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Identifying Peer Effects under Reflection: A Panel-Data Approach

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Abstract

We propose a new approach to identifying peer effects that addresses the reflection problem by using the timing of decisions. The approach combines panel data with the ordering of decisions to separate peer influence from simultaneity. Variation in the order of decisions and in exposure to peers provides the basis for identification, allowing estimation of peer effects in settings where standard approaches are not informative. We illustrate the method using a multi-level panel of more than 2,000 judicial rulings over a 16-year period, where cases are randomly assigned to judges. The data allow us to implement the approach and examine the sources of peer influence. We find heterogeneous and asymmetric responses, with both the magnitude and direction of effects differing across types.

JEL classification

C18, C23, C81, D85

Keywords

peer effects, reflection problem, judicial decisions

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1 Introduction

We develop an identification strategy for estimating heterogeneous and asymmetric peer effects in multi-level panel settings. The approach addresses the reflection problem —the challenge of separating mutual influence from correlated behaviour in network settings. It uses variation in how cases or tasks are assigned to decision-makers, along with the timing of decisions, to isolate peer effects. We illustrate the method using decisions by judicial officers adjudicating dismissal disputes in Australian labour courts. This setting is useful because the sequence of decisions is precisely observed and cases are randomly assigned. The application serves as an empirical illustration; the approach applies to a broad class of environments in which assignment and timing provide comparable variation.

A central difficulty in estimating peer effects is that individuals both influence and are influenced by others in their network, which complicates causal identification. This reflection problem arises in many settings including education, workplaces, and social interactions, where behaviour is observed simultaneously — that is, individuals both affect and respond to each other's actions— and sorting may confound inference.

In such settings, individual behaviour may depend not only on one's own characteristics but also on the behaviour and attributes of others in the relevant group. Following the literature on social interactions, these influences can be decomposed into endogenous effects (dependence on others' behaviour), exogenous or contextual effects (dependence on others' observable characteristics), and correlated effects arising from shared unobserved factors, see Manski (1993, 2000), Brock and Durlauf (2001). Distinguishing between these channels is important for both identification and interpretation, as they have different implications for policy. Endogenous effects are of particular interest because they can generate social multiplier effects.

A large literature studies peer effects in settings such as education, labour markets, technology adoption, health behaviour, and financial decision-making[1]. Many papers report patterns

[1]See for instance Sacerdote (2001), Lin (2010), Arcidiacono et al. (2012), for social interactions and educational achievement, Topa (2001) and Cornelissen et al. (2017) for labour market outcomes, Conley and

consistent with social influence, but credible identification remains challenging without variation that separates peer behaviour from confounding factors. This difficulty remains even in studies that use network structure, group composition, or instrumental variables (e.g., Lee (2007), Bramoullé et al. (2009)). It persists in settings with detailed data and motivates the search for identification strategies that address simultaneity directly and distinguish between different channels of interaction.

Peer effects are notoriously difficult to identify in the presence of simultaneity, especially in the linear-in-expectations framework, due to the reflection problem, endogenous group formation, and limited variation in networks, see Bramoullé et al. (2020). In many applications, however, simultaneity partly reflects how the data are recorded: individuals act at different points in time, but outcomes are observed jointly at discrete intervals, making behaviour appear simultaneous. Information on the timing of actions can therefore help address the identification problem.

In this paper, we propose an identification strategy based on this insight. By using the temporal ordering of decisions within a network, we can determine which outcomes precede others and thereby identify the direction of influence, avoiding the simultaneity that underlies the reflection problem. Unlike approaches that rely on network structure or external instruments for identification, our method uses the timing of decisions to separate peer effects from simultaneity and isolate endogenous behavioural responses. It also allows for heterogeneous and asymmetric effects, as well as time variation in interactions, making it possible to study how influence varies across individuals and over time. We illustrate the method using judicial decisions, but the approach applies more broadly to settings in which outcomes are repeatedly observed, interactions unfold over time and the assignment process provides usable variation. For instance, the method could be applied to identify peers effects in faculty staff productivity

Udry (2005) for learning new technologies, Lee et al. (2014) for smoking behaviour, and Bursztyn et al. (2014) and Breza and Chandrasekhar (2019) for financial and saving decisions. Studies have also looked at social effects behind macro-economic phenomena such as international trade (Chaney (2014)), spread of productivity shocks in the economy (Acemoglu et al. (2012)), knowledge spillover across regions (Autant-Bernard and LeSage (2011)), incidence of public policy (Besley and Case (2000)), tax competition between regions (De Paula et al. (2024), etc - see reviews by Paula (2017) and Bramoullé et al. (2020)

or herding effects among traders in financial markets.

