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Agenda

Advancing economics in business

Regaining control: using time series to determine cause and effect

In medicine, random trials are used to determine the effects of a new treatment. Key to this is providing a placebo drug to a control group and comparing the observed effects on the treatment group against this. While such trials may not be feasible in a business and economics setting, it is nonetheless possible to identify proxy control groups and employ time-series econometric techniques to estimate the true causal impact of economic events. These methods are useful to commercial businesses, regulators and competition authorities alike

It can sometimes be difficult to determine whether certain events were caused by 'interventions' or other factors—or indeed whether they would have occurred anyway. Did the introduction of a particular drug really cause an improvement in the health of patients taking it after two years, or was this down to other factors, such as improved lifestyle, or natural recovery? Despite what the politicians say, did the economy really improve as a consequence of a new administration being in power, or were other factors more important?

Epidemiologists looking to explore the effects of new drugs attempt to ascertain cause and effect through random trials. Prospective patients are randomly split into two sub-samples. One is given the new treatment, and the other—the control group—is given a placebo. The effects on health observed for the treatment sample might then be compared with those of the control group—with the difference in health outturns between the two representing the causal effects of the drug.

However, in many economics and business settings, it is difficult—if not impossible—to conduct random experiments of this kind. Moreover, it is not possible to control for all potential factors in a statistical analysis based on observed data. Therefore, identifying whether an observed effect is real can be challenging.

As the expression goes, 'correlation does not necessarily imply causality'. The following examples show how the question of causality, rather than the presence of correlation, is at the heart of the issue.

- In its recent crackdown on collusive behaviour, the European Commission fined the members of rubber cartels over €243m.[1] The Commission has encouraged 'any person or firm affected by anti-competitive behaviour … [to] bring the matter before the courts of the Member State and seek damages'. But what would the situation have been had the cartel not existed?
- A company relaunches one of its products in a blaze of publicity, intending to remind its customers of the attractiveness of the product. But does the marketing campaign have any impact on sales and, if so, how long does the effect last?
- After having been awarded a franchise, a train operator announces that it will make radical improvements to the service. But what would be the effect of this on passenger numbers and revenues over and above the status quo?

Common themes pervade these examples—cause, effect, and the 'what if' counterfactual. Whether it is a competition authority investigating a cartel, a business marketing one of its products, or a train company improving its services, each might wish to answer the question:

> What was (or will be) the effect of the relevant event on some outcome variable (demand, prices, revenues, profits) compared with the counterfactual?

In other words, one might look for an answer about real 'causal effects' when other explanations have been discounted.

It may be possible in business settings to undertake some kind of randomised trial. For example, to explore the impact of advertising on demand, a company might advertise in one region but not in another—assuming that they have similar demographics. Yet there may be practical or commercial constraints on conducting such experiments in other areas of business. While random trials may not be feasible, it is nonetheless still possible to identify proxies for the relevant control groups, and to employ particular econometric techniques—eg, dynamic time series—to estimate causal impacts of commercial initiatives and events.

These approaches are discussed in this article in the context of recent work undertaken by Oxera in the rail sector, but are readily applicable to a wide range of sectors, types of causal event, or outcome variables of interest. Such methods can be employed by both commercial businesses and competition authorities alike.

Non-experimental data: an analyst's nightmare?

As explained above, to ascertain causal effects, ideally a series of controlled experiments would be conducted, randomly changing the levels of X—the explanatory variables—to explore the effect on the outcome, or dependent variable, Y.

Although the use of field experiments has increasingly given economic analysts the ability 'to let questions determine the data to be obtained, instead of the data determining the questions that can be asked',[2] the examples above suggest that, in many cases of interest to regulatory or competition authorities, as well as to businesses, recourse to experimental data may still not be possible. Often, the use of observed (non-experimental) data will be necessary.

In undertaking a statistical analysis, using non-experimental data will require controlling for all important factors that might drive the outcome variable. Failure to do so might lead to 'spurious regression' as a result of omitted variables (other X variables are important) and reverse causality (Y causing X). Furthermore, it may be difficult to obtain good-quality data from a representative sample, thereby creating a risk of measurement error, misspecification and selection bias.

In the case of a cartel being investigated, the prices of the two firms involved, Y, might move together over the period. Could this be considered an indication of a price-fixing event, X? Not necessarily. What about other explanations, such as movements in input prices (eg, oil), common to both firms? Moreover, models of perfect competition also predict that the prices of the two firms should move together, as industry costs change.

In short, while 'the controlled experiment' is a practitioner's dream, distinguishing causal effects from non-experimental data can be their worst nightmare.

To make matters worse, when using non-experimental data, causal effects may build up only gradually. Thus cartel agreements may have only a slow impact on prices, as existing contracts cannot be changed immediately.

