Visualizing environmental econometrics using directed acyclic graphs

Pierce Donovan[†]

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Abstract

Environmental and resource economists have gravitated toward writing empirical papers with an emphasis on causal inference. Yet the concomitant efforts to promote statistical rigor have not facilitated similar improvements in the transparency and accessibility of causal knowledge. In this data and methods feature, I demonstrate how to implement Directed Acyclic Graphs in order to more easily communicate empirical research in environmental economics. I then provide suggestions for integrating this innovation into future presentations, publications, peer reviews, and pedagogy.

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[†]Assistant Professor, Department of Economics, Connecticut College
email: `pdonovan@conncoll.edu`
web: `piercedonovan.github.io`
[††]This paper is a work in progress, and I would gladly accept any feedback you have for improving it.

A framework for communicating causal knowledge

Most empirical papers in environmental economics are now structured around a single statistical inference of interest, with an emphasis on how the authors' identification strategy supports a measurement with a justifiably-causal interpretation (Segerson, 2019). In many cases, the storytelling appears to take more effort than the underlying statistics, perhaps because designing clever identification strategies for causal inference is difficult. It is clearly the thoughtful communication of our research design that now defines "rigor" in empirical papers, rather than a barrage of specification tests.

There is still a need for a systematic framework for presenting causal knowledge. In order to claim that some observed variation is equivalent to something that could have been derived from an experiment, we invoke economic theory or our intuition about the underlying data generating process. Theory helps us understand the causal channels through which an intervention may impact an outcome of interest. Intuition about the context and data at hand informs our research design and any potential pitfalls concerning identification. Theory and intuition together help us understand the applicability of our results to other settings. Yet papers often appear to tackle the issue of communicating theory and empirical assumptions—prior subjective information—in an ad hoc manner.

I want to keep building on our "credibility revolution" with increased clarity, transparency, and testability of different *causal* hypotheses. Most economists have become comfortable with creating a correspondence between a [non-exhaustive] set of plausible empirical assumptions—mostly related to functional form or different sets of control variables—and the sensitivity of resulting inferences. But this sensitivity analysis is less likely to reveal some objective truth than it is to invite opportunities for selective reporting and other questionable research practices (Ferraro and Shukla, 2020). Even with the most honest reporting, the selection of regressions run is often determined haphazardly, and without justification beyond the mere permutation of various control variable sets. I would like to add some structure to this selection process.

Directed Acyclic Graphs (DAGs) (Pearl, 1995) can systematize our thinking about how we create causal models, inform empirical research, and cut down on [unintentionally] misleading research practices. DAGs share causal knowledge, allowing us to concisely and transparently outline an identification strategy and explain under which conditions this strategy would successfully yield a causally-interpretable measurement.

The primary function of this paper is not to create another outline of Pearl's *do-calculus*—the logical engine that powers the graphical approach—nor judge the relative merits of DAGs against alternative procedures like the econometric causal model or the potential outcomes framework—for these writings, look to Heckman and Pinto (2015) or Imbens (2020) and their derivatives. Much of that discussion focuses on the things DAGs were never designed to do. I want to talk about where they excel: DAGs primarily provide us with a way to systematically choose conditioning variables, sources of data, and empirical methods in a manner that holds us accountable and can be easily understood and validated by a wider audience of researchers, students, and stakeholders.

In this data and methods feature, I instead lay out an introductory reference to help you implement DAGs in your own work and augment your understanding of causal inference. With this article, I aim to lower the costs of adoption for an emerging method of broad applicability in environmental economics.

If you find yourself interested in further study after this article, I can recommend four books to you. Pearl and Mackenzie (2018) provides a short history of causal inference and further motivation for the adoption of DAGs. Pearl (2009) details the underlying mathematical formalization. And within the realm of economics, two recent graduate-level textbooks by Cunningham (2021) and Huntington-Klein (2022) make good use of DAGs as a pedagogical aid to explain methods in applied econometrics research.