The empirical implementation uses a multi-level panel dataset of more than 2,000 judicial decisions with precise timing. This allows us to construct sequential measures of peer behaviour based on the ordering of decisions and estimate a linear-in-means model using an extension of standard fixed-effects methods. The results show substantial heterogeneity in endogenous peer effects, highlighting the importance of allowing for such differences when modelling social interactions.

The remainder of the paper is organised as follows. Section 3 describes the data sources and key variables. Section 4 sets out the model and estimation strategy. Section 5 reports the empirical findings. Section 6 concludes.

2 Literature review

2.1 Identification and the reflection problem

The reflection problem remains a central obstacle in the estimation of peer-effects. When individual outcomes and peer behaviour are observed at the same time, it is difficult to determine whether peers influence the individual or the individual influences their peers. As shown by Manski (1993) and subsequently by Moffitt (2001) and Angrist (2014), endogenous, exogenous, and correlated effects are not separately identified in certain classes of linear-in-means models without additional sources of variation.

A large literature has sought to overcome this problem by exploiting features of network structure or group composition. Bramoullé et al. (2009) and related work (De Giorgi et al. (2010), Laschever (2013), and Bramoullé et al. (2020)) show that identification is possible in settings with sufficiently rich network structure, where individuals are not all connected to each other. Other approaches rely on variation in group membership, mobility across groups, or instrumental variables. While these methods have advanced the literature, they typically require strong assumptions on network formation, exogeneity, or the availability of

valid instruments, which may limit their applicability.

Panel data provide additional opportunities for identification, but do not by themselves resolve the reflection problem. A number of contributions develop estimators that exploit panel structure under specific restrictions. For example, Arcidiacono et al. (2012), Mas and Moretti (2009), and Cornelissen et al. (2017) identify contextual effects under assumptions on mobility and fixed effects. Their extensions that incorporate endogenous effects require additional exclusion restrictions. More recent contributions (e.g., Miraldo et al. (2020), Hong (2024)) allow for richer forms of interaction but rely on assumptions about network structure, error terms, or time-invariant interaction matrices. Estimation in these settings is often technically demanding and depends on the validity of these restrictions.

A related strand of the literature considers identification with unknown but stable network structures. De Paula et al. (2024), for example, use high-dimensional methods to show that endogenous and exogenous effects can be identified when individuals are repeatedly observed under a fixed interaction matrix. These approaches further expand the set of identifiable models, but continue to rely on assumptions about the stability of interactions over time. More generally, most existing strategies depend either on network structure, on exclusion restrictions, or on strong assumptions about the evolution of peer groups. In addition, all these approaches involve the use of complex algorithms in their estimation procedures (e.g., non-linear least squares, GMM, adaptive elastic-net GMM, etc).

Our approach differs by using the timing of decisions as a source of identification. By exploiting the order in which actions occur, we separate peer influence from simultaneity without relying on network structure or external instruments. This provides a simple and broadly applicable way of identifying endogenous peer effects in settings where individuals act at different points in time.

2.2 Applications to judicial decision-making

Our empirical application relates to a literature that studies peer effects in judicial decision-making. This work shows that judges' decisions depend on the characteristics and behaviour of their peers, with evidence from appellate courts indicating that panel composition can affect voting patterns and case outcomes (e.g., Kim (2009)).

Subsequent research has explored the mechanisms underlying these effects, distinguishing between deliberation, strategic behaviour, and broader group dynamics. In Freyens and Gong (2020), we study peer effects among the judges with the same data set, but we did not make full use of the data. These studies provide evidence consistent with peer influence, but face similar identification challenges arising from simultaneity, selection, and correlated effects.

In our setting, the combination of random assignment and precisely observed timing allows us to address these issues directly. While the judicial context is well suited to illustrate the approach, the identification strategy applies more broadly to environments in which interactions unfold over time and comparable variation is available.

