

A Critical Exploration into Employing Synthetic Control Models in the History of Economic Thought

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Abstract: This thesis explores the place of synthetic control models in the study of the history of economic thought (HET). Synthetic control models, a causal model used for comparative case studies, can provide both epistemic and non-epistemic value to HET if employed correctly. Practitioners in HET should not immediately close the door to this new methodology and rather must discuss the potential value and set the standards for its use. This thesis explores the whole of the conversation by addressing the what, why, how and who about the use of synthetic control models in HET.

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1) Introduction

Over the last few decades, economics has seen a rise in quantitative methodologies and studies in what some deem an empirical turn (Hamermesh, 2013; Angrist et al., 2017) and what others deem an applied turn (Backhouse and Cherrier, 2017). Despite the nuances between the two, both sides agree quantitative and empirical methods are moving forward within the field. In addition, this rise in quantitative studies is not isolated in a select group of economic subfields but rather is widespread (Angrist et al., 2017). This includes subfields which usually lean on qualitative methods such as the history of economic thought.

Over 25 years ago, Backhouse et al. (1997) noted the potential of quantitative methods in the history of economic thought, from here on out abbreviated as HET, by surveying the literature at the time which engaged with such methods. More recently, the rise in quantitative methods in HET is evident by a few cases. First, a section devoted to quantitative methods in Till Duppe and Roy Weintraub's book from 2018 on *A Contemporary Historiography of Economics*. And second, it is evident by a special issue from the Journal of Economic Methodology (JEM) in 2018 on the rise in quantitative methods in the historiography of economics. The edition explored the place of quantitative methods in HET by looking at the potential epistemic value through four examples on the use of quantitative methods. The edition concluded that the continuation of quantitative methods in HET could bring value to the field, but caution needed to be heeded (Cherrier and Svorenčík, 2018).

The papers in both Duppe and Weintraub (2018) and the JEM special issue focus primarily on bibliometric methods which are typically statistical methods to analyze books, articles, or other publications. This included methods such as network analysis (Claveau and Herfeld, 2018; Herfeld and Doehne, 2018) or topic modeling (Ambrosino et al., 2018) as those are some of the primary methods employed up to that time. However, there is a new quantitative method on the horizon which needs attention, and that is synthetic control models.

Synthetic control models are a form of causal model, like difference-in-difference, which allow us to compare the effects of what actually happened from a specific event to what could have happened in a hypothetical scenario. We can compare the outcome of a real event to a hypothetical counterfactual to determine a causal impact. The model has been widely popularized in policy analysis because of its ability to assess an outcome on one single subject such as a country, a state, or an institution (Abadie, 2021a). Synthetic controls allow us to make causal claims on comparative case studies between one entity and a handful of other similar entities.

Synthetic controls are knocking at the door for practitioners in HET. This is particularly the case following the publication and discourse around Phil Magness and Michael Makovi's paper *Mainstreaming of Marx: Measuring the Effect of the Russian Revolution on Karl Marx's Influence* (2023). Their essay aims to assess how the Russian Revolution in 1917 impacted the academic validation and acceptance of Karl Marx. Magness and Makovi released a preprint of their paper in November of 2022 which led to significant discourse and contention on

#EconTwitter around their use of this new methodology in the context of a HET topic. The views were largely skeptical of Magness and Makovi's study and so also skeptical of the value of synthetic control models.

Despite what the debate around Magness and Makovi (2023) may suggest, synthetic controls have value to offer to HET. The aim of this thesis is to thoroughly explore both the epistemic and non-epistemic value which synthetic controls can offer. There are three primary reasons why practitioners in HET must acknowledge and explore synthetic controls before writing them off. First, synthetic controls can offer potential epistemic value for understanding and exploring questions in HET. For one, many questions and claims made in HET are naturally quantitative and even causal in nature, so adding an empirical analysis to such claims can only strengthen such arguments. In addition, the qualitative and quantitative histories can diverge and show different stories, as evident by the example on the history of the efficient market hypothesis from Jovanovic (2018). So, providing an additional quantitative history could shed new light.

Second, given the overall rise in empirics across economics, there are potential non-epistemic consequences for introducing a quantitative method into a largely qualitative field of study. There can be positive value such as increasing the prestige or visibility of HET. However, this may also have a downside as some practitioners in HET are incentivized to prioritize the quantitative empirics over sound qualitative analysis.

Last and somewhat bluntly, this methodology and other empirical causal methods will likely continue. Whether they are a passing fad or something more persistent, we cannot know at this point. Nonetheless, these methods are currently present. If practitioners in HET ignore the use of this methodology to answer HET related research questions, this does not mean that econometricians or others with less knowledge and training in history will employ them. Practitioners in HET should have one of the largest voices to set the standards and expectations for applying such a causal method, so must be engaged in conversation around these methods and not ignore them.

Thus, this thesis aims to be a doorstop and prevent practitioners in HET from immediately closing the door on this new methodology. The hope is to provide a thorough introduction so practitioners in HET are equipped to engage in conversation around this method both in the form of formulating projects which can be solved with a synthetic control and in the form of critiquing and assessing projects which employ the model.

The thesis is structured in four primary parts which explore the what, why, how and who of synthetic controls in HET. The first part consists of one chapter, chapter 2, which explains what synthetic control models are. The chapter is structured first with a general explanation about the model in more simple terms. Then second, an explanation with the more technical econometric language so practitioners in HET are aware of the jargon. The chapter concludes by going through one example from the policy analysis literature, Abadie et al. (2015) on the impact of German Reunification on West German GDP, and a second example from the

economic history literature, Gilchrest et al. (2022) on the economic impacts of oil discovery in Venezuela in the 1920s.

The second part of this thesis, chapter 3 and 4, dives deep into *why* synthetic controls can bring epistemic value to HET by first, exploring the argumentation about the role of quantitative methods in HET in general and second, why synthetic controls are the most approachable and applicable causal models for use in HET. Chapter 3 starts by summarizing the existing arguments on the place of quantitative methods in HET from Backhouse et al. (1997) and Edwards et al. (2018). What is largely agreed upon is that practitioners in HET tend to make generalizations which are quantitative in nature and so could be expected to provide evidence to such claims. I expand this argument to say practitioners in HET already make statements which are also causal in nature and so it would not be far-fetched to provide empirical support for such claims. The chapter finishes with a few existing claims in HET which are causal in nature and which synthetic controls could be applied to gain more knowledge.

Chapter 4 aims to explain why synthetic control models are the best causal model for HET. Synthetic control models superiority can be understood by the points that they are for 1) approachable for practitioners in HET and 2) applicable for cases in HET. They are approachable as they have a relatively easy to read output with a visual graph and because they are transparent so we can trace how the counterfactual --the hypothetical comparison-- is created, as argued by Abadie (2021a). Second, synthetic controls are applicable because they intuitively fit cases in HET and are also relatively flexible models. The models are relatively flexible because they rely more on contextual requirements, qualitative knowledge, and assumptions about the case study at hand, rather than hard statistical assumptions. It is this heavier emphasis on contextual requirements which makes synthetic controls malleable and usable for case studies in HET. However, this flexibility leaves room for vulnerability in the modeling as there is more subjective judgment to determine whether the contextual requirements hold. These contextual requirements are the greatest limitation and weakness of synthetic controls. So, this leads us to our third part on *how* to properly employ synthetic controls in HET.

The third part consists of two chapters, 5 and 6, which aim to address how to apply synthetic controls in HET. Chapter 5 aims to provide a framework and outline requirements which practitioners in HET should follow to reach a justified conclusion. The chapter starts by building on the contextual requirements outlined by Abadie (2021a) with their specific relevance for HET and then suggests three additional, implementation related, requirements to help practitioners fulfill the contextual requirements and reach a justified conclusion. Given the emphasis on these requirements in synthetic control models, these models must be approached with the firm belief that qualitative analysis grounds and structures the whole model. These requirements cannot be relaxed.

From there, chapter 6 applies the framework outlined in chapter 5 to the primary existing case of synthetic controls in HET, Magness and Makovi (2023). With the framework, it is argued that Magness and Makovi's study falls short by failing to meet all three implementation

requirements as well as Abadie's contextual requirements. Simply, their analysis fails for a few reasons which can be boiled down to the fact that they make too broad a conclusion and miss substantive historical detail.

The fourth and final part of the thesis, chapter 7, explores the non-epistemic considerations through the lens of who may choose to employ synthetic controls in HET. This chapter also aims to address any general anxieties practitioners in HET may feel towards adopting a quantitative method and discussing further the concerns from Cherrier and Svorenčík (2018) about a potential divide. While the introduction of such a causal empirical model may be outside of the comfort zone for many practitioners in HET, these methods cannot be ignored and overall are much more accessible and relevant than many may realize.

2) The what: understanding synthetic controls

Synthetic control models are a form of causal model that aim to compare an affected unit to an unaffected control unit. The model does so by identifying a possible counterfactual, a theoretical scenario which allows one to ask, “what could have happened?”. The model is largely attributed to Alberto Abadie who explains the original purpose of the model was to “measure effects of large aggregate events” (Abadie, 2021b). So far, there is one published case of synthetic control models in HET and that is Magness and Makovi (2023) on the impact of the Russian Revolution on the influence of Karl Marx in the social sciences. Magness and Makovi are one of the first to apply a synthetic control model to cases in HET, although it has been used widely in policy analysis (Abadie et al., 2010; Abadie et al., 2015) and comparative case studies in economic history (Gilchrist et al., 2022; Grier and Maynard, 2016).

