Class 11 - Techniques IV - Endogeneity

Agenda

- The perils of endogeneity: what, why, when, how (30 minutes)
- Application paper discussion (30 minutes)
- *Break*
- Replication presentation (15 minutes)
- Skills corner - Class walkthrough in R (25 minutes)
- General discussion (15 minutes)

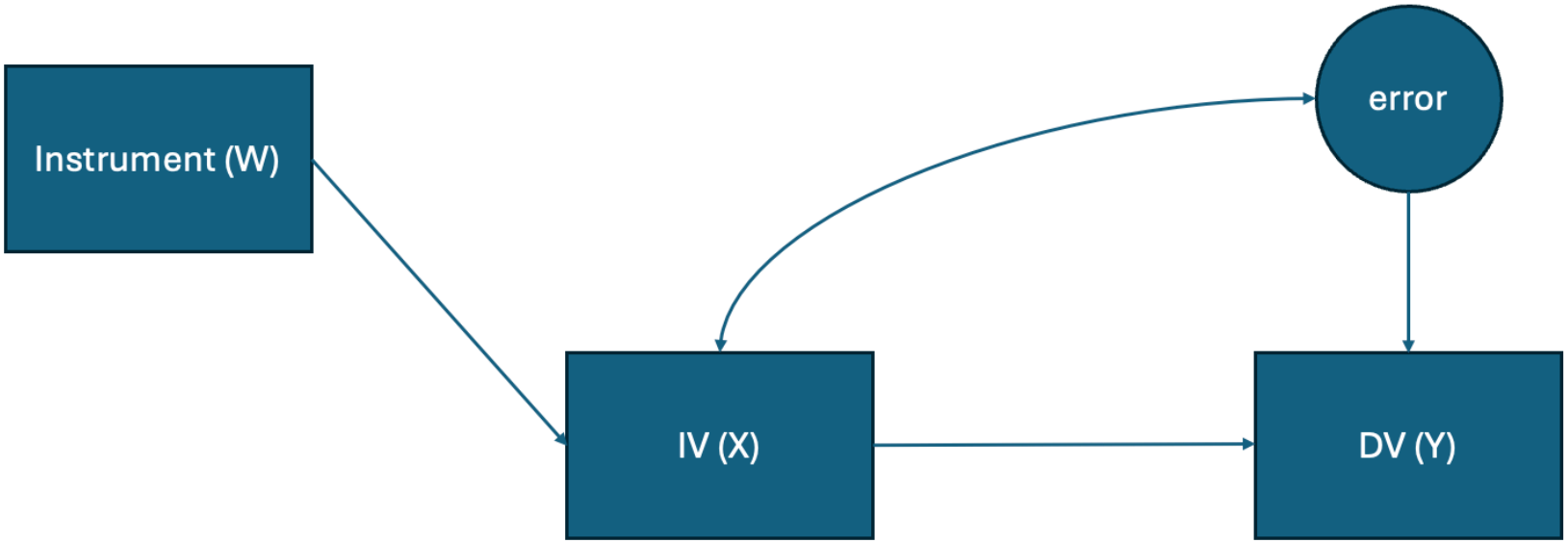
The perils of endogeneity

What is endogeneity?

Endogeneity arises when a regressor is correlated with the error term, thereby violating the most important OLS estimation assumption, the exogeneity condition, specifying that u has an expected value of 0. (Bascle 2008, 288)

What is endogeneity?

Nomological network view:



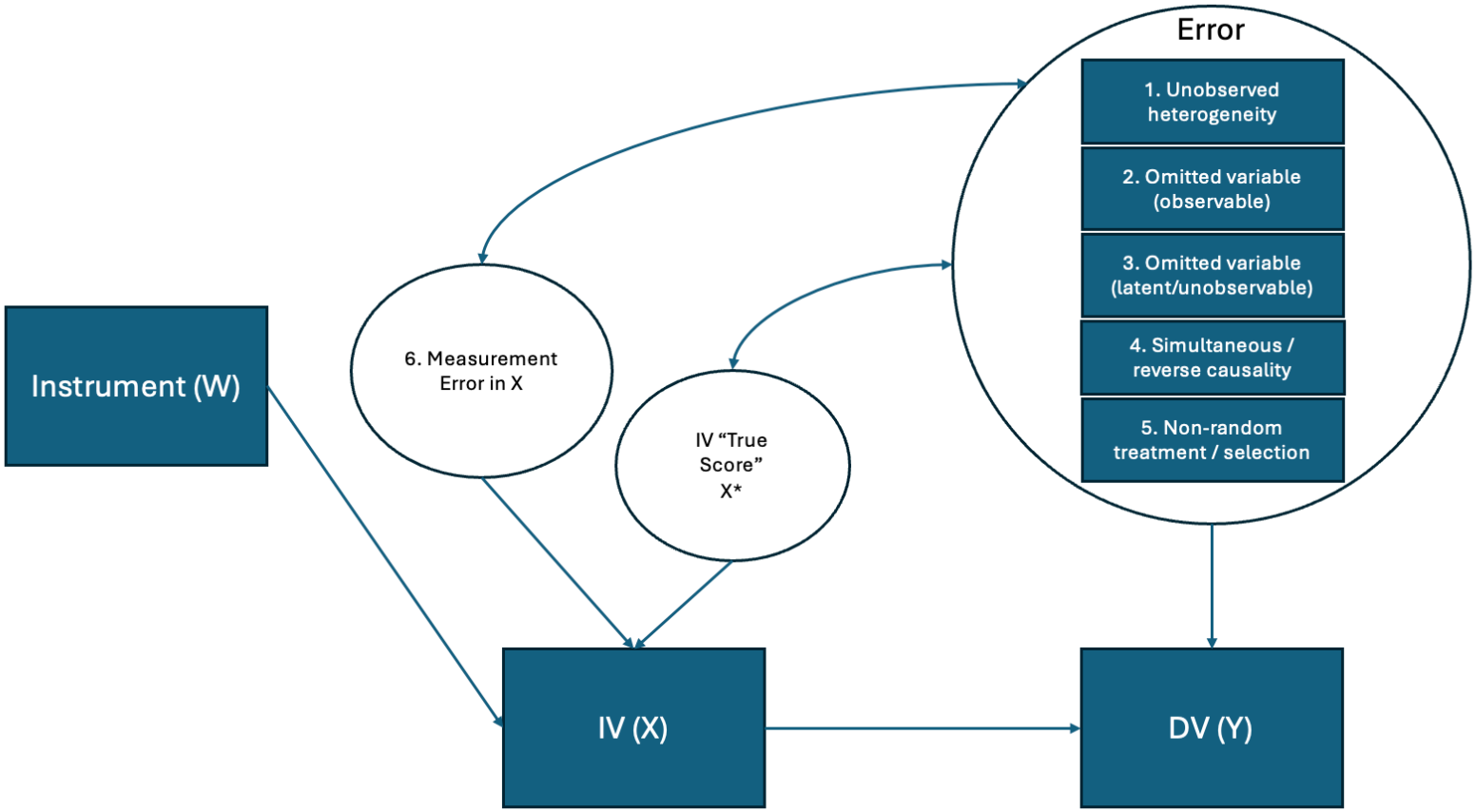
Regression model view:

$$Y = \beta_0 + \beta_1 X + \epsilon;\ E[\epsilon | X \neq 0]$$

Why is endogeneity problematic?

- A theoretical problem
  - We fail to capture the underlying dynamics of the process
  - We draw the wrong conclusions from our analyses about which variables matter or the direction of causal flow
- An empirical problem
  - We cannot recover causal effects due to a lack of "identification"
  - We may not even be able to come up with estimates at all if the model is structurally unidentified (e.g., supply and demand models)
  - Our effect estimates can be **significantly** biased, and even in the wrong direction without correction

What issues can cause endogeneity?



What issues result in endogeneity?

1. Unobserved heterogeneity: Individual idiosyncratic deviations from the overall mean of the DV in a manner that is correlated with the IVs (e.g., firm "quality" likely correlates with size)
2. (Observed) omitted variable: We have left out an observable variable (omitted variable, OV) that is correlated with the IV and DV (e.g., OV = average temperature, IV = gunshots, DV = ice cream sales)
3. (Unobserved) omitted variable: We have left out an unobservable variable that is correlated with the IV and DV (e.g., IV = study hours, DV = GPA, OV = g (general mental ability))

What issues result in endogeneity?