New rolling-stock may not bring instantaneous improvements in service quality to rail passengers, but may suffer from initial reliability problems. Customers may face switching costs or information problems in considering new products, services or quality improvements, so demand adjustments may be lagged.[3] Likewise, customers might become used to the new facilities, products or services, and any initial demand increase may diminish over time. The notion that consumers' tastes are affected by past consumption is well established in psychology and has a long history in economics thought.[4]

Dynamic effects are important because competition authorities, parties claiming damages, or train operating companies improving their rolling-stock are often interested not only in establishing whether a certain event has had an impact on some outcome variable, but also in a characterisation of how this potential impact has evolved over time. How long did the cartel last? What was the extent of the damage over this period? What are the short-, medium- and long-term impacts on the passenger demand of new rolling-stock? For how long does an advertising campaign have an impact on consumers' perception?

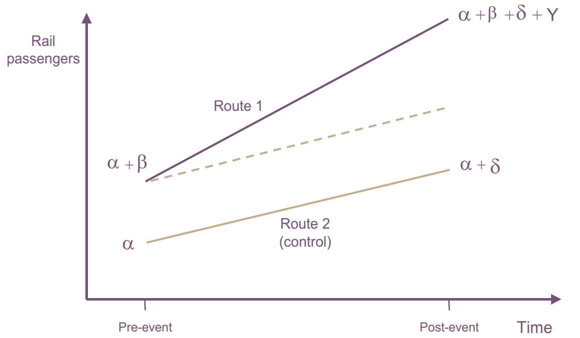
Considering these aspects together suggests that causal effects are, in many cases, an essentially dynamic phenomenon, and hence should be assessed by methods that explicitly take into account such dynamics. Time-series econometrics and the use of control groups are two of the available analytical methods suitable for the characterisation and estimation of such dynamic impacts from non-experimental data.[5]

Controlling the flow

When assessing the potential causal effect of certain events by one econometric method or another, it is important to control for the influence of all relevant factors, while excluding those that are not relevant.[6] However, in practice, it might not always be possible to include all relevant explanatory variables in the analysis. This may be because the necessary data is not readily available, or because the relevance or existence of certain factors is simply not known. Under such circumstances, a confident estimate of the potential causal effect might be difficult to achieve.

One way to control for such omitted or unobserved variables is the use of a proxy control group. Here, a

Figure 1 The use of control groups



Source: Oxera.

second dataset is obtained which—as far as possible—contains all variables apart from the one of interest. These are assumed to be the same in the control group as in the sub-set under investigation. The use of control groups to analyse the impact of events such as the introduction of new rolling-stock on certain train routes is illustrated in Figure 1.

In the figure, suppose that in the period before the introduction of new rolling-stock on route 1, passenger volumes on that route are $\alpha + \beta$, and α on route 2, the control group. There is a trend in passenger growth of size δ on both routes. In addition, new rolling-stock increases passenger demand by γ on route 1. As this stylised example illustrates, it can often be quite difficult, or even impossible, to distinguish between factors such as a general trend growth and the influence of other events from investigating one time series alone. Looking at only route 1 in Figure 1 would not reveal that the increase from a pre-introduction level $\alpha + \beta$ to a post-introduction level $\alpha + \beta + \delta + \gamma$ is composed of a general trend, δ, and an effect of new rolling-stock, γ.

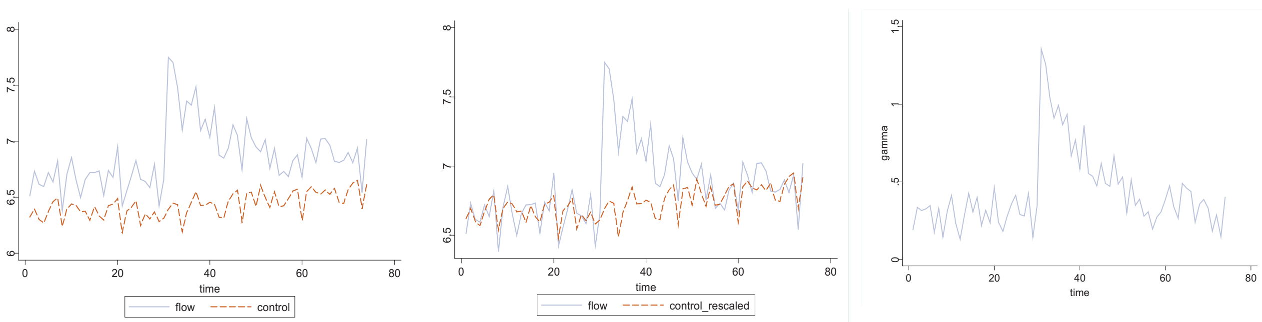
To control for trend growth, it is usual to subtract pre-event from post-event passenger numbers. This would give passenger growth of $\delta + \gamma$ for route 1 and δ for the control route. The effect of new rolling-stock can now be readily elicited by looking at the difference between route 1 and the control group, route 2. Whereas the trend in passenger growth is present on both routes, only route 1 is affected by the new rolling-stock. Thus, its effect in this stylised example can be calculated as $(\delta + \gamma) – \delta = \gamma$. This technique is akin to 'difference in difference' modelling—removing unobserved effects over time and across sub-groups.