The goal of this chapter is simple and straightforward. The aim is to introduce practitioners in HET to synthetic control methods. We will start in section 1 with an explanation of synthetic control methods from a general and intuitive point of view. We will then go into section 2 and explain the more technical sides of synthetic control models. Section 3 walks through one example employing synthetic controls from the policy analysis literature and one example from the economic history literature.

2.1) General idea and intuition

We can understand synthetic controls by first explaining their comparative nature and by second breaking down the intuition behind the concept of the “synthetic” unit. Synthetic control models are a statistical causal model. Like most causal models, synthetic controls allow us to see how a unit, X, was affected by one specific event, Y. We can draw a causal inference on how Y impacted X. For example, we can see how the implementation of smoking policies, an event Y, decreases the number of cigarettes sold, the affected unit X.

We can draw a causal inference between how Y impacts X by comparing the affected unit of interest, the treated unit, to another unit which is entirely unaffected—the control unit. So, we see the impacts of our specific event Y on unit X by seeing how it does not affect a representative unit Z. For example, if the state of California implements a smoking policy Y, then we can see how this affects cigarette sales in California, X, by comparing this to cigarette sales in Arizona, Z. So, the effect of Y is based on the difference between X and Z. Figure 1 depicts how this causal arrow may look.

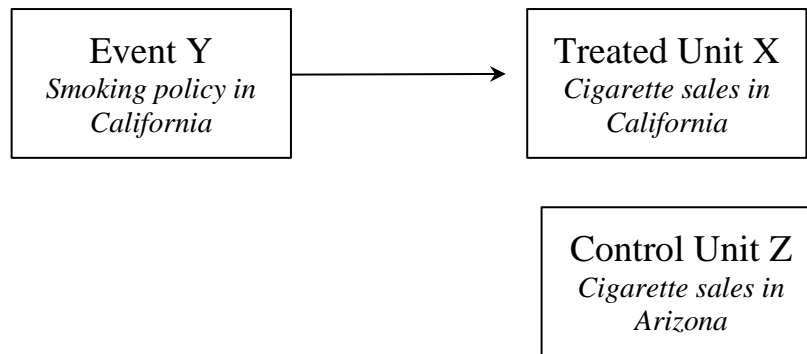


Figure 1: Causal representation of Event Y on Treated Unit X

One of the main ways synthetic control models differ from other statistical models, is based on the control unit which it uses to compare to the treated unit. Typically, statistical models require a number of individual units that are affected by the event and several individual units which are unaffected by the event to represent the treatment and control groups. However, synthetic control models can determine a cause-and-effect link with only one individual entity representing the affected unit. Returning to our smoking example, say we want to understand the effect of a smoking policy on cigarette sales. Most causal models would require comparing the cigarette sales in multiple states which enacted smoking policies to multiple unaffected states to validly draw a causal inference. With synthetic control models, we can look at just the specific smoking policy in California and compare that to multiple other states. Synthetic control models allow us to look at one specific case.

We have emphasized the comparative nature of synthetic control models and next we must break down the concept and use of the term *synthetic*. In these models, the word synthetic can be understood to mean something which was purposefully created and composed. Closely related synonyms to synthetic in the case of these models can be replica, fake, a mimic. So, a synthetic control unit can also be understood as a replica control unit, a fake control unit, and even a mimic control unit.

With synthetic controls, we can evaluate the effect of a specific event Y on one individual entity X, by comparing it to an unaffected representative unit, Z. By comparing between an affected unit X and an unaffected representative unit Z, we get to ask the question, “what would have happened had event Y not occurred?”. Synthetic control units draw a cause and effect by creating the counterfactual: the case of what would have happened if the specific event had not occurred. By comparing the reality of what happened to the hypothetical case of what could have happened –the counterfactual—we can determine the causal effect of our specific event Y on the outcome X.¹

¹ I recognize that by pulling in the discussion of counterfactuals, I may open myself up to discussions on causality. Those familiar with debates in causality will recognize the Lewisian nature of synthetic controls. However, for the sake of this project, the literature on causality will not be engaged with as the arguments are more concerned by causal inference rather than causality. Scott Cunningham suggests causality represents the philosophical idea, whereas causal inferences is the statistician’s view on causality (Cunningham, 2023).

Another key characteristic of synthetic control models is the way it creates the representative unaffected unit Y. The synthetic control is meant to mimic the treated unit X in the scenario where the event of interest had not occurred. So, in the case of the smoking policy, our representative unit could be built from the cigarette sales in the states which were unaffected such as Arizona, Nevada, or Oregon. The representative unit Z is constructed by combining different portions of these unaffected entities to mimic our affected unit. It is this representative unit which is then compared to the affected unit X. In the smoking case, the representative unit Z may be composed of say 20% Arizona, 30% Nevada, and 50% Oregon. This representative unit composed of the unaffected states serves as our counterfactual of what could have happened to the cigarette sales in California had the smoking policy not been implemented.

This representative unit Z is our synthetic control. In this model, the synthetic control can loosely be understood as a replica of our affected unit, and more specifically the counterfactual to our affected unit. Synthetic means the constructed replica. To pull it all together, a synthetic control model compares an affected, treated unit, X, to a constructed and unaffected representative unit, Z, to determine the causal impact of a specific event, Y. This comparison is done graphically and so visually shows how the treated unit may, or may not, converge from the unaffected units given the intervention or occurrence of a specific event.

2.2) Technical points of synthetic controls

This section will give a definition of synthetic controls from a more technical perspective and provide a terminology list.

For those with an understanding of econometric and causal models, synthetic control models are a methodological mix of difference-in-difference estimation and matching. Difference-in-difference draws a causal inference by comparing a collection of treated units to a collection of untreated, control units following the event or intervention of interest. The model is only valid if the treated outcome and the control outcome have a similar and parallel trend prior to the event of interest. By holding this assumption, practitioners can then assume that any differences between the treated outcome and control outcome are due to the intervention. Synthetic controls are similar in that they compare a treated outcome to a control outcome, however, the assumptions about the trends of the units in the pre-treatment period are not as strict. Matching is also about comparing a treated unit to a non-treated unit.

Note, throughout this thesis the terms synthetic control model, synthetic control methods, and synthetic controls will be used interchangeably. This is solely meant to refer to any model which uses a synthetic unit. There is the standard form of synthetic control model explained by Abadie (2021a). But also other advanced forms which focus on alleviating bias form the synthetic unit and this includes synthetic difference in difference (Arkhangelsky et al., 2021), the augmented synthetic method (Ben-Michael et al., 2021), or a penalized synthetic control for disaggregated data and multiplicity of solutions (Abadie and L'Hour, 2021).² These other

² There is a growing literature on the methodological pieces of synthetic control models. For more on matrix or tensor completion, see Amjad, Shah, and Shen, (2018); Agarwal, Shah and Shen (2020); Athey, Bayati,

advanced forms are useful but will not be mentioned explicitly throughout this project; the focus will be on Abadie’s standard synthetic control model.

There are a few terminologies to know: synthetic control, donor list, treatment, intervention, post-treatment period, pre-treatment period, and predictor variables or covariates. These concepts are the bread and butter of every synthetic control model; you can’t have the model without these elements. For those who are newer to this model, Table 1 outlines a definition for each terminology.

Table 1:

Terminology	Definition
Synthetic Control	An optimally weighted constructed unit on which to compare the unit of interest.
Donor List	A compilation of units which are similar to the unit of interest but unaffected by the intervention. It is this list of units that is used to optimally weight the synthetic control.
Treatment or Intervention	The event or instance which (potentially) impacts the variable of interest. Should occur at one point in time.
Post-treatment period	The time period following the intervention. This is where the outcome is assessed. If the variable of interest and the synthetic control diverge, then it may suggest a causal impact.
Pre-treatment period	The time-period prior to the intervention.
Predictors	The variables used to create the synthetic control by optimally weighting units in the donor list to match the variable of interest on the pre-treatment period.

Synthetic control models work by optimizing a fake, i.e., *synthetic*, replica of the variable of interest by weighting a list of similar units on a set of predictors --pre-treatment variables or covariates-- in the pre-treatment period. This synthetic unit is then compared to the actual, real

Doudchenko, Imbens, and Khosravi (2021); Bai and Ng (2020). For more on the statistical elements of drawing an inference, see, Cattaneo, Feng, Titiunik (2021); Chernozhukov, Wuthrich, and Zhu (2021); Firpo and Possebom (2018). For cases working with functional and distributional outcomes, see, Chernozhukov, Wuthrich, and Zhu (2019); Gunsilius (2020). For cases with a large t-statistic, see, Botosaru and Ferman (2019); Ferman (2021); Li (2020).

unit of interest in the post-treatment period to graphically, and thus visually, see the effect of the treatment or intervention on the outcome of focus.