3 Data

We use a dataset of 2,151 unfair-dismissal cases decided by around 80 commissioners of Australia's federal labour tribunals—Fair Work Australia (FWA) and its predecessor, the Australian Industrial Relations Commission (AIRC)—between 2000 and 2016. The data are constructed from electronic transcripts of decisions, which record case outcomes together with detailed information on the parties and case characteristics. The structure of the data is central to our analysis. Commissioners decide multiple cases over time, and for each decision we observe the exact date. This allows us to order decisions within peer groups and construct sequential measures of peer behaviour. These measures vary within peer groups as decisions accumulate over time. Commissioners are observed repeatedly, which yields a multi-level panel in which decisions are nested within individuals and time periods. Two institutional features are particularly important for identification. First, cases are assigned to commission-

ers through roster systems that approximate random allocation. The assignment process is administrative and does not depend on case characteristics or commissioner preferences. This limits concerns that case characteristics are systematically matched to particular decision-makers. Second, commissioners hold tenured positions and their mobility across jurisdictions is limited, which reduces concerns about endogenous network formation. We define peer groups at the level of state jurisdictions. Commissioners are assigned to one of five state panels—New South Wales, Victoria, Queensland, South Australia, and Western Australia—and interact primarily within these groups. This reflects the organisation of the tribunal system, in which cases are lodged, allocated, and decided within state divisions. We treat these state panels as reference groups within which peer influences may arise. We further partition peer groups into distinct "camps" based on judicial background—specifically, whether commissioners previously held union affiliated roles (Unionists) or not (Non Unionists). This classification enables us to examine potential heterogeneity in peer effects, including whether decisions made by peers from different camps exert differential influence on commissioners within the same camp or across camps. In Figure 1, we illustrate the structure of our data using a hypothetical panel with three commissioners (A, B, and C) observed over three periods. The periods are of fixed length—for example, a quarter, half year, or year. Each commissioner decides an uneven number of cases across periods (represented by the dots), and for each decision we observe the exact date. For instance, Commissioner A decides 4, 3, and 2 cases in Periods 1, 2, and 3, respectively. In this example, Commissioners A and B share similar professional backgrounds and therefore belong to the same "camp." This setup allows for the possibility that peer influences may differ depending on whether peers come from the same or different camps. Within each reference group, we observe the timing of decisions at a fine level. Although commissioners decide cases at different points in time, researchers often analyze outcomes within discrete periods (such as half-years). Using the exact timing of decisions, we construct measures of peer behaviour based on decisions that precede a given case within the same peer group and period. These sequential measures form the basis of our identification strategy. The main outcome variable is whether a case is decided in favour of

the employee. We also observe a set of case-level characteristics that may affect decisions, including indicators of summary dismissal, measures of employee skill, and the types of claims advanced by the parties. These variables vary across cases and over time and are included as controls in the empirical analysis. Table 1 summarises the composition of the data. Over the sample period, an average of around 47 commissioners decide approximately 77 cases per half-year. The composition of peer groups evolves slowly over time, reflecting infrequent entries and exits of commissioners. Changes in legislation and in the composition of commissioners imply that the interaction environment may not be strictly constant over long horizons. The institutional environment changed over the sample period, including two major reforms in 2005 and 2009 that affected the scope of unfair dismissal protection. These changes influenced both the volume of cases and overall decision patterns. In the empirical analysis, we allow for time variation to account for such shifts. However, these changes occur gradually. We therefore treat peer groups as fixed within short time intervals and allow interactions to vary across periods. Within each period, we assume that decisions may be influenced by earlier decisions within the same group but not by those that occur later. Finally, we include peer-group averages of case characteristics to account for contextual effects. Given random assignment of cases and the inclusion of time-varying controls, we expect such effects to be limited, but their inclusion helps ensure that estimated peer effects are not driven by common shocks within groups.

4 Model

4.1 General settings of the linear-in means models

A standard cross-sectional linear-in-means model takes the form

$$y_i = \rho \bar{y}_{(i)} + \gamma \bar{\mathbf{X}}_{(i)} + \beta \mathbf{X}_i + \epsilon_i. \tag{1}$$

where the outcome y_i of individual i in the reference group N_i she belongs to is assumed to be determined by 1) her own characteristics $\mathbf{X}_i$, which is a vector of K variables, 2) the average outcome of her reference group except herself $\bar{y}_{(i)} = \frac{1}{m_{ij}-1}\sum_{j\in N_i} y_j$ (where mij is the number of peers in i's network), 3) the average characteristics of her reference group $\bar{\mathbf{X}}_{(i)} = \frac{1}{m_{ij}-1}\sum_{j\in N_i} \mathbf{X}_j$ bar herself, and 4) unobserved errors. This model assumes that the social network matrix is known and the peers exert the same influences on individuals. The parameter ρ represents the 'endogenous' network effect, and γ represents the contextual network effect. If the error term ϵ_i is correlated with those of the other individuals, there are also correlated peer effects in the model. In this model, because individual outcomes are observed simultaneously and the identification conditions (e.g., those discussed in Bramoullé et al. (2020)) are satisfied, Equation 1 can be estimated by instrumenting the endogenous variable $\bar{y}_{(i)}$ with higher-order peer outcomes, such as the outcomes of peers-of-peers.