In the next two sections, I provide a primer on DAGs and several applications to further illustrate their utility. In the final section, I discuss the merits of integrating this innovation into future presentations, publications, peer reviews, and pedagogy.

A primer on Directed Acyclic Graphs

A DAG represents our best understanding of the various causal and spurious links between variables of interest within the particular setting in which data are collected. It can help us determine an identification strategy, validate claims of causal identification in regression output, and suggest other scenarios in which our results are likely to apply. This section provides a minimalist introduction to their interpretation.

Figure 1 provides a representative DAG. Our initial task is to center our thinking around a particular relationship of interest, say $T \rightarrow Y$. Directed arrows like $T \rightarrow Y$ convey statements like "the outcome Y is in part determined by the status of some treatment T." Additional [indirect] causal relationships between T and Y may be mediated by other variables (e.g. M). As we expand our model, we want to consider any variables which could distort the observed relationship between T and Y away from the sum of the causal effects.

Spurious relationships between T and Y are created by confounding variables—those which influence both T and Y—like X or Q. If we do not mitigate the effects of confounding variables, our estimate of the treatment effect will be biased. On the other hand, variables

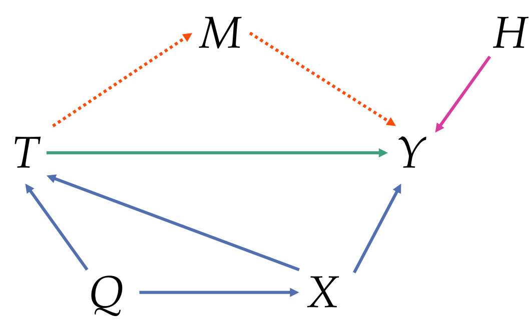

Figure 1: A representative DAG. Some variables—and the graph edges related to them—may not be observable, and we can emphasize these with dashed arrows. I use color in my figures to distinguish different types of relationships, although this is merely a stylistic preference.

like H will not influence the causal interpretation of a measured correlation between T and Y, since they do not contribute to a spurious relationship. Thus the DAG has already given us a way to differentiate between malignant and benign sources of variation.

If data on X and Q are available, we can employ a simple matching strategy to control for these confounding variables. Regression will automatically isolate the causal relationship between T and Y from the variation induced by changes in X or Q. In the language of DAGs, we are "closing" these non-causal paths between T and Y.

What if a variable like Q wasn't observable? This is where the term "acyclic" deserves a moment of explanation. As you may guess, this feature disallows loops—no variable will ever be found to be a descendant of itself. While this may feel restrictive—your understanding of causality may allow for simultaneity, for example—most causal relationships can be safely recast acyclically. The restriction allows us to use our DAG to quickly make statements about conditional independence, e.g. "Y is independent of Q conditional on X." Since variation in Q can only impact Y through an intermediate effect on X, controlling for the variation in X also halts the pass-through of information from Q to Y. Thus the requirement for closing a spurious path between T and Y can be relaxed to either controlling for a confounding variable along that path, or one of its descendants. Here, once X is controlled for, the status of Q becomes immaterial with respect to the identification of the effect of T on Y.

When reporting regression output, the marginal "effect" on Y attributable to T reflects all remaining "open" paths from T to Y. It is our responsibility to determine whether or not this variation generates a measurement of a causal effect. In the present case, a viable control strategy for measuring $T \to Y$ would be to control for X, since X additionally blocks the path including Q and H is harmless. We cannot disentangle the direct effect from the indirect effect here, as the variable M is unobservable.

Applying DAGs to environmental economics

Now that the groundwork has been laid, I will demonstrate how to implement DAGs through the use of several bespoke toy examples in environmental economics. Although these examples are fairly straightforward without the use of DAGs, my point is to show how discussions of research design can be made more clearly and succinctly with the aid of the graphical approach. In this way, DAGs are hardly redundant, but augmentative.

