Coefficients

Model	JL	JL x PAT	JL x Pat x Size
Pre-Sample Innovator (Dummy)	**3.682*** **	3.653***	3.645***
Pre-Sample Innovator (Count)	**129.6*** **	129.3***	126.8***
Ln (Employment)	**0.583*** **	0.585***	0.572***
Joiner (%)	**-0.562*** **		
Leaver (%)	**0.00628** **		
Joiner – New (%)		-1.084***	-1.020***
Leaver – Exit (%)		0.126***	0.289***
University Graduates (%)		1.005***	1.005***
Joiner - Patenting Firm (JP) (%)		3.666***	
Joiner - Non-Patenting Firm (JNP) (%)		-0.640***	
Leaver - Patenting Firm (LP) (%)		0.0176	
Leaver - Non-Patenting Firm (LNP) (%)		-0.00212	
JP - Large Firm (%)			2.977***
JP - Medium Firm (%)			5.803***
JP - Small Firm (%)			8.732***
JNP - Large Firm (%)			0.155
JNP - Medium Firm (%)			0.304
JNP - Small Firm (%)			-2.153***
LP - Large Firm (%)			0.0204
LP - Medium Firm (%)			0.0428
LP - Small Firm (%)			3.831***
LNP - Large Firm (%)			0.00269
LNP - Medium Firm (%)			0.0143
LNP - Small Firm (%)			-0.367***
Constant		-10.04***	-9.919***
Observations		3,736,125	3,736,125

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Transformed regression coefficients

Variable	Increase in expected patent filings associated with 10 p.p. increase in selected workforce cohort
Joiners (%)	-6%
Leavers (%)	0%
Joiners - Patenting Firm (%)	44%
Joiners - Non-Patenting Firm (%)	-6%
Joiners - Small Patenting Firm (%)	140%
Joiners - Medium Patenting Firm (%)	79%
Joiners - Large Patenting Firm (%)	35%
Joiners - Small Non-Patenting Firm (%)	-19%
Joiners - Medium Non-Patenting Firm (%)	
Joiners - Large Non-Patenting Firm (%)	
Leavers - Small Patenting Firm (%)	47%
Joiner - Skill level 1 (%)	37%
Joiner - Skill level 2 (%)	13%
Joiner - Skill level 3 (%)	-13%
Joiner - Skill level 4 (%)	-19%
Joiner - Skill level 5 (%)	-32%

Analysis – Main Findings

- Evidence suggests labour mobility plays a role in knowledge transfer - which is translating to patenting.
- Effect moderated by patent-status of previous firm suggests the impact is related to productivity/innovation enhancing labour reallocation rather than solely mobility.

Implications

- Slowdown in overall labour mobility less concerning (in this context), reduced mobility in and out of patenting firms even more concerning.
- Conditions which promote labour mobility (removal of non-compete clauses) may be beneficial to innovation and patent outcomes.
- Industrial/Innovation policies which grow the number of knowledge-intensive firms in the economy, and the pool of workers employed in those firms, may improve the likelihood that labour mobility results in meaningful spillovers.

Analysis – Other Findings

- Stronger impacts of knowledge flows from small firms suggest internal collaborative density of the firm is important for knowledge spillovers.
- Conversely, talented workers may be leaving small firms which are unable to commercialise/patent new ideas.
- Small firms may also have weaker enforcement capabilities.

- Irrespective of patent-status, mobility of higher skilled workers is most beneficial to innovation.
- Positive effect of knowledge exchange offsetting loss of human capital?

Key Findings

- In Australia, firms with a higher proportion of new joiners (relative to a firm's existing employee base) tend to patent more, but only when those joiners have come from patenting firms.
- Joiners' impact is influenced by the size of their previous firm, with joiners from small patenting firms being most impactful.
- A higher proportion of Leavers shows few significant effects on patent outcomes, however leavers to small patent-holding firms have a significant positive effect.
- Joiners hired directly from university employment and recent university graduates also have significant effects on patent output.

Next Steps

- Explore causality through patent citations.
- Quantify economic significance of reduced labour dynamism.
- Impact of international mobility.
- Explore the impact of joiners at different stages of firm's life – e.g. Early joiners / startups initial teams.