2.3) Case examples employing synthetic controls

With the housekeeping definitions out of the way, let's apply this to two examples: one from the policy and event analysis literature and a second from the economic history literature. In the realm of policy analysis, synthetic controls have been widespread with two notable examples: one looking to evaluate the effects of a tobacco policy in California (Abadie et al., 2010) and one aiming to assess the economic impacts of German reunification (Abadie et al., 2015). In economic history, one particularly impactful study has been analyzing the economic impacts of oil discovery in Venezuela in the 1920s.

In the case of German reunification, Abadie et al. (2015) uses a synthetic control model to determine the economic impacts of reunification in 1990 on West Germany. Typically, finding concrete answers to questions as this are difficult because we cannot go back in time to see how else things would have gone; there is no control to compare to. However, this is exactly what synthetic control attempts to let us do. In this case of German reunification, the treated unit is West Germany, and the focus of analysis is GDP. Abadie et al. (2015) are able to identify *what could have happened* by comparing the actual GDP of West Germany to a synthetic, "fake" West Germany created by an optimally weighted selection of similar countries. The optimal weighting is decided by matching the treated unit, West Germany, against the list of possible control units on a selection of predictor variables during the pre-treatment period. In Figure 2, we see the output graph from Abadie et al. (2015). What the study shows is actual West Germany (solid line) had a lower GDP than the synthetic West Germany (dotted line) which suggests German reunification caused a decline in West German GDP and so had a negative economic impact.

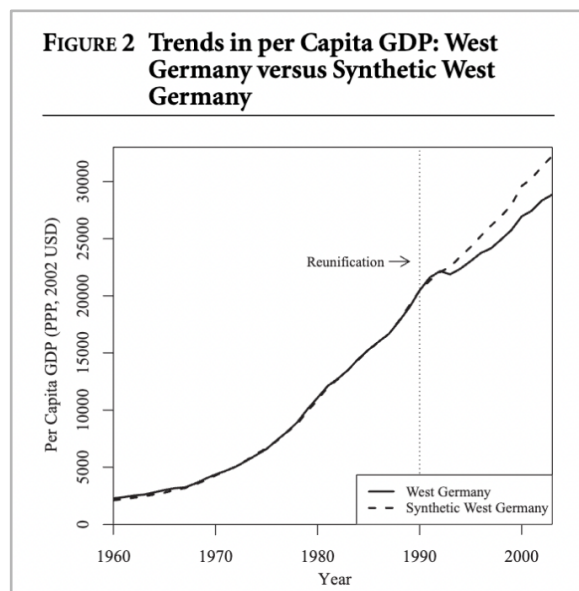


Figure 2: Synthetic control output from Abadie et al. (2015)

Before we continue, let's get more into how Abadie et al. (2015) created their synthetic West Germany. The model creates a synthetic West Germany given a donor list of relatively similar units, in this case other OECD countries, by weighting the OECD countries given a set of predictor variables in this case economic indicators, such as inflation and unemployment, and matching them to the actual West Germany on a set time period prior to 1990. For this case, the synthetic country was composed of Austria, the United States, Japan, Switzerland, and the Netherlands. Intuitively, this collection of countries makes sense because the combination of these countries' economic standing in the 1980s were most similar to that of West Germany. With GDP as the outcome of interest- an economic factor- it is best practice to create and define the similarities of donor pool on this outcome of interest- economic factors and standings- so thus using the OECD which is a group of countries based on economic conditions limits bias and improves the inference capabilities.

This synthetic control model allowed Abadie et al. (2015) to create the hypothetical situation for West German GDP if reunification had not occurred and then compare this hypothetical situation to the actual situation. Thus, synthetic control models allow us to visualize the counterfactual; we see what *could* have happened.

As a second case, we can look to the literature in economic history. A handful of economic historians have begun to engage with the usefulness of the model for comparative case studies in economic history (Gilchrist et al., 2022; Grier and Maynard, 2016; Geloso and Bologna, 2020). Gilchrist et al. (2022) reviews the properties of synthetic control methods to examine their usefulness for comparative case studies in economic history, albeit with some necessary conditions. In addition, Gilchrist et al. (2022) then apply their guidelines to study the impact of oil discovery in Venezuela in the 1920s on the country's long-term economic growth. In their study, the variable of interest is GDP per capita of Venezuela and their donor list is compiled of 56 countries. Figure 3, graphs GDP per capita of Venezuela versus the synthetic Venezuela which is composed of growth and development characteristics of Burma, Mexico, Chile, Brazil, South Korea, Jordan, Philippines. What we see is a sharp increase in the GDP per capita of actual Venezuela relative to synthetic Venezuela, following the discovery of oil in 1920. In this case, Gilchrist et al. (2022) can reproduce the hypothetical scenario of what Venezuelan growth could have been in the 1920s if they had *not* found oil. Thus, giving us a better understanding of the impact of oil discovery.

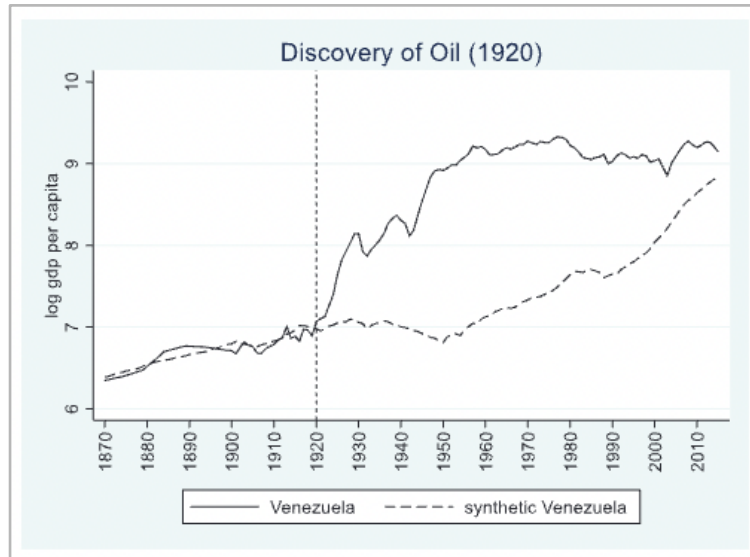


Figure 3: Synthetic control output from Gilchrist et al. (2022)

The use of synthetic control in policy analysis and economic history, specifically, has grown over the last decade and even few years. Particularly given the use in economic history, it is only a matter of time before synthetic control is approached in other cases relating to economics and history, i.e., HET. So, to bridge synthetic control methods into the study of history of economic thought is solely a step and not a leap. The following section will share a few explicit examples of where synthetic controls could be made useful in HET to get deeper conclusions.

The goal of this chapter was to introduce synthetic control methods. What should be remembered is that synthetic control models allow us to identify the hypothetical outcome of what could have happened. The following section will continue to convince the reader on the value of synthetic controls by engaging with the discussion about the place of quantitative methods in HET.

3) The why, part 1: arguments for quantitative and causal methods in HET

The aim of the previous chapter was to explain what synthetic control models are. The aim of the following two chapters is to explore broadly why synthetic controls have any epistemic value to offer to HET. This first chapter will synthesize the existing arguments on why we should consider quantitative models in the first place and expand the discussion to causal models in general. Chapter 4 will then make the argument for why synthetic control models are a relevant and useful causal model, especially in comparison to other models such as difference-in-difference. By the end of the two chapters I hope to have convinced you of the epistemic value of exploring synthetic controls as a method in HET to accompany existing qualitative methods.

We start in section 1 of this chapter with a general conversation about the place of quantitative methods in HET. Section 2 will expand these arguments and look at the more specific case of causal methods in HET. Section 3 will then look specifically at synthetic controls to show how existing causal generalizations in HET can be further built on with the quantitative synthetic control models. Section 4 concludes with a brief discussion on the place of where synthetic controls fit into the research agenda in HET.

3.1) Quantitative methods in HET

With the rise in quantitative methods in the field of economics, the question about the role of quantitative methods in HET has persisted (Backhouse et al., 1997; Edwards et al., 2018). Especially with the rise of digital technologies, the use of quantitative methods is becoming more accessible and receiving more attention about the impact of mixing qualitative and quantitative methods in HET (Cherrier and Svorenčík, 2018). In this section, we will start by exploring the arguments made for including quantitative methods in general.

First a distinction should be made about what we mean by quantitative methods and how synthetic controls relate. By quantitative, what is meant is any method which employs statistical or numerical evidence, rather than qualitative which focus primarily on textual analysis. New methods relevant to HET include citation analysis, network analysis, topic modeling, quantitative organizational history, prosopography, and correspondent factor analysis (Edwards et al., 2018). Now these are primarily forms of bibliometric studies. Whereas synthetic controls are a causal model and so allow us to not only explore relations between entities like the bibliometric studies, but also to make a causal inference. To my knowledge, synthetic controls are the first causal model to be used in HET (Magness and Makovi, 2023).