4. Simultaneous / reverse causality: either we have the direction of causality wrong (Y -> X) or they cause each other / are codetermined (X <-> Y) (e.g., price and quantity in a market setting)
5. Non-random selection in groups: Individuals self-select into a state or treatment or there are differences in surivival or attrition (e.g., IV = hospitalization, DV = general health, selection effect = need for treatment)
6. Measurement error in X: We cannot measure X perfectly, which at a minimum attenuates the relationship between X and Y, but if the measurement error in X is correlated with Y, we come back to the omitted variable bias problem

How can you correct for endogeneity?

Approach 1: Isolate exogenous variation in X

- Instrumental variables (IV) / Two stage least squares (2SLS): Can address all of these issues, but finding relevant and exogenous instruments is tough (Bascle 2008)
- Heckman selection / Tobit-2 / Tobit-5 models: Can address (5), possible to perform using functional form alone but stronger when with an exclusion condition (i.e., an instrumental variable)

How can you correct for endogeneity?

Approach 2: Excise or extract endogenous elements from e

- Include omitted variables: Can address (2), the essence of adding control variables to a model (Carlson and Wu 2012)
- Fixed effects panel specifications: Can address (1),(2),(3) if the OVs are [time invariant], but can exacerbate (6) (Bascle 2008)
- Dynamic model specifications: Can address (2) (3) (4), but caution required since this can introduce other endogeneity problems, especially with panel data (known as the Nickell bias)

How can you correct for endogeneity?

Approach 3: Punt on fixing and instead assess threat to inference

- Impact Threshold of Confounding Variables (ITCV) and Robustness of Inference to Replacement (RIR) ask the question: How big of a confounding effect would an endogeneous problem need to have to overturn the inference in a model where it is not modeled?
- This can be a nice tool to have in the back pocket for reviewers

Analyzing data in the presence of endogeneity

How do you perform a (basic) endogeneity analysis?

1. Proactively identify the potential cause(s) of endogeneity.
2. Run your models in a typical fashion.
3. Run alternative models (discussed above) that are consistent in the presence of endogeneity (example of 2SLS on next slide).
4. Use appropriate tests to determine which model is preferred (e.g., Durbin-Wu-Hausman, exogeneity, relevance tests). (Bascle 2008)
5. Perform typical statistical inference based on the preferred model.
6. It often helps to report test statistics, and space permitting, the results from alternative models to give the reader

Example: Running 2SLS

1. **(Hard part)** Find instrument(s) for each of your endogenous variables.
2. If you are lucky enough to have an embarrassment of riches with multiple instruments for each, use them so you can test for exogeneity!
3. Verify the instruments are sufficiently strong (e.g., first stage F test)
4. Run the 2SLS procedure (next slide)

Example: Running 2SLS

What is 2SLS doing? In essence, the following[1]: $Y = \beta\hat{X} + e$

Such that: $\hat{X} = W\hat{\delta}$

And $\hat{\delta} = (W^T W)^{-1} W^T X$

Where W is the set of the exogenous variables + instruments, and X is set of exogenous and (instrumented) endogenous variables.

This procedure "purges" X of its endogenous part and only relies on the **exogenous variation** present in W.

[1] Don't run this yourself since the standard errors will be wonky! Use the output from the software which makes the necessary corrections. Also note that in regular OLS, X "instruments" for itself.

Why not just use the models robust to endogeneity always?

- Multiple endogeneity issues: each may require non-compatible solutions.
- No free lunch: models robust to endogeneity pay a price (typically small-sample bias and efficiency).
- Many endogeneity tests compare two estimators - one that accounts for endogeneity and one that does not.
- If the test fails, endogeneity is a problem and you need to use the estimator that is "consistent" in the presence of endogeneity.
- If the test passes, it is better to use the 'standard' estimator: it is has more power and is more precise (tighter sampling distribution).

Applications

Application readings

Let's level-set people's familiarity with these pieces.

- Bascle, G. 2008. Controlling for endogeneity with instrumental variables in strategic management research. Strategic Organization 6(3): 285-327.
- Fox, B. C., Simsek, Z., & Heavey, C. 2023. Venture team membership dynamics and new venture innovation. Strategic Entrepreneurship Journal.

Bascle (2008)

- What was this paper about?
- What were the findings?
- What was the method?
- What makes sense? What was confusing?