In the context of standard panel data, where individuals are observed over multiple periods but only once in each period, the model can be expanded to

$$y_{i,t} = \rho_y \bar{y}_{(i),t} + \gamma_x \bar{\mathbf{X}}_{(i),t} + \beta_x \mathbf{X}_{i,t} + \alpha_i + \gamma_\alpha \bar{\alpha}_{(i),t} + \epsilon_{i,t}, \tag{2}$$

where α_i is the time-invariant individual fixed-effect, and $\bar{y}_{(i),t} = \frac{1}{m_{ij,t}-1}\sum_{j\in N_{i,t}} y_j$. $\bar{\mathbf{X}}_{(i),t}$ and $\bar{\alpha}_{(i),t}$ are similarly defined. Three points are worth noting. First, as discussed in Bramoullé et al. (2020), identification generally becomes easier when more information is available. For instance, one can reasonably assume that correlated effects operate only through individual fixed effects, with no cross sectional correlation in $\epsilon_{i,t}$. Second, in this setting the social network matrix is typically time-varying unless the underlying network remains completely unchanged over time. Third, when the network matrix varies over time, the corresponding time-varying and unobserved term $\bar{\alpha}_{(i),t}$ cannot be easily eliminated through standard transformation. This is why various restrictions have been imposed to make the model estimable. A common assumption is that the social network matrix is time-invariant, though this becomes unrealistic in panels spanning long periods. De Paula et al. (2024) instead assume that

correlated effects take the form of "common shocks," such that $\bar{\alpha}_{(i),t} \equiv \alpha_t$. Even with these restrictive assumptions in place, the model still requires complex estimation procedures to get consistent estimates due to the reflection issue.

4.2 Our model

Definitions and notations of terms

Suppose we observe Commissioner i deciding C_i cases in total. The variable y_{i,c_i} is the outcome of the c_i-th case by Commissioner i. It indicates whether the commissioner awards the case to the employee (the plaintiff $y = 1$) or the employer (the defendant, $y = 0$). The date of the decision is denoted $d(i, c_i)$. All the cases are ordered such that if $c_i < s_i$, then $d(i, c_i) < d(i, s_i)$. The cases fall into one of the pre-defined periods t ($t = 1, \ldots, T$) of equal length tl, during which the reference group and environment can be assumed to be reasonably stable. We choose $tl = 180$ days for our benchmark specification, but we also estimate models using several alternative window lengths to assess the sensitivity of the results: 90, 120, 150, and 210 days, respectively. Denote the starting and ending days of Period t as b_t and e_t, respectively, a case is included in the period if $b_t < d(i, c_i) < e_t$. During each period t, the total number of cases decided by Commissioner i is $n_{i,t}$. The total number of cases decided by Commissioner i is thus $\sum_{t=1}^{T} n_{i,t} = C_i$. We make the following assumptions about the reference group and the set of cases they have decided that may affect the commissioner and the case under consideration.

Assumption 1: Commissioners are considered peers of Commissioner i in Period t if they were already on the panel at the start of that period. That is, 1) commissioners who join the panel during Period t are not treated as peers of the existing commissioners, whereas 2) commissioners who leave the panel during Period t continue to be regarded as peers for that period. In each period t, the panel therefore consists of m_t incumbent commissioners.

Assumption 2: The outcome of any case c_i handled by Commissioner i may potentially be influenced only by cases decided before it, within a reference period tc_{i,c_i} of fixed length tc and

only by commissioners in her reference group [2]. For example, for case c_i, this reference period is $[d(i,c_i) - tc, d(i,c_i))$. Suppose case c_i is decided in Period t, during which Commissioner j is in Commissioner i's reference group. Then all cases c_j decided by Commissioner j that satisfy $d(i,c_i) - tc < d(j,c_j) < d(i,c_i)$ $(c_j = 1, \ldots, C_j)$ are assumed to potentially affect the outcome of case c_i.