Arguments for understanding the place of quantitative methods in HET started with Backhouse et al. (1997) where they categorized the existing quantitative work in HET. At the time, combining quantitative methods into a largely qualitative practice may have appeared counterintuitive and an undesirable practice. However, they acknowledged that economists' lack of interest in the past and historian's tendency to be focused on "texts, great individuals and non-quantitative studies" was a "mistaken attitude" (Backhouse et al., 1997, p. 19). Even prior to this were explorations from practitioners in HET of quantitative methods. This includes

Coats (1969) which looked at the role of editorship by counting theoretical papers in the *American Economic Review*, *Quarterly Journal of Economics*, and *Journal of Political Economy*. Stigler (1964) which looked at long run trends of the US economic journals. And Biddle (1996) which was a citation analysis on the reputation and influence of Wesley Mitchell.

More recently, the *Journal of Economic Methodology* devoted a whole issue to the topic of quantitative methods in HET and economic methodology. The edition acknowledged the increase in quantitative methods within HET and argued HET was facing a “methodological moment” (Edwards et al., 2018, p. 284). The special issue as a whole aimed to showcase a handful of cases utilizing quantitative methods and to explore the possibilities a mix of qualitative and quantitative methods can offer.

Based on the 2018 JEM edition and Backhouse et al. (1997), there are a number of reasons to consider the value in quantitative methods. There are three primary points laid out by Backhouse et al. (1997). They argue quantitative methods are useful for 1) understanding the average economist rather than the exceptional; 2) data can paint a new picture or shed light on patterns or puzzles that need attention; and 3) practitioners in HET tend to make generalizations that are quantitative in nature anyways and thus should be expected to provide evidence to such generalizations if feasible.

More recently, these points from Backhouse et al. (1997) on the value of quantitative methods have been echoed throughout the JEM issue. Edwards et al. (2018) open the special issue by building on the point from Backhouse et al. (1997) that practitioners in HET make statements which are quantitative in nature. Edwards et al. (2018) pull three statements from recent publications in HET to make their point. They show that throughout these statements, practitioners in HET rely on words such as “the most”, “the majority”, and the “widespread view” which all suggest there is a clear numerical dominance of one side. Edwards et al. (2018) then argue practitioners should explore the value and use of such quantitative methods more as they already tend to draw conclusions based on this style of evidence anyways.

Moreover, Cherrier and Svorenčík (2018) close off the special issue by making three additional suggestions on the epistemic value of quantitative methods. They suggest there is value in complementing studies in HET with quantitative methods because 1) it can help identify patterns; 2) it can be used for exploratory purposes (Herfeld and Doehne, 2018); and 3) it can help fight against confirmation bias and shield against Whig history (Herfeld and Doehne, 2018). Similar to Edwards et al. (2018), Cherrier and Svorenčík (2018) believe there is potential for quantitative methods in HET.

To summarize, Backhouse et al. (1997) and Edwards et al. (2018) both make the point that practitioners in HET make statements which are already quantitative in nature and so should not shy away from then engaging with quantitative methods to help properly back up such claims. Then, Backhouse et al. (1997) and Cherrier and Svorenčík (2018) share the belief that there is value in qualitative methods for identifying patterns and exploring. While they do not necessarily differ on the other points of value, they do not explicitly state them.

There are many reasons to consider the value of quantitative methods in HET. Different practitioners will find more or less value amongst the different points. My goal is not to say which of these is the primary epistemic reason for considering quantitative methods in HET. Rather, I care more about the fact that there are several relevant points of value which quantitative methods can assist. What we see from the above lists is there is a breadth of epistemic opportunity for quantitative methods in HET.

3.2) Causal methods in HET

As of now, many of the uses of quantitative methods in HET are using bibliometric analysis and other methods with a key focus on identifying relations between elements of study (see Journal Economic Methodology 2018 special issue). Synthetic controls differ from these models as it is a causal econometric model; the goal of the method is to make a causal inference. As of now there are no causal methods commonly used in HET. So why should we introduce causal methods at all?

Backhouse et al. (1997) suggested one of the reasons practitioners in HET should value quantitative methods is because they tend to make quantitative generalizations anyways. This is something Edwards et al. (2018) also builds on by arguing that practitioners in HET tend to make statements which are quantitative in nature but with a lack of quantitative evidence. Edwards et al. (2018) provides three examples from recent literature, including one from Backhouse and Cherrier (2017) on the age of the applied economist. Edwards et al. (2018, p. 283) quotes Backhouse and Cherrier to make his point: “it is probably safe to say that *the vast majority* of economics was applied in some way (Backhouse and Cherrier, 2017, p. 26).” What Edwards et al. (2018) points out is how common the use of such quantitative generalizations are.

These generalizations do not stop at being solely quantitative but in some cases causal. Meaning practitioners in HET can be inclined to make statements which suggest a causal relation between entities. One example is throughout Backhouse and Cherrier (2017). In their paper, Backhouse and Cherrier make a handful of claims which suggest some form of cause and effect. These include:

“...computerization and new, more abundant and better data have *enabled this transformation* [in growth of empirical research and decline in theoretical research].” - p. 2

“The development of new techniques associated with behavioral and experimental economics, and the use of ‘quasi-experimental’ methods, *transformed* parts of the subject (the so-called empirical turn discussed above).” - p. 14

“...the diversity of applied economics practices is the result not only of idiosyncratic combinations of modeling techniques, datasets, software, and hardware: it was also a

consequence of the variety of sites, old and new, where applied economics was practiced, and the changing demands patrons and clients were imposing on economists.” - p. 20

Throughout these statements, key verbs such as transform and consequence are used to suggest a cause-and-effect relationship from one element to the next. These are simple statements, however, there is no quantitative or empirical evidence to back them up. While Backhouse and Cherrier (2017) provide extensive qualitative support for these statements which are causal in nature, they provide little quantitative causal evidence. And as Backhouse et al. (1997) suggested about historian’s statements which are quantitative in nature, if practitioners in HET make statements which are causal in nature, then they should also be expected to provide thorough evidence as support.

However, making *strong* causal inferences is a difficult task.³ There can be a number of confounding factors at play which qualitative studies may fail to recognize or properly account for. In addition, making a causal claim through econometric means suggests there is some control of the variable of interest that can be compared to. This is the primary difference between making a causal statement based on empirical means versus qualitative means. By using a model such as synthetic controls, practitioners in HET will have a control element to compare their treated unit of interest to. By comparing the variable of interest to some unaffected control, a more thorough statement can be made about the cause-and-effect nature of an intervention. This is where synthetic controls can be useful.

3.3) Relevant cases in HET for synthetic controls

Research questions and projects which practitioners in HET pursue already tend towards not only quantitative generalizations, as suggested by Edwards et al. (2018) and Backhouse et al. (1997), but also causal generalizations. Synthetic controls can already naturally fit into the research agendas of many practitioners in HET, and potentially open new research agendas by providing an additional tool for drawing conclusions. The rest of this section will explore the exact relevance of synthetic controls to questions in HET by first giving a list of HET topics which are relevant to quantitative methods in general and then providing three examples which are relevant to synthetic controls.

Backhouse et al. (1997) explore the use of quantitative methods in economics to get a sense of the state of quantitative methods in HET. Backhouse et al. (1997) start by building on Colander (1989) who suggested three reasons as to why economists may tend towards quantitative work: 1) prurience and professional interest; 2) case study of economic theory; 3) case study in the sociology of scientific knowledge. Of which, the one of particular interest for us is the third category. Backhouse et al. (1997) expand on this list given by Colander to create a list of 6 topics which make quantitative analysis relevant for HET and then categorize existing quantitative studies in HET into their table. These six categories are roughly: 1) trends in

³ Quantitative evidence is not necessary to make a causal inference and hence why the word stronger is added to the statement. However, quantitative evidence can help provide an additional view.

economic associations and journals as an indication of professionalization and development of economics; 2) departments as producers of economics and economists; 3) influence of individual economists on other economists (i.e., citation analysis); 4) classic paper replications; 5) authorship puzzles; 6) economists and policymaking.

To reproduce such a table nowadays would be a thesis in itself and that is not the goal of this project. But what is useful, is to understand the classification Backhouse et al. (1997) use for understanding what topics are deemed worthy for quantitative analysis in HET. The category of strongest interest for studies with synthetic controls are categories 1, 2, 3 and 6, and particularly 3 with the emphasis on citation studies. The first three categories place an emphasis on understanding some form of causal relation: an impact, a cause, or trend. Synthetic control models can be used in HET to analyze the change and progression of ideas and individuals. It is a temporal model with the treatment being represented as a date in time. In addition, it allows us to look at one key observation or the treated unit. We can single out an individual, idea, institution to understand more of its relation to others.

As of now the only published study using synthetic control in a HET topic is from Magness and Makovi (2023) who ask, “how did the Russian Revolution impact the academic influence of Karl Marx?”. Their study would fall under the third category from Backhouse et al. (1997) as their study is about understanding more of the nuance of Marx’s legacy and academic influence. Magness and Makovi (2023) conduct a citation analysis and see how citations of Marx change relative to a synthetic Marx following the Russian Revolution in 1917. Their study is by no means a picture-perfect example of how to use synthetic controls in HET (this will be expanded on in the sixth chapter), but it provides an example to start with.