Experimental sources of variation sever spurious links

Does the built environment influence transportation modality? To many, induced demand is taken as a maxim. But this ignores the idea of residential sorting; individuals with preferences for transit or walkability will tend to move to places with those amenities. This confounding factor is not observable, and a naïve regression of transit decisions on built environment would pick up both the causal and spurious paths in Figure 2.

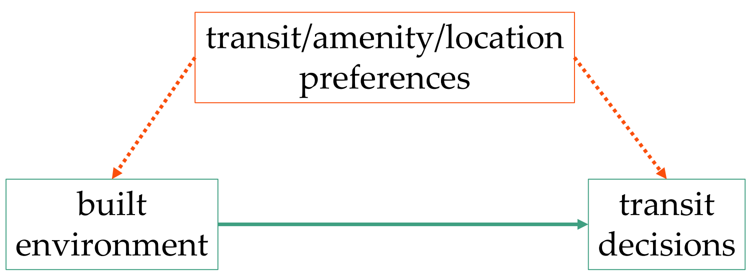

Figure 2: A naïve regression of transit decision on built environment without controlling for preferences results in a biased estimate. Randomization would trim the arrow from preferences to the built environment, thus removing the confounding factor.

One source of potentially-useful identifying variation comes from housing lotteries. For those entering lotteries, preferences become irrelevant, and people take what they are awarded. Some properties may be closer to metro lines and others could have more readily-available parking—this variation in the built environment is unrelated to individual preferences. Using the DAG above, random assignment would sever the arrow between preferences and the built environment, thus eliminating the confounding issue.

Understanding mechanisms prevents over-conditioning

Matching strategies are more complicated than we think, yet I have witnessed researchers consider control variables simply because they are available for inclusion. Many of these control decisions are made without any causal logic to back them up. To illustrate,

Figure 3 warns us of a potential pitfall when addressing the following question: how do droughts impact tree health?

Figure 3: Controlling for a mediator will close a causal path, preventing the estimation of an indirect effect.

The DAG assumes that there is no direct impact of rainfall on tree health. Most species will absorb water via their roots, and so rainfall impacts tree health through the mechanism of changing the moisture level of the soil. An econometrician not thinking about causal mechanisms may consider controlling for soil moisture in a dataset comprising of various climates or soil types, perhaps because they are vaguely worried about some unknown confounding factor. But this would be a blunder, as soil moisture is clearly not a confounder in this DAG. An unconditional regression of tree health on rainfall is best.

This brings me to "over-conditioning," which amounts to eliminating the very variation that you wanted to exploit. The effects of rainfall can't "reach" the tree health variable without impacting soil moisture—but controlling for soil moisture closes this path.

Some control variables are better left alone

Some research design strategies can inadvertently introduce bias to estimators. As luck would have it, DAGs make it incredibly easy to spot bad controls. To illustrate, let's imagine that we'd like to estimate the impact of increased PM2.5 levels on respiratory health, using readily-available data from hospital admissions. Figure 4 provides a model of a data-generating process which takes into account how our sample is being collected.

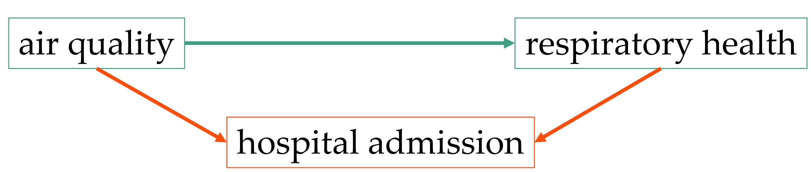

Figure 4: Collecting data using a selected sub-sample will result not only in a lack of *external* validity, but *internal* validity as well, due to collider bias.

Some variables create spurious correlations between treatment and outcome only once they are controlled for. In the present case, bad air quality and poor respiratory health can independently send someone to the hospital—these are substitute causes for appearing in the data. Since each observation is a hospital admit, I know that an observation with better air quality is more likely to represent an individual with poor respiratory health.