Assumption 3: The influence of each peer j on the case of interest c_i operates through the average outcome of all cases decided by j within the reference period of case c_i. Denote the average outcome by Ey_{j,c_i} and define it as:

$$Ey_{j,c_i} = 1/n_{j,c_i} \sum_{c_j \in tc_{i,c_i}} y_{j,c_j}$$

where n_{j,c_i} is the number of cases decided by Commissioner j within the reference period of case c_i. The averages of the case characteristics (e.g., EX_{j,c_i}) are defined in the same manner. We assume that each commissioner's decision depends on both observed and unobserved characteristics of the cases, the decisions made by their peers on earlier cases, the composition of cases decided by different groups within their reference panel, and time-varying unobserved heterogeneity. Formally, the decision making process is represented by the following model:

$$y_{i,c_i} | \{d(i,c_i) \in \ t\} = \rho_y \bar{Ey}_{(i),c_i} + \gamma_x \bar{\mathbf{EX}}_{(i),c_i} + \beta_x \mathbf{X}_{i,c_i} + \eta_{i,t} + \epsilon_{i,c_i}, \tag{3}$$

where $\bar{Ey}_{(i),c_i} = \frac{1}{m_t - 1} \sum_{j \in N_{i,t}} Ey_{j,c_i}$ is the (moving) average of the Ey's over all peers of i (if she is one of the existing commissioners in the period, otherwise the factor would be $1/m_t$). The other $\bar{\mathbf{EX}}$ terms in the equation are defined similarly. The idiosyncratic error term ϵ_{i,c_i} is assumed to be uncorrelated with all other terms in the model as well as across cases.

The term $\eta_{i,t}$ represents an unobserved, individual-specific, time-varying effect but is fixed within each period. This term may be correlated with the observed covariates X, and it must be correlated both with the peer influence term Ey term and across individuals. The

[2] tc is assumed to be the same as tl in our model but in general they could be different

reason is that $\eta_{i,t}$ consists of two parts. The first is the commissioner's own true unobserved time-varying heterogeneity. The second is the influence of the average of peers' unobserved time-varying fixed effects – i.e., the unobserved part of the contextual effect.[3] This second component is necessarily correlated across commissioners, regardless of whether the first component is correlated across individuals. Since these two parts cannot be separately identified, $\eta_{i,t}$ captures them jointly. Compared with models such as De Paula et al. (2024), where correlated effects are restricted to time-invariant fixed effects or time-varying group-level shocks, the specification we describe here is more general.

The endogenous network effect is captured by ρ_y. Because the Ey term reflects outcomes of cases decided prior to y_{i,c_i}, it is predetermined. The contextual effects associated with contemporaneous case level characteristics are measured by the γ_x's. As mentioned earlier, since cases are randomly allocated to commissioners, these contextual effects should be insignificant. By transforming the data —subtracting each individual's period specific mean—we remove $\eta_{i,t}$ from Equation 3 and estimate the model consistently using OLS on the transformed data.

4.3 Heterogeneous and asymmetric endogenous network effects

Equation 3 imposes homogeneous and symmetric endogenous network effects, implying that each peer exerts the same influence. However, commissioners belong to two ideologically distinct groups—the Unionists and the Non unionists—and the influence they exert on one another may differ across and within these groups. To accommodate such potentially heterogeneous and asymmetric endogenous network effects, we extend the model to allow the strength of peer influence to vary by group affiliation. Specifically, we write:

$$y_{i,c_i}|\{d(i,c_i) \in t\} = \sum_{u=0}^{1}\{\rho_u^1 \bar{Ey}_{i,c_i}^u \cdot \mathbf{1}(U_i=1) + \rho_u^0 \bar{Ey}_{i,c_i}^u \cdot \mathbf{1}(U_i=0)\} + \tilde{\gamma}_x \bar{\mathbf{EX}}_{(i),c_i} + \tilde{\beta}_x \mathbf{X}_{i,c_i} + \tilde{\eta_{i,t}} + \tilde{\epsilon}_{i,c_i}. \tag{4}$$

Compared to Equation 3, the endogenous network effects are split into four components:

[3] If the first component is denoted $\alpha_{i,t}$, then the second component can be expressed as, e.g., $\gamma_\alpha \bar{\alpha}_{(i),t}$ where γ_α is the associated coefficient.

$u = 1$ indicates the Unionists, $u = 0$ indicates the Non-unionists and $\bar{Ey}^u_{i,c_i}$ are for the corresponding groups, the coefficients ρ^1_u $(u = 1, 0)$ are the endogenous network effects of reference group u onto a unionist commissioner, and ρ^0_u onto a non-unionist commissioner. That is, the impacts from the Unionist or Non-unionist peers are allowed to be different and depend on the camp the individual commissioner belongs to.