Nonetheless, there are other scenarios where synthetic controls can be employed. To further prove the relevance and usefulness of synthetic controls, I’ll present three cases where the model could be used to help provide a more *thorough* answer. I want to emphasize my use of the word *thorough* here, rather than something such as concrete or accurate. This point will be emphasized in the following section, but for now understand that synthetic controls must be used as a complement to answering existing questions in HET. Synthetic controls can not be the sole means for answering research questions in HET and should be supported by traditional qualitative methods.

Anyhow, here are three cases in which synthetic controls can deepen our understanding of an existing argument:

Case 1: The age of the applied economist: how the funding decisions of the Reagan administration impacted the American research agenda. In their essay, *the Age of the Applied Economist*, Backhouse and Cherrier (2017) argue the field has shifted to hold a focus on applied research and away from the theory driven research in the 1950s and 60s. Interestingly, when exploring reasons as to why this shift occurred, they mention how the funding decisions of the Reagan administration with the National Science Foundation (NSF) may have played a role: “...in 1981 Reagan made plans to slash the Social Sciences NSF budget by 75 percent, forcing

economists to spell out the social and policy benefits of their work more clearly (Backhouse and Cherrier, 2017, p. 25)”. With synthetic control, an analysis could be done to compare the American research agenda before and after the change in funding in 1981 to understand how policy and funding decisions can impact the trajectory of research. A synthetic American research agenda could be created using the agendas across other countries such as the UK, Germany, and even Australia with a variable of focus being number of applied papers or even number of theoretical papers. This topic could fall under Backhouse et al. (1997) first category.

Case 2: The Office for Strategic Services (OSS) and Interdisciplinarity: how the problem-based organization of the OSS during WWII encouraged interdisciplinary cooperation amongst economists and other disciplines. As argued by Katz (2013), the problem-based organization of the OSS during WWII led to an increase in economists' willingness to work across disciplines following the end of WWII. This is a statement which has been thrown around but has no empirical proof. As stated earlier, quantitative proof is not necessary to justify the argument, but it would help strengthen the argument, especially given the causal nature of the claim. In this case, a synthetic control model could be used to draw a causal inference to say more concretely, “the OSS caused an increase in interdisciplinarity”. This topic would relate to Backhouse et al. (2017) second category as it is about the production of research. In addition, having a more thorough answer to this argument could help shed light on the profession today as academia is increasingly discipline based.

Case 3:⁴ The 2008 Financial Crisis and Hyman Minsky: how the crisis encouraged a revival in Minsky’s work. The 2008 financial crisis, in many eyes, was an unprecedented collapse that the predominant theory could not explain. This led economists to search for answers which some found in the work of Hyman Minsky (Minsky 2008). Many people may find a quantification of this phenomena, an increase in the citations of Minsky, an unnecessary exercise. However, what synthetic control can offer is the ability to compare the increase in citations to this donor list and better understand how the crisis set Minsky apart from his contemporaries. The treated unit can be citations of Minsky (2008), the treatment being the year 2008 to mark the beginning of the Financial Crisis, and the donor list can be composed in different ways. As one example, it could be based on other Keynesian economists to see how the crisis impacted the influence of Minsky as a *Keynesian* economist (Keynesian simply meaning descending from the work of Keynes). Based on the way the synthetic control is created and modeled, we can extract more nuanced and specific conclusions. This case would belong to Backhouse et al. (1997) third category about the influence of an economist.

Each of these three cases already have well established conclusions with the standard qualitative methods typically pursued by practitioners in HET. But synthetic controls would allow for a stronger conclusion as they are a causal model and can help account for other correlations and specific or nuanced details by comparing to a control unit. Hopefully these

⁴ This case is based on the existing paper from Needler (2023) which started as a bachelor’s thesis. The paper uses a synthetic control model to determine the impact of the 2008 financial crisis on the work of Hyman Minsky. The project does not meet the necessary qualitative standards explored in chapters 5 and 6, so will not be explored in excessive detail. However, portions of the paper may be referenced as a learning tool.

three cases have presented a worthwhile argument to make the reader at least intrigued by synthetic controls.

3.4) Synthetic controls as complementary evidence

Before we venture further, we must take a step back and be more detailed about *where* synthetic controls fit into the current research agenda. We have mentioned so far that synthetic controls must act as a complement to qualitative studies in HET, but what exactly does this mean? There are two sides to this. First on how synthetic controls serve as evidence when answering research questions in HET, and second, on how synthetic controls interact and relate with the existing qualitative evidence.

First, we must understand how synthetic controls can serve as evidence. Simply, many practitioners in HET hold the belief that quantitative methods, such as synthetic controls, should just complement existing qualitative studies in HET. This opinion that quantitative methods cannot eclipse existing qualitative practices has been reiterated by proponents on the use and value of quantitative methods including Backhouse et al. (1997), Edwards et al. (2018) and Cherrier and Svorenčík (2018). These practitioners in HET have argued:

“Whilst quantitative analysis will never (and should never) replace more traditional historical research, it is an invaluable complement to such work.” -Backhouse et al. (1997, p. 20)

“Quantitative history should not replace qualitative history, but complement it, contributors preach *and* practice in their papers.” -Cherrier and Svorenčík (2018, p. 369)

“...they [authors in the JEM special issue] all present their models as complementary (not a replacement) to traditional - qualitative - ways of advancing the historiography and methodology of economics.” -Edwards et al. (2018, p. 287)

This view that quantitative methods must act as a complement to traditional and qualitative methods is deeply rooted in the profession. While many practitioners in HET see the value in quantitative methods, they all agree it cannot eclipse qualitative study. However, even if they cannot overtake qualitative methods, the quantitative methods can still offer a different perspective and thus bring epistemic value. One evident example is from Jovanovic (2018) who shows through a citation study that the quantitative and qualitative histories on the efficient market hypothesis marginally differ and thus the quantitative perspective should also be considered. So, when it comes to understanding how synthetic controls fit into answering questions in HET, it should be understood that this method is complementary in the sense that it sits side by side with the qualitative method and cannot be a supplementary replacement to it. This is not to say that the findings of the quantitative methods will be complementary and supportive to the qualitative findings, but rather that the methods must cohabitate.

Second, we must understand that the creation of synthetic controls relates to qualitative evidence in that they are dependent on the qualitative knowledge. This dependency is common for most quantitative models but is particularly important for synthetic controls given the contextual requirements which will be expanded on in chapters 4 and 5. At the heart of it, quantitative methods are informed by qualitative evidence and so for the case in HET, must be grounded by a deep historical understanding.

To relate this more directly, we can see this complementary and even dependent position as the place of synthetic controls in the case studies suggested above. In each instance, there has already been a generalization of a causal nature made through qualitative analysis in the traditional means of practitioners in HET. The synthetic control is introduced to build on the existing qualitative work and either provide support for the qualitative claim or refuting evidence which suggests the claim at hand may need additional discussion.

To conclude, practitioners in HET tend to make causally charged generalizations throughout their qualitative work but do not provide empirical evidence to back up such claims. This point echoes that made by Backhouse et al. (1997) and Edwards et al. (2018) that practitioners in HET already make quantitative generalizations. After suggesting that practitioners in HET already make causal generalizations, a few case examples were explored where generalizations have already been made and known and synthetic control models were suggested on how to build a model to provide empirical causal answers. The following chapter goes deeper into arguing for the case of synthetic controls models as the primary causal model for practitioners in HET.

4) The why, part 2: synthetic controls as the best causal model for HET

The goal of this chapter will be to show why synthetic controls are particularly well suited for studies in HET. Synthetic control models are the best suited causal model because they are 1) the most accessible due to their easy to interpret outputs and transparency; and 2) the most applicable because the original goal of the model intuitively fits the goals of case studies in HET and because the creation of the model is more flexible given the fewer statistical requirements. However, this note on fewer statistical requirements should not be understood that synthetic controls do not have fewer requirements overall, rather they have fewer statistical requirements and more “contextual requirements” as termed by Abadie (2021a). It is with these contextual requirements-- which can be understood as normative and historical assumptions-- where the qualitative expertise of practitioners of HET come into play.

We start in section 1 by diving into why synthetic controls are an approachable model. Then section 2 will go into why they are applicable models based on the intuitive and flexible nature.

4.1) The approachability of synthetic control models for practitioners in HET

Synthetic control models are accessible. While most practitioners in HET may have little training in quantitative, and even causal, methodologies, it is not a far cry for practitioners to understand and interpret synthetic controls. This is because they are fairly easy to read relative to other econometric outputs because it is a graph and not a large table full of numbers, t-statistics, and p-values. In addition, synthetic control models are transparent, which is argued by Abadie (2021a).

First, synthetic controls are easy to interpret relative to the statistical outputs of other causal models. Unlike a difference-in-difference model or even simple linear regression, a synthetic control model outputs a graph and not a statistical table. The graph plots two lines, usually one solid line of what actually occurred, and a dotted line of the synthetic control or counterfactual of what could have happened. The horizontal or x-axis is usually the time frame. Then there is typically a vertical line at the point in time of the event to divide the time period prior to the event and the time period after the event. So, a practitioner in HET simply needs to distinguish between the dotted and solid lines and how they interact following the event or intervention of interest.