STRATEGIC ORGANIZATION Vol 6(3): 285–327
DOI: 10.1177/1476127008094339

http://so.sagepub.com

Controlling for endogeneity with instrumental variables in strategic management research

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Abstract

This article offers a framework to understand how endogeneity arises and how to control for it with instrumental variables to estimate causal relations with observational data. It builds on the state-of-the-art research in applied and theoretical econometrics to highlight the importance of endogeneity and review the methods that can be used to address it with instrumental variables. The article also discusses when the Heckman two-step procedure can be used, as well as the tests, methods and assumptions that researchers should check when using instrumental variables. To ease implementation of the instrumental variables techniques, the author offers the STATA commands of the exposed tests and methods. Further, an empirical example is provided along with the utilized STATA codes. In the end, this article serves as a 'toolkit' allowing scholars not only to understand whether endogeneity is present in their empirical setting, but also to assess the empirical validity of their work when using instrumental variables.

Key words • causal relations • endogeneity • instrumental variables

Researchers in strategic management are often interested in causal relationships. For instance, does geographic or business diversification create shareholder value? To make causal statements about the impact of a change in policy (e.g. diversifying) on an outcome (e.g. shareholder value), researchers have two options: they can use randomized controlled experiments or observational data. In randomized controlled experiments, which are often undertaken in medicine or psychology, subjects are randomly selected and then randomly assigned to either a treatment group, which receives the treatment, or a control group, which does not receive the treatment. The causal effect of the treatment is then the impact of the treatment on an outcome.

However, since in our field randomized controlled experiments are often

Fox Simsek and Heavey (2023)

- What was this paper about?
- What were the findings?
- What was the method?
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Received: 24 May 2021 | Revised: 11 May 2023 | Accepted: 12 May 2023
DOI: 10.1002/sej.1473

RESEARCH ARTICLE

STRATEGIC ENTREPRENEURSHIP JOURNAL WILEY

Venture team membership dynamics and new venture innovation

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Abstract

Research Summary: Although pre-entry startup experience is widely recognized as a driver of innovation in new ventures, a core feature of new venture teams is that their membership is fluid. In this article, we theorize and test whether venture team membership fluidity incrementally explains new venture innovation. We also investigate and demonstrate that team fluidity conditions the impact of pre-entry startup experience present at founding. Testing our hypotheses with a cohort of 440 new ventures tracked for 8 years, we find support for the model across a wide range of specifications. Our study advances current understanding of the relationship between pre-entry experience and new venture innovation, as well as novel insights into the central but often overlooked role of team fluidity.

Managerial Summary: New ventures rely on innovations to establish a market presence and compete against established firms. Even though team members are an essential source of inspiration, ideas, and resources to foster innovation, teams often change substantially as the venture evolves. We ask the question—does modifying the make-up of the team make it more likely that the venture can innovate? We contend that such change significantly shapes the cognitive and interpersonal processes by which team members contribute to innovations. Our results suggest that new ventures undergoing member change can boost inno-

Break

COFFEE BREAK

Replication Presentation

- Replication: Fox, B. C., Simsek, Z., & Heavey, C. 2023. Venture team membership dynamics and new venture innovation. Strategic Entrepreneurship Journal.

Class walkthrough in R

Preparation for next class

Next class

Your draft paper is due before we meet for our final workshop and the final paper is due by May 3.

Next class

Design I: Quasi-experimental data

1. Grant, A. M., & Wall, T. D. 2009. The Neglected Science and Art of Quasi-Experimentation. Organizational Research Methods, 12(4), 653-686.
2. Shadish, W. R., & Cook, T. D. 2009. The renaissance of field experimentation in evaluating interventions. Annu Rev Psychol, 60, 607-629.

Next class

Design I: Quasi-experimental data

Applications:

3. Shu, L. L., Mazar, N., Gino, F., Ariely, D., & Bazerman, M. H. (2012). Signing at the beginning makes ethics salient and decreases dishonest self-reports in comparison to signing at the end. Proceedings of the National Academy of Sciences, 109(38), 15197–15200. doi:10.1073/pnas.1209746109 (see also https://datacolada.org/109)
4. Replication: Penrosian capacity as a constraint on entrepreneurial growth: An exploratory study employing the dot-com bubble (working paper)

References

Bascle, Guilhem. 2008. "Controlling for Endogeneity with Instrumental Variables in Strategic Management Research." *Strategic Organization* 6 (3): 285–327.

Carlson, Kevin D., and Jinpei Wu. 2012. "The Illusion of Statistical Control." *Organizational Research Methods* 15 (3): 413–35.