This story is tricky to work out in your head. Thankfully, DAGs make it easy to spot the issue. Whenever you spot a variable in a DAG that invites a collision of two arrows (like hospital admission), then the variable is called a "collider" on that particular path from treatment (air quality) to outcome (respiratory health). Stratifying on a collider variable will open an otherwise closed path. Thus we never want to control for collider variables, because leaving them out of our control set automatically closes a related non-causal path.

Some people may mistakenly reduce this example to an external validity concern. However, the measured relationship between air quality and respiratory health won't even be *internally*-valid here. The collider bias will act to reduce—or even flip the sign of—the measured air quality "effect" within the hospitalized sub-sample.

A new flavor of sensitivity analysis

DAGs are agnostic to the functional forms you choose to model relationships between variables. This abstraction frees us up to think about alternate causal hypotheses, each represented by a different DAG. A new type of "robustness check" involves re-validating (and modifying) a proposed identification strategy under different DAG configurations.

Let's consider another example. Does adopting an electric vehicle decrease household emissions? We would expect the direct effect to be positive due to increased mineral extraction and fossil fuel-derived electricity demand. However, the bulk of the adoption effect is likely indirect and negative, through the replacement of a gas-powered car. As a straw-man, consider the economist who controls for the number of gas-powered cars in the household. This would be a blunder, as they have closed a causally-interpretable path. By controlling for the number of gas-powered cars, we remove the replacement channel.

Further, including other household characteristics in the DAG would likely reveal how a bias in the measurement in the direct effect manifests using this strategy. For example, households with car enthusiasts are drawn to gas-powered cars and to driving more often, making our control variable into a collider and introducing a spurious correlation.

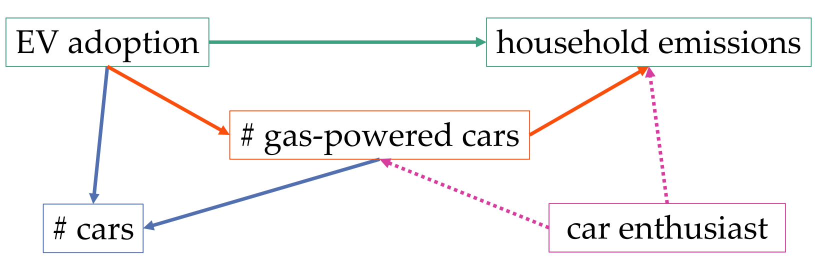

Figure 5: The true impact of electric vehicle adoption on household emissions is only revealed if we *omit* controls for the number of cars in the household, gas-powered or otherwise.

But many economists would say the replacement story is obvious. I've heard that. But I've also heard this: we apparently want to control for the total number of cars instead. In my mind, this is also a blunder. Figure 5 shows why. In my mental model, the total number of cars acts as a collider. When we stratify on the number of cars in the household, we implicitly assume that there is a replacement of a gas-powered car for every electric vehicle adopted—which is unlikely. Thus we move from an underestimate to an overestimate of the decrease in emissions.

This collider story is easily missed, but is easy to figure out with the help of the DAG. Depending on your data source or setting, your DAG may not alert you to a problem with these controls. But my model says that we should neither control for the number of electric vehicles nor the number of household cars in general.

DAGs efficiently communicate our assumptions

The simplicity with which DAGs can explain the instrumental variables strategy is something to behold. Please forget for a moment everything you may know about instrumental variables, as I walk through another example.

Fishing quota systems have revolutionized the organization of fisheries, ensuring the biological sustainability of the exploited species and maximizing the value of an authorized total allowable catch. In these systems, fishers explicitly own shares of this total allowable catch and are free to trade these fishing rights among themselves. Quite naturally, the market for quota shares guides ownership into the hands of the most efficient fishers, therefore increasing the economic rents that accrue to each share.