Figure 1 shows the output from Abadie et al. (2015) where they try to determine the economic impact of German Reunification in 1990 on West Germany. In this case, West Germany is the solid line and the synthetic or replica West Germany is the dotted line. The vertical line in 1990 represents the point in time of reunification. What we can see is that following 1990, the solid line dips and falls below the dotted line. This represents that the actual GDP of West Germany fell below the GDP of the synthetic control made to mimic the GDP of West Germany had reunification not occurred. So, what this suggests is that the reunification in 1990 had a negative impact on West German GDP based on the projection of what could have happened. So, determining whether there is a causal effect is based on a visual image and not about dissecting t-statistics and p-values.

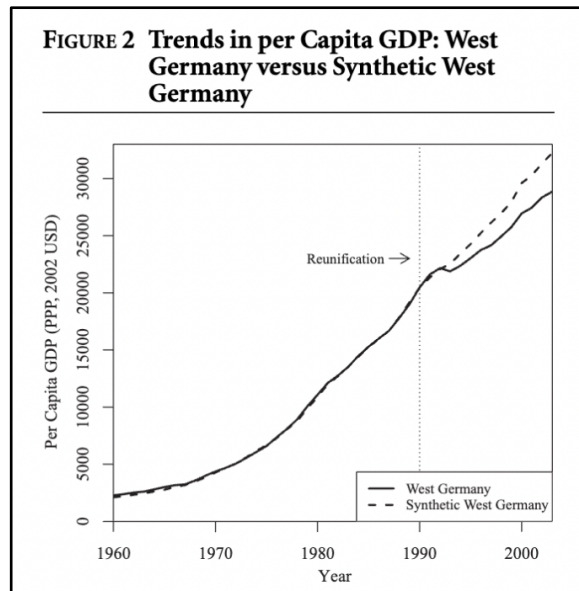


Figure 1: Graphical output of the synthetic control from Abadie (2021a)

While some of the jargon around synthetic controls may feel as a barrier (see chapter 2 for a terms list), there is more emphasis on a visual component than on a numerical component. This emphasis on a visual output, should be more appealing and approachable for practitioners in HET. It is feasible for practitioners in HET to be able to understand and interpret the output of a synthetic control model with little additional econometrics training.

Second, synthetic controls are accessible in that they are transparent and do not pose a black box concern. In this case black box is meant to refer to something where the internal workings are unknown and so we don't know how the inputs lead to the outputs. This is not the case for synthetic controls as we know how the inputs --the donor list and predictor variables-- lead to our visual graphic output with the synthetic control through the listing of the weights of each component in the synthetic control. We can see and understand the internal workings of how the control and counterfactual are produced. As Abadie argues, this is one of the main benefits of synthetic control methods relative to other causal models since the counterfactual is transparent to us based on the weights of units from the donor list (Abadie, 2021a).

With synthetic controls, the setup of the donor list and the clear weights assigned to create the unit of comparison, the synthetic control, gives the reader a clear picture. We can take the example of West German reunification again (Abadie et al., 2015). If an historian was not satisfied by the blanket statement, "German Reunification had a negative impact on West German economic outputs", they are able to look at the optimal weightings and which countries were used to create the synthetic West Germany to further assess the claim. For this case, the synthetic control was created given a donor list of OECD countries and weighted based on a set of economic based predictors, such as inflation rates and unemployment rates. The synthetic West Germany was composed of 42% of Austria, 22% of the United States, 16% of Japan, 11% of Switzerland, and 9% of the Netherlands. By knowing this exact breakdown of what creates the synthetic West Germany, the historian can respond with more detailed knowledge

on if this control is a feasible comparison to draw the conclusion that reunification had a negative economic impact on West Germany. The inner workings of a synthetic control model are transparent as we can see how the control unit is created.

Economists and historians can understand where results (i.e., the counterfactuals) are coming from since the weights of the synthetic unit are known. With synthetic controls, there is no black box concern: the whole process is understood. There are no deceptive changes from input to output. Especially for practitioners of HET, this level of transparency means that any causal conclusions can be finely scrutinized. Thus, based on both the graphical, visual output, and the transparency of synthetic control models, these models should be viewed as accessible by practitioners looking to assess and understand synthetic control models in HET.

In addition, a point should be made for practitioners in HET who are interested in not only assessing the model but creating their own model. Even without extensive training in econometric software and coding, these types of analyses are becoming more accessible with the rise in Open AI softwares such as ChatGPT. There should be less unease about implementing or creating a synthetic control because these AI softwares can help write your code and also help you through any errors. For example, you can simply ask ChatGPT to provide you the code for running a synthetic control in Stata (see Appendix A.1). So, while some practitioners in HET may feel uncomfortable by the rise of quantitative methods and potential for the use of causal empirical methods, synthetic controls are within their reach and ability.

4.2) The applicability of synthetic control models to cases in HET

The reason synthetic controls are applicable is because the model has an intuitive fit, meaning that it naturally fits case studies in HET, and also, they are more flexible and malleable to different case studies since they don't rely as heavily on statistical requirements rather, they rely more on contextual requirements. This means there is more space to adjust the model to fit our cases in HET even when we may be working with poorer data quality. Nonetheless this flexibility means we can build a valuable model as long as we can rely on our contextual requirements, which are more about normative and historical assumptions and so elements which should feel accessible for practitioners in HET.

We will first look at the intuitive value of synthetic controls. When it comes to thinking about employing causal methods in general, students are typically taught to choose a model that not only fits the data but also that intuitively fits the problem or case at hand. This means choosing the model that is best suited to the research question and not the data. One example is using a probit or logit model for answering questions about the likelihood or probability of an outcome occurring. Different causal models were created with different cases or problems in mind, so it is important to match the model to the question and case at hand.

Synthetic control models were created for the sake of analyzing case studies and large one-off events, primarily in policy. They allow us to focus and narrow in on a specific event or

intervention and its effects on a single subject such as an individual or institution. The emphasis of synthetic controls for case studies means they fit questions or topics designed to provide a detailed explanation of one subject or phenomena. The original purpose for synthetic controls thus naturally also fits the research questions and topics proposed in HET as many of the goals are typically around focusing on an individual, an idea, or an institution. Research questions in HET tend to narrow into one subject or phenomena as is the aim of synthetic controls.

This is also a good point to acknowledge general concerns about casual and empirical methods. Ronald Coase famously suggested, “if you torture the data long enough, it will confess”. There is a concern that the heavy modeling techniques used by many econometricians can misconstrue the data and lead to inaccurate conclusions. This is not a direct concern for the use of synthetic controls in HET because they have this intuitive fit. As the way of econometric models go, synthetic control methods are one of the least “problematic”. Aris Spanos emphasizes how curve-fitting is one of the largest failures in econometrics right now (Spanos, 2021, p. 419). Spanos argues that the desire to prioritize “goodness of fit” with the data does not lead economists to properly learn from their data. For synthetic controls and particularly with historical data which at times can be weak, this is less of a problem. Synthetic controls require fewer observations and less strict statistical requirements when compared to other causal models such as difference-in-difference and regression discontinuity design. For practitioners in HET looking to employ synthetic controls, this means they create their model to fit the historical situation they want to model and not to fit the data and thus the results they want to see. As Spanos argues, this is the way econometrics should be heading: intuitive fitting.

In addition, Kevin Hoover argues there are at least four purposes for econometrics when linking between empirical evidence and theoretical understanding (Hoover, 2006, p. 65). Two of these purposes, the role to test an implication of a theory and the role to measure an unknown value, are the crucial purposes for employing synthetic control methods. Simply, synthetic control methods are used to test, or measure based on existing knowledge of an event. The theory and hypothesis come first. Especially in the case of historical events where data can be minimal and unreliable, theory must come first as suggested by Hoover. This emphasis on theory first makes synthetic controls an intuitive fit for many case studies in HET. So, as econometric methods go, synthetic control methods are one of the best to employ in historical case studies because the model is not about curve-fitting, and it pins on having a theory or hypothesis first. Synthetic control methods are about seeing if the numbers have an *additional detailed* story to tell, not if they are the story.

Moreover, synthetic controls are applicable because they are flexible. When placed next to other similar causal models, synthetic controls may appear to have less assumptions to draw a valid claim. However, it is not that they have less assumptions, it is rather that they have less statistical requirements and more contextual requirements. What we mean by these contextual requirements, as termed by Abadie (2021a) is that the researcher needs to have substantial knowledge about the treated unit, the intervention, and the donor list to hold internal validity of the causal conclusions. We will go into the exact details of the contextual requirements in the following chapter about how to apply synthetic control models. But for now, understand

these contextual requirements as forms of normative and historical assumptions about the question at hand.

In many cases, causal empirical models have statistical requirements on the data quality and number of observations. With historically based case studies, it is not always feasible to have access to high quality data as well as enough observations for both the treatment and control groups. This is part of what makes synthetic controls more flexible and malleable to cases in the history of economic thought. The looser requirements on statistical assumptions give practitioners in HET more wiggle room to apply the model, as long as the contextual requirements hold. Synthetic controls share similarities with difference-in-difference models as they both are about comparing a treatment to a control following an intervention. What differs though are the necessary assumptions to hold internal validity in the causal claims made. With difference-in-difference models there needs to be the assumption of parallel trends or that the treatment and control follow a similar, i.e., parallel, trend before the intervention. This assumption is what allows researchers to make a causal claim about the intervention on the treatment and can be determined through statistical analysis. However, this assumption can be quite difficult to hold. In fact, it is an assumption that is relaxed with synthetic controls and is held by the contextual requirements for an available comparison group meaning that the control units are relatively similar.