To summarise, the setting is similar to a standard spatial autoregressive panel data model, but with four key differences. First, the 'spatial lags' can reasonably be assumed to be uncorrelated with the contemporary error terms. Second, with multi-level panel data the inclusion of time-varying unobserved individual heterogeneity is controlled for. These two features are crucial to enable our stronger identification of endogenous effects relative to earlier, standard models. The third feature is that the model allows estimation of potentially heterogeneous and asymmetric network effects. Last but not least, the model can be estimated straightforwardly using OLS on the transformed data.

5 Results

Table 3 reports estimates of endogenous peer effects from Equations (3) and (4) under OLS and fixed effects specifications. The coefficient ρ_y captures the endogenous peer effect under homogeneity, while the coefficients ρ^q_u $(u, q = 0, 1)$ allow peer effects to differ across groups. The results are based on a reference period of half a year (180 days). Because peer behaviour is defined using the ordering of decisions within groups, these estimates isolate peer influence from simultaneity. The estimates differ markedly across specifications. OLS estimates show no evidence of peer effects, whereas fixed effects estimates indicate a significant negative effect in the homogeneous specification. This difference reflects the role of unobserved heterogeneity, which biases OLS estimates. Under the homogeneous model, the fixed effects estimate of ρ_y is negative and statistically significant, suggesting that higher peer propensity to award cases to employees is associated with a lower probability that a given commissioner does so. This finding is difficult to reconcile with a uniform influence across commissioners and

points to the limitations of imposing homogeneous peer effects. Allowing for heterogeneity changes the results substantially. The fixed effects estimates indicate that most endogenous peer effects are not statistically different from zero, with one notable exception: Unionist commissioners respond negatively to the decisions of Non-Unionist peers (ρ_0^1). In contrast, we find no significant response in the opposite direction. This pattern implies that peer influence is both heterogeneous and asymmetric, and that the negative effect in the homogeneous specification reflects the aggregation of these underlying differences. Estimates of own case characteristics, reported in Table 4, are broadly consistent with prior work. By contrast, the coefficients on peer averages of case characteristics are uniformly insignificant, indicating no detectable contextual peer effects through these channels. This is consistent with the random assignment of cases. Finally, we examine the sensitivity of the results to the length of the reference period. When the period is shortened to 90 days, the results remain broadly similar, although estimates are less precise. When the period is extended to one year, the peer effect estimates become insignificant. This pattern is consistent with the identification strategy: shorter periods preserve meaningful variation in the ordering of decisions, while longer periods weaken the assumption of a stable interaction environment.

6 Conclusions

This paper proposes an identification strategy for peer effects that addresses the reflection problem in panel settings. The approach uses information on the timing of decisions to separate peer influence from simultaneity and to estimate heterogeneous and asymmetric effects. We illustrate the method using decisions by commissioners in Australian labour courts. The empirical results highlight the importance of allowing for heterogeneity in peer effects: specifications that impose homogeneous responses yield patterns that are difficult to interpret, whereas more flexible specifications reveal systematic differences in how individuals respond to their peers. We also find little evidence of contextual peer effects, suggesting that influence operates primarily through observed decisions. More broadly, the approach

applies to settings in which individuals act over time and the timing of actions is observed. It provides a simple way to study peer effects in such environments and may be useful in a range of empirical applications. By showing how timing can be used for identification, the paper broadens the scope for credible empirical analysis of peer effects.

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Table 1: Number of Commissioners and cases per period by panel

	All		Unionists		Non-Unionists	
	Commissioners	Cases	Commissioners	Cases	Commissioners	Cases
Total	47.14	76.82	20.25	32.46	26.89	44.36
	(3.8)	(37.4)	(2.9)	(20.2)	(3.5)	(18.0)
NSW	15.46	23.68	6.64	11.82	8.82	11.86
	(1.6)	(10.7)	(1.8)	(8.9)	(1.2)	(3.6)
QLD	5.68	9.82	1.39	1.93	4.29	7.89
	(0.7)	(8.6)	(0.5)	(2.6)	(0.8)	(6.8)
SA	3.29	5.18	1.00	0.46	2.29	4.71
	(0.5)	(5.4)	(0.0)	(0.8)	(0.5)	(4.8)
VIC	19.65	31.32	10.18	16.00	9.46	15.32
	(2.5)	(13.4)	(1.3)	(8.2)	(2.1)	(7.3)
WA	3.07	6.82	1.04	2.25	2.04	4.57
	(0.8)	(6.7)	(0.5)	(2.8)	(0.9)	(4.3)
Total	80	2,151	38	909	42	1,242

Standard deviations (over periods) are in the parentheses.