How much of the variation in the price of quota is due to changes in fleet efficiency (i.e. catch per unit effort), as opposed to changes in the demand for the fish harvested? A potential problem with separating these two impacts is the fact that any market development that increases the value of the quota may additionally incentivize investment that leads to greater efficiency. Figure 6 shows how uncontrolled demand side factors create spurious relationships when interpreting the effect of gains in fleet efficiency on quota price.

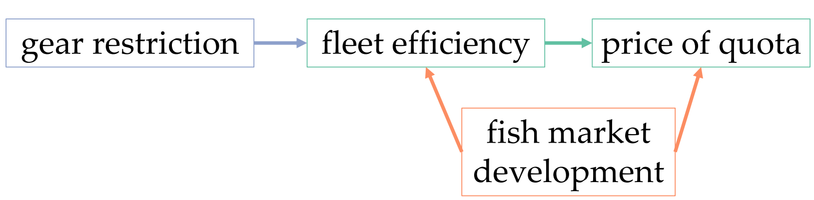

Figure 6: Armed with a DAG, the verification of an instrumental variables strategy can be done with a cursory glance.

Now imagine a potential regulation brought about due to concerns about the bycatch of an endangered species often found co-mingling with the targeted species. Perhaps a restriction on a certain type of gear or fishing location. This restriction reduces the efficiency of the fleet, impacts the value of fishing quota through this efficiency mechanism, and is plausibly exogenous with respect to shifts in demand.

Figure 6 shows exactly what these features buy us. The regulation turns fleet efficiency into a collider variable along the spurious path from gear restriction to the quota price. And it acts as a mediator on the causal path. Thus an unconditional regression of the price of quota on the gear restriction variable provides a causally-interpretable estimate. A regression of fleet efficiency on the gear restriction is similarly unbiased. Dividing the two relevant regression coefficients yields the instrumental variables estimator for the effect of changing fleet efficiency on the price of quota—another causally-interpretable estimate.

Our DAG reveals the familiar identification assumptions for the instrumental variables estimator—"relevancy, independence, and validity"—just by checking for the presence or absence of three key arrows in the above DAG. Given our story above, we draw an arrow from gear restriction to fleet efficiency, but not to (or from) the price of quota or fish market development variables. Immediately, we're able to transparently communicate to others what we believe to be true about our instrument, and readers can now easily follow (or dispute) our assumptions.

DAGs can take us beyond *Mastering 'Metrics*

I think we were somewhat lucky to understand methods like instrumental variables before being exposed to DAGs. I also think that as DAGs become more familiar, a new collection of research design strategies is bound to emerge. With one more example, I'll illustrate a new method that exists outside the contemporary applied econometrics literature. I will show that we can still generate an unbiased estimate of a treatment effect even with selection into treatment, as long as an exogenous mediator variable exists between treatment and outcome.

How beneficial are climate resilience-motivated crop insurance programs in developing nations? We would expect the most savvy farmers to have the most interest in an insurance program if made available—as well as the most sophisticated farming operations. Any naïve regression strategy would clearly pick up this selection bias.

Figure 7 shows how we can get past this selection problem. Consider the mechanism through which crop insurance would lead to a benefit. If there is no adverse weather event (and thus no crop damage), then the crop insurance will have no impact on income.

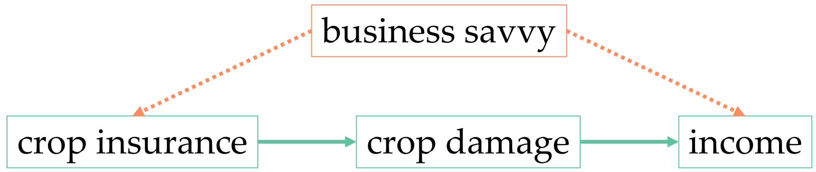

Figure 7: When an exogenous mediator exists, we can separately identify the effect of treatment on the mediator and the effect of the mediator on the outcome, then chain these effects together.