Moreover, with synthetic controls, one of the main assumptions is that the units in the donor list are *untreated* or unaffected by the intervention. This is understood as the contextual requirement for no interference between units (Abadie, 2021a). In cases in policy and even history, this is best determined from a deep knowledge and understanding of the situation, and not from statistical tests. Other causal models have more rigid statistical assumptions which for cases in history can potentially be much harder to reach given poorer data. However, synthetic controls rely more on contextual assumptions informed by historical and normative knowledge of the case which allows historians to apply the model more widely.

However, this flexibility comes at a price. There is no hard and fast way to make these contextual requirements aside from having extensive knowledge and a strong qualitative foundation. In addition, since they are based on qualitative knowledge, they are open to more debate and scrutiny than the more straightforward statistics or numbers. So, synthetic controls can be subject to poor creation and potentially extrapolation if there is not a strong core qualitative base. Edwards et al. (2018, p. 287) emphasizes this point for quantitative methods in HET in general by saying “Data do not speak for themselves, and the quantification of some components of economic knowledge does not necessarily inform us about the full content and dynamics of it.” While the flexibility in assumptions through the contextual requirements is valuable because it allows us to use the model more widely, it also means the model is subject to stronger bias and more vulnerability of weak and poor causal claims that do not match the story or research question being asked.

Essentially, for synthetic controls to provide any causal knowledge in HET the contextual requirements must hold and thus must be based on a strong qualitative grounding. The

flexibility of these contextual requirements is a strength for synthetic controls because it makes them applicable to case studies which otherwise may not have enough observations or strong enough data for other causal models such as difference-in-difference. However, it is these contextual requirements which also form the biggest weakness of synthetic controls. If the contextual requirements are not met and a synthetic control is not created properly, it is more likely to make unjustified causal claims.

In this chapter, I argued that synthetic control methods are the most valuable causal model for HET. Econometric and causal models are frequently degraded for not acknowledging enough theory and relying too heavily on data, as well as being unapproachable and difficult to interpret in many ways. Thus, this may lead many practitioners in HET to be cautious towards econometric models. However, even without any formal training in econometric modeling, synthetic controls can be accessible and appropriate for HET. Moreover, I argued synthetic controls were valuable because they are 1) accessible for the practitioners due to their visual output graph and transparency and 2) applicable to the questions and cases at hand given the intuitive fit and flexibility of the model given the larger emphasis on contextual requirements over statistical requirements. However, it is this point of flexibility that also sets up synthetic controls to be vulnerable to extrapolation and poor causal claims, the biggest weakness of the model. This leads us into our next chapter where I will lay out how to appropriately employ synthetic controls in HET to avoid succumbing to unjustified claims and not meeting the contextual requirements.

5) The how, part 1: requirements for employing synthetic controls in HET

The goal of the following two chapters is to argue *how* to appropriately use synthetic control methods in HET. This chapter will be focused on providing a framework for how to approach synthetic controls in HET and the following chapter will apply this framework to Magness and Makovi's *Mainstreaming of Marx* (2023). The following two chapters are aimed at practitioners in HET who are either curious about creating and modeling their own synthetic control or to those wanting to understand how to evaluate and assess synthetic controls in HET. Note that both chapters will focus solely on the points of *how* within the context of cases in HET. For more general information or specific statistical points for implementation, see Abadie (2021a).

This chapter is split in two. First, we'll discuss the necessary contextual requirements which are needed for any synthetic control model and outlined by Abadie (2021a) with specific emphasis on the relevant contextual requirements for cases in HET. Specifically, the contextual requirements for "no interference" and an "available comparison group" need particular attention. While these contextual requirements make synthetic controls more applicable to case studies in HET as argued in the previous chapter, these two contextual requirements are also the largest limitation of the model. In some ways, these two contextual requirements can be easier to hold than strict statistical requirements, but they can also be more likely to create holes in the validity of a model.

As such, the second part of this chapter will outline what I deem *implementation* requirements. These three requirements are meant to provide actionable steps that practitioners can take to help support them in meeting the difficult contextual requirements, and thus are necessary points to meet if the causal conclusions are to be justified. These points should be understood as the bare minimum. The three requirements are as follows, 1) a narrow research question, or at least well-defined; 2) corroboration of the limitations; 3) reflective conclusions. To build a valid and knowledge worthy synthetic control, a researcher in HET must follow these requirements which are all informed by a strong qualitative foundation of the topic at hand.

These implementation requirements may appear obvious and as a "no-brainer", so to speak, for any quantitative analysis. However, as will be shown in the following chapter with Magness and Makovi (2023), these points are not always put into practice and must be reiterated particularly in order to meet the contextual requirements. Moreover, while this chapter will provide a general guideline based on the above implementation requirements, I'll provide specific details about applying such a framework to bibliometric or citation-based case studies in HET. Up to this point, this thesis has stayed general about the potential topics and questions which synthetic controls models can be applied to. However, at this point in the literature, the primary use of synthetic controls has been for understanding the impact of external events on the work and ideas of economists, such as the impact of the Russian Revolution on the work of Karl Marx (Magness and Makovi, 2023) or the impact of the 2008 Financial Crisis on the work of Hyman Minsky (Needler, 2023). For the sake of detail and example, this chapter will provide

specific points to consider when engaging a synthetic control as a bibliometric or citation analysis.

5.1) Contextual requirements

As we've already mentioned, quantitative studies in HET must act as complements to existing qualitative studies when it comes to how synthetic controls can be used to answer research questions in HET (see chapter 3). But when it comes to forming and creating synthetic control models the key to a strong synthetic control is a qualitative foundation. Synthetic controls are dependent on qualitative knowledge. You can have a qualitative analysis without a synthetic control analysis. But you cannot have a synthetic control analysis without a qualitative analysis. This is especially evident by the need for the contextual requirements and also later the implementation requirements.

It is not enough to say that synthetic controls must serve as complements to qualitative studies; those qualitative studies must ground and inform the creation of the synthetic control. As explained in chapter 4, one of the primary benefits of synthetic controls is that they are applicable models to case studies in HET because they are flexible models with less statistical requirements. This is appealing as it means a causal analysis can be applied to a wider range of comparative case studies and specifically those of large events or single entities, i.e., one country, institution, or individual. However, this relaxing of the statistical requirements also means that more emphasis must be placed on the contextual requirements- conditions around the context that are informed by historical and normative knowledge of the case at hand- to create a valid claim. More attention must be paid to the historical details: the traditional qualitative analysis which practitioners in HET are comfortable by.

These contextual requirements are assumptions about the case itself which must hold for the model to be causally valid. Meaning, if these contextual requirements are not met, then there is no valid control from which to compare the unit of interest to. Abadie (2021a) lists six contextual requirements that he deems necessary for a valid synthetic control model for events in the context of policy analysis. These six requirements include the need for the availability of a comparison group, no interference, no anticipation of the event of interest, the size of the effect and volatility outcome, the convex hull condition, and requirements on the time horizon (Abadie, 2021a, p. 409-412).

Of the six criteria, the first three are especially relevant for case studies in HET and will be built upon in this section. The other three requirements will not be given explicit attention because they are either more statistically inclined or more relevant for current day policy analysis, but nonetheless should be mentioned. Two of the requirements are statistical in nature and relate to the statistical workings of the synthetic control. These statistically inclined contextual requirements include, first, the "size of the effect and volatility outcome" which is the concern that if the effect of intervention is relatively small and there is a lot of volatility in the outcome, then it will be difficult to detect the impact of the intervention as it is difficult to distinguish between noise and trends. Second, the "convex hull condition" which relates to the

optimal weighting of the unaffected units. The third, contextual requirement is about the time horizon of the outcome which is primarily a concern for the analysis of recent policy measures. The requirement for a reasonable time horizon is so that the impact of the intervention emerges in a reasonable time frame following the intervention for it to be noticed in the data. For cases in HET, this is likely not as much of a concern since they are historical cases. It must be noted these three requirements should not be totally ignored, rather it is just that they do not need additional emphasis for case studies in HET. For more information see Abadie (2021a, p. 408-412).

It is the three other contextual requirements on no anticipation, the availability of a comparison group, and no interference that are especially relevant for practitioners in HET and deserve further attention. These requirements are dependent on qualitative knowledge as they are based on a sound understanding of the event or intervention of interest. It is these three contextual requirements which are of concern for practitioners in HET because it is these requirements which leave room for poor modeling and thus an invalid or unjustified conclusion.