Table 2: Proportion of cases awarded to the employees

	All	By Unionists	By Non-Unionists
Total	0.397 (2,151)	0.441 (909)	0.366 (1,242)
NSW	0.371 (663)	0.417 (331)	0.325 (332)
QLD	0.313 (275)	0.389 (54)	0.294 (221)
SA	0.517 (145)	0.385 (13)	0.530 (132)
VIC	0.463 (877)	0.496 (448)	0.429 (429)
WA	0.220 (191)	0.238 (63)	0.211 (128)

Numbers of cases are in the parentheses.

Table 3: Estimates of the endogenous effects(Reference period=180 days)

Parameter	Equation (3)		Equation (4)	
	OLS	FE	OLS	FE
ρ_y	0.064	-0.186		
(Overall)	[1.02]	[-1.63]		
ρ_0^1			-0.087	-0.381**
$(Non-U \rightarrow U)$			[-1.14]	[-2.51]
ρ_0^0			-0.290**	-0.151
$(Non-U \rightarrow Non-U)$			[-3.99]	[-1.04]
ρ_1^1			0.103	0.365*
$(U \rightarrow U)$			[1.29]	[1.90]
ρ_1^0			-0.111	-0.408**
$(U \rightarrow Non-U)$			[-1.53]	[-2.67]

* significant at 10% level; ** significant at 5% level. $t-$values are in the brackets.

Table 4: Estimates of Parameters of Equations (3) & (4) (Reference period=180 days)

Variable	Equation (3)				Equation (4)			
	OLS		FE		OLS		FE	
	Own case characteristics X							
Constant	0.319**	[8.88]			0.332**	[10.29]		
Summary	0.188**	[7.67]	0.187**	[7.79]	0.184**	[7.54]	0.185**	[7.71]
Skilled	-0.034	[-1.36]	0.003	[0.12]	-0.029	[-1.16]	0.009	[0.38]
$drsn_{ee1}$	0.168**	[6.61]	0.149**	[6.16]	0.165**	[6.51]	0.143**	[5.94]
$drsn_{er1}$	-0.165**	[-7.52]	-0.164**	[-7.64]	-0.164**	[-7.54]	-0.164**	[-7.68]
	Peer's average case characteristics (EX)							
$E(Summary)$	0.018	[0.26]	0.105	[0.82]	0.032	[0.46]	0.103	[0.80]
$E(Skilled)$	-0.039	[-0.55]	0.012	[0.11]	-0.042	[-0.59]	-0.015	[-0.14]
$E(drsn_{ee1})$	0.074	[1.01]	-0.028	[-0.24]	0.248**	[2.95]	0.170	[1.11]
$E(drsn_{er1})$	0.088	[1.50]	-0.129	[-1.19]	0.096	[1.64]	-0.142	[-1.31]

* significant at 10% level; ** significant at 5% level. $t-$values are in the brackets.

Table 5: Variable definitions and sample statistics

Variable	Definition	Mean
Skilled	Dummy, 1 if the employee is the most skilled (ANZCOSKI)	.226
$drsn_{ee1}$	Dummy, 1 if the employee's major allegation is on procedural	.207
$drsn_{ee1}$	Dummy, 1 if the employer's major allegation is on specific facts	.333
Summary	Dummy, 1 if the case is a summary dismissal case	.225
No of cases		2,151

Table 6: FE Estimates of endogenous network effects for alternative reference period lengths

Variable	90 days	120 days	150 days	210 days
	Homogenous network effects Equation (3)			
ρ_y	-0.049	-0.101	0.004	0.006
	[-0.56]	[-1.05]	[0.04]	[0.05]
	Heterogeneous network effects Equation (4)			
ρ_0^1	-0.217**	0.017	-0.443**	-0.436**
	[-2.40]	[0.15]	[-3.08]	[-2.34]
ρ_0^0	0.134	0.084	-0.193	0.057
	[1.44]	[0.72]	[-1.58]	[0.39]
ρ_1^1	-0.137	0.150	0.203	0.094
	[-1.02]	[1.02]	[1.32]	[0.50]
ρ_1^0	0.096	-0.316**	-0.205*	-0.133
	[0.93]	[-2.76]	[-1.76]	[-1.06]

* significant at 10% level; ** significant at 5% level.
$t-$values are in the brackets.