As drawn, this mediator variable provides a way out. We can identify the first link in the causal chain with a simple regression of crop damage on crop insurance. We do not have to worry about the spurious path from crop insurance to crop damage, since income assumes the role of a collider and omitting that variable closes this path. We can also identify the second link by regressing income on crop damage while controlling for crop insurance, which breaks the other non-causal path. By chaining these impacts together, we recover a causally-interpretable estimate of the effect of crop insurance on income.

Figure 7 implies three assumptions about this mediator. To start, our mediator must intercept all causal paths from crop insurance to income. If there was some sort of direct causal path, then we would not be able to avoid the initial bias we were trying to remedy. This is similar to the "only through" assumption in instrumental variables. The other two assumptions require the crop damage variable to be unconfounded with respect to crop insurance and income. This means the business savvy variable—or any other unobservable—cannot create a non-causal path involving the mediator.

You might think that I've hidden an arrow here. Why couldn't the savviest of farmers mitigate their exposure to weather-related damages through siting or some other mechanism? In this case, I can propose a modification to the DAG. Conditional on the known risk of a disastrous weather event, the event itself is now plausibly-exogenous with respect to the business savvy of individual farmers. Thus adding a measurable control variable like "risk of damage" in between the business savvy and crop damage variables would signal that a control strategy is available to sever this spurious link. We should then run the two aforementioned regressions above while controlling for exposure risk.

Opportunities for implementation

When we lack the facilities to present causal knowledge, we approach causal inference blindfolded. Since identification strategies are nuanced and borne out from a place of deep familiarity earned by dozens of hours of work by the econometrician, without a visual aid, we face the additional challenge of explaining our work to other blindfolded individuals.

Economics is one of the rare disciplines that uses presentations to improve papers in progress—rather than report on finished products. Yet the status quo presentation moves very quickly and inadvertently utilizes lots of hand-waving through claims of causal effect identification. I often must suspend disbelief in order to enjoy a talk, but this puts me in a weaker position of understanding and makes me less likely to be able to follow along with or provide feedback to the presenter. I believe that the demonstration and consequent discussion of a DAG during a presentation may have the power to push us out of this local maximum and increase the potential benefit of presenting our work.

Since DAGs force us to carefully think through the identifying variation that we want to exploit, they provide us with an opportunity to rework the entire research process. By starting with a story and a DAG—much like starting with any theoretical model—we learn what data needs to be collected (and in what context) in order to answer a question of interest. We do not need to act on vague hunches, and can instead employ an iterative process of collecting ground truths and updating the DAG.

In our writing, the use of DAGs can substantially reduce the time and real estate devoted to the justification of a particular identification strategy. DAGs also engender more cogent feedback from our peers. When reviewers ask us for some sort of sensitivity analysis, they now have a language for raising concerns about causal hypotheses, which are [arguably] of more value than semi-inspired modifications to the authors' preferred specification. A new causal hypothesis generates a new DAG, which then organically motivates a new regression. This is objectively better than suggesting different fixed-effects.

DAGs create tremendous value as a pedagogical tool. Graduate studies in economics already emphasize the development of causal effect identification skills, but I think we can start even sooner. My undergraduate econometrics course—titled *Causality*—attracts a wide-variety of students to economics through its primary emphasis on the causal storytelling skills that we pick up as econometricians. My use of DAGs only increases access to this class and further facilitates the building of this particular competency. I believe that prioritizing this objective in economics education may similarly increase our ability (and that of our students) to communicate with policymakers and stakeholders.

DAGs are not limited to toy models. A common "anti-arrow" complaint discards DAGs because they are technically redundant. Indeed, there are some tasks—like the determination of the *type* of treatment effect measured—that are better suited to alternatives like the potential outcomes framework. Even so, we have now seen the DAG's promise for uses like model prototyping and communication to non-experts. Environmental economists ultimately hope to generate research that informs environmental policy, and I think that this article has introduced a tool to make this more likely.

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