Figure 2 illustrates the analysis of the dynamic impact of an event such as the introduction of new rolling-stock on rail passenger demand using a control group to capture exogenous demand drivers.[7] The control flow ('control') in the example closely tracks the flow under investigation before the event that occurs in period 30,[8] as shown in the first two graphs in Figure 2.

The first chart shows how, across the periods, the level of rail traffic for the flow being studied is consistently higher than the control group flow (corresponding to β in Figure 1). Taking account of this difference, it is possible to rescale the flow being studied (the second chart in Figure 2). This reveals that passenger demand has tended to pick up from around period 40, as the upward trend in the control route suggests.

The occurrence of the event in period 30 increased passenger demand on the flow under investigation, but did not affect the control route. The third chart of Figure 2 depicts the difference between the flow under investigation and the re-scaled control flow (corresponding to γ in Figure 1). This difference captures the impact of the event in period 30. The graph indicates that the event had an immediate demand-uplifting effect, which then gradually diminished thereafter. One possible explanation might be that passengers have become accustomed to the event and have adjusted their expectations accordingly. The two series appear to be in

Figure 2 Dynamic impact on rail passengers



Note: The graphs show rescaled passenger numbers for a certain train route in logarithms. Each year is divided into 13 four-week periods which are depicted on the ordinate.
Source: Oxera.

line again from around period 50. To gain additional insights into the dynamics of the impact (ie, the time series of gamma), pure time series as well as deterministic econometric models can be applied to estimate short-, medium- and long-term responses, for example.

Control groups are also a valued source of additional information in antitrust cases. For example, in a number of merger cases in Europe and the USA, competition authorities have compared market outcomes such as bidding behaviour or prices in different regional markets, where in some markets both merging parties were present and in others only one of them was present—to assess the competitive constraint the merging parties impose on each other. Prominent cases include *Staples* and *Oracle/Peoplesoft*.[9]

Such 'comparator markets'—ie, geographically separate markets—are also used in cartel cases to assess potential overcharges of alleged cartels. For example, the German Federal Supreme Court states that the preferred method of estimating cartel overcharge be through comparison of market outcomes with similar, 'comparator', markets.[10] Under the rules, other methods should be considered only when this approach is not viable.

Conclusion

If non-experimental data is used, assessing the impact of a variety of events ranging from antitrust cases to changes in the quality of services or products requires controlling for the potential drivers of the outcome variable.

In practice, however, it may not always be possible to include all relevant explanatory variables in the analysis which, in addition, might be aggravated by a complex dynamic pattern of the transmission of the events. In the absence of the ability to conduct controlled experiments, the use of control groups in combination with time-series econometric methods may provide a suitable approach to estimate such dynamic impacts, and hence may provide regulatory and competition authorities, businesses and customers alike with a toolkit to ascertain causal effects.

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[1] European Commission (2007), 'Antitrust: Commission Fines Producers of Chloroprene Rubber €243.2 Million for Market Sharing and Price Fixing in the EEA', IP/07/1855, December.
[2] Duflo, E. (2006), 'Field Experiments in Development Economics', paper prepared for the World Congress of the Econometric Society, MIT, January.
[3] See *Agenda* (2005), 'Consumer Responses: How Quick are They?', May, available at www.oxera.com.
[4] See, for example, Hinde, R. (1970), *Behavioral Habituation*, New York: Cambridge University Press. An early reference in the economics literature is Marshall, A. (1920), *Principles of Economics*, London: Macmillan. A more recent account can be found in Campbell, J. and Cochrane, J. (1999), 'By Force of Habit: A Consumption-based Explanation of Aggregate Stock Market Behaviour', *Journal of Political Economy*, **107**, 205–51.
[5] See, for example, Hendry, D.F. (1995), *Dynamic Econometrics*, Oxford University Press, or Harvey, A.C. (1993), *Time Series Models*, Harvester Wheatsheaf.
[6] Although the inclusion of irrelevant variables in a regression would still lead to consistent estimates of the regression coefficients, the precision of these estimates will tend to be lower when irrelevant variables are included. This may create a risk of considering a variable to be statistically insignificant when in reality it is not.
[7] Although the data series have been slightly modified to preserve anonymity, their main features remain intact.
[8] Each period covers a four-week time span such that each calendar year is divided in 13 four-week periods.
[9] *Federal Trade Commission v. Staples*, Inc., 970 F. Supp. 1066 (D.D.C. 1997); Case No COMP/M.3216 – *Oracle/Peoplesoft*.
[10] BGH WuW/ E DE-R 1567, 1571 – Berliner Transportbeton I.

If you have any questions regarding the issues raised in this article, please contact the editor, Derek Holt: tel +44 (0) 1865 253 000 or email d_holt@oxera.com

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