Figure 1: Data structure of a panel (illustration)

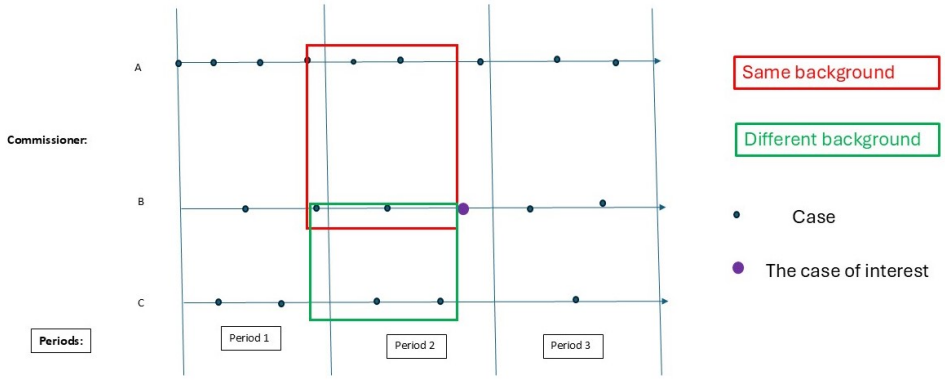

Figure 2: No of Commissioners by half-year periods

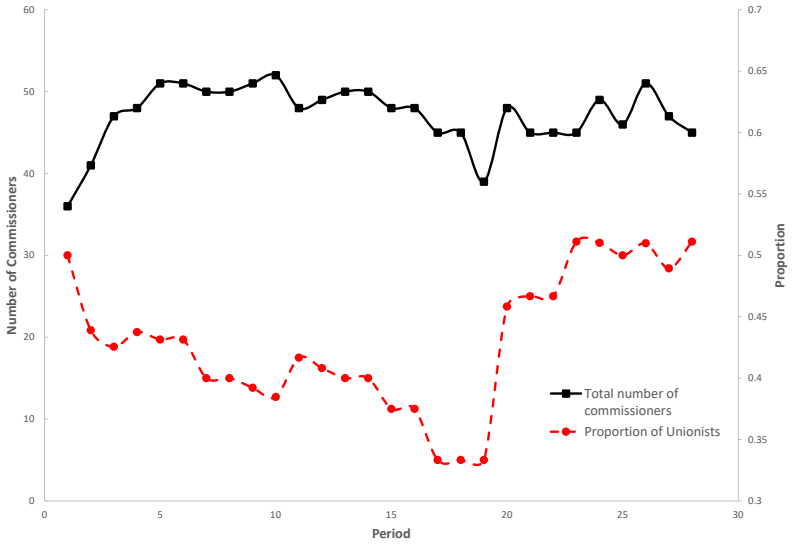
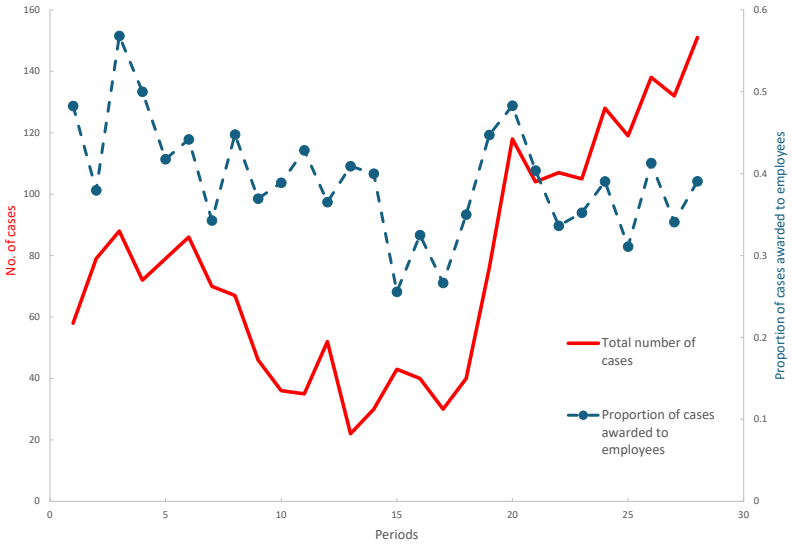
Figure 3: No of cases and their outcomes by half-year periods