The first relevant contextual requirement is fairly straightforward. The requirement for no anticipation means that impacts of the intervention or event do not precede the date of the intervention. This means there were no forward-looking anticipations; there must be a clear-cut time as to when change from the intervention begins. Within HET this could be a concern in the case of understanding the impact of an external event on the work of one economist. Take for example, the case of how the 2008 Financial Crisis impacted the work of Hyman Minsky. If many economists slowly began to see the crisis ensuing and began to anticipate the collapse and thus looked to Minsky's work before 2008, then this would skew the timing of the impact. Determining the presence of anticipation comes down to knowing historical details of the case at hand. It should be noted that Abadie (2021a) suggests this concern can be adjusted with backdating techniques when running the model.

The last two contextual requirements --for an available comparison group and no interference-- are closely related but can still be distinguished apart from one another. These are arguably the most important and also hardest assumptions to hold when creating a synthetic control because they impact the validity of the synthetic unit so whether it is a valid comparison. First, the requirement for an available comparison group meaning there are similar units available. Abadie argues the need for this requirement is based on the intuitive need to create a relatively similar comparison since synthetic controls are a form of comparative case study. This may seem simple however, what is particularly important is that these units of comparison do not adopt similar interventions as the one of interest. For example, Arizona would be a poor comparison for California in the case of estimating the impacts of a tobacco policy if Arizona implemented a similar policy. In addition, the comparison units must be relatively similar and there should be a common thread which connects all units.

Second, Abadie argues for the additional contextual requirement of no interference. This is equivalent to the stable unit value treatment assumption for those with a knowledge of econometrics. It means that the outcome of a unit should be unaffected by the treatment of

another unit. Essentially, the comparison units which create the synthetic control should be unaffected by the intervention of interest. This also means assuming that spillover effects are nonexistent which, as Abadie acknowledges, is a lofty restriction when designing a synthetic control. If there are comparison units which are impacted by the intervention of interest, then Abadie suggests they should not be included in the donor list. However, this can create some tension with the requirement for an available comparison group as some of the best units of comparison may be removed if it is believed there is interference.

Let's understand these two requirements in more depth through the case of evaluating the economic impacts of German Reunification on West Germany (Abadie et al., 2015). As a reminder, Abadie et al. (2015) use a synthetic control to see how German Reunification in 1990 impacted the GDP of Western Germany. To conduct this study, Abadie et al. (2015) create a synthetic control based on a donor pool of OECD countries. For the comparison of the treatment unit, West Germany, to the synthetic control to be valid, the units which compose the synthetic control needed to be relatively similar to the treatment unit but also unaffected by the treatment event. These two points echo the contextual requirement for an available comparison group and no interference, respectively.

Abadie fulfilled the contextual requirement of an available comparison group by choosing to create his donor pool based on other OECD countries; this was the common thread connecting all of his units. However, this means that he also needed to make the assumption that the other OECD countries were economically unaffected by German reunification; he needed to assume no interference. This means assuming that the reunification in 1990 had no economic impact on Austria, the Netherlands, the US, and the other OECD countries in the donor list.

Balancing the tradeoff between these two contextual requirements cannot be done solely on statistics but rather on extensive contextual knowledge, likely of a qualitative nature, of the event at hand. A researcher must understand the relations and have a sense of what is going on in West Germany, East Germany, and the other OECD countries if the historical assumption is to hold. Researchers can not only rely on their technical abilities, but also must have a strong qualitative foundation to properly fulfill the contextual requirement for a comparison group.

Especially for cases in HET, practitioners must understand the details on the intervention at hand as well as on their units of comparison to not only meet the contextual requirements for an available comparison group and no interference, but also to find a balance between them. For the case of understanding the effect of the 2008 financial crisis on the work of Hyman Minsky this translates into having knowledge on how the crisis impacted the work of other economists at the time. Whose work received additional attention? Whose work became ignored? Citation patterns cannot capture all the nuance of the impact that an event like 2008 holds. A practitioner in HET must rely on additional qualitative sources to know what units may serve as worthy points of comparison who were unaffected by the intellectual scramble following the 2008 financial crisis.

The contextual requirements for no anticipation and for an available comparison group and no interference, begin to depict the extent to which one must have a detailed qualitative knowledge. Particularly, the requirements for the availability of a comparison and no interference can be difficult requirements to meet as it is a tricky balancing act between a comparison unit being similar enough to the treatment, but not too similar that it is also affected by the intervention and thus an invalid comparison. This balancing act is best informed by qualitative knowledge; however, this means that it is also based on the subjective belief of the readers and researchers whether there is enough detail and a strong enough normative and historical foundation to hold the two requirements.

The difficulty of meeting *both* the contextual requirements of an available comparison group and no interference is the biggest limitation of a synthetic control model. It may be easy to meet one requirement and not the other, but for the validity of the synthetic control unit to hold, both requirements must be met. This leads us to my implementation requirements which are meant to help provide a clear means for creating a synthetic control that can meet these contextual requirements.

5.2) Implementation requirements

One of the largest limitations of synthetic control models is how easy it is to fail to meet the contextual requirements outlined by Abadie (2021a) and thus conclude with invalid or biased conclusions. In this section, we will outline three implementation requirements practitioners must keep in mind when creating and assessing synthetic controls in HET to help meet these difficult contextual requirements. These three implementation requirements create the structure of our synthetic control model, while strong qualitative knowledge around the contextual requirements create our foundation. The purpose of outlining these requirements is to show necessary steps to help meet the difficult contextual requirements and get to a justified conclusion. Again, these requirements may appear obvious, but they must be reiterated and, in addition, will be explained for the specific cases of using synthetic controls to conduct bibliometric and citation studies in HET.

Our three implementation requirements to lead to a justified conclusion are 1) a narrow, or at least well-defined, research question; 2) corroboration of the limitations; 3) a reflective conclusion. The narrow or at least well-defined research question acts as the frame; it provides a clear and defined outline for which to build the model around. Corroboration of the limitations acts as a means to reinforce the frame; every structure has weaknesses, and it is better to acknowledge them and take them into account thus reinforcing them rather than ignore them and let them stand as holes. Lastly, if the first two points are fulfilled well, then they must be reflected on when making the final conclusions. A reflective conclusion is like adding the final coat of paint; it is how you wrap it all up at the end and present your argument based on the foundation, structure, and reinforcements.

These implementation requirements are primarily created as a way to understand how to get the best donor pool and data. In many cases, these are the two pieces which create the most

controversy and problems for synthetic controls. Particularly for cases in HET, these two elements- the donor pool and data- will need a strong qualitative understanding to implement correctly. Likewise, it should be noted that these suggestions should be applied to all research anyways; they are standard best practice. However, adherence to these practices must be applied when using synthetic control in HET to draw justified conclusions.

5.2.1) Narrow, or at least well-defined, research project

The first requirement is to have a narrow research project and if not then it must be well-defined. This means having a narrow scope when crafting any research questions or hypotheses. The narrower the scope of the project, the more detail and thought which can go into each element of creating the synthetic control model. Specifically, a narrow project will help lead to a stronger creation of the donor pool along with decisions on the data. If the research question is too broad, then it will be harder to clarify these elements, and thus harder to meet the contextual requirements for an available comparison group and no interference between units.

A narrow scope for synthetic controls in HET is one which focuses on details around the event or available comparisons. The purpose of having a narrow scope is to make it easier for the scale of the project to balance the tradeoff between the contextual requirement for an available comparison and no interference to find the right comparison units and availability of data. Two of the primary contextual requirements from Abadie (2021a) are to have the availability of a comparison group which means there is a similarity or common thread underlying the units but also that there is no interference or spillover effects between these units. By defining a narrower scope, it can be easier to firmly determine what units are similar but also unaffected by the event of interest and thus allow for a stronger list of comparison units.

Moreover, with a narrow, or at least well-defined, project it should be clearer how to match an appropriate donor pool and data set. First with the donor pool, a defined research question will suggest a specific point of commonality between the treated unit and the untreated units of comparison. The case of West Germany reunification is a good example. Abadie et al. (2015) address the defined project on the economic impacts of reunification on West Germany and define economic impacts as the GDP. What is defined about this question and project is their decision to look specifically at West Germany and not Germany as a whole and specifically at economic impacts rather than other social or political ramifications. The narrow points here are West Germany and economic impacts. The characteristics of East and West Germany around the time of reunification were starkly different. The Abadie et al. (2015) choice of West Germany as the treated unit and economic impacts as the outcome of interest created a natural donor pool with the OECD. The point of commonality between West Germany and the other OECD countries was they were all industrialized economies. This point of commonality matches the outcome of interest Abadie et al. (2015) wished to analyze. Thus, having a narrow or at least well-defined project can help the model to meet the contextual requirement for an available comparison by creating a clear point of commonality on which to connect the treated unit to the untreated units of the donor pool and to the outcome variable of interest.

In a similar way, a narrow research question will mirror the data source. The connection between the data source and research project should be clear and specific. For example, trying to analyze the whole effects of an intervention creates too broad a project. A specific outcome of interest is necessary, such as GDP in the case of German reunification. If Abadie et al. (2015) had broadly asked how German reunification impacted the political, social, and economic status of West Germany, they likely would have ended with a synthetic control which did not represent the goals of their research question. Rather, GDP is known as a clear and defined proxy to measure the economic status of a country.

For bibliometric and citation studies in HET, a narrow or at least well-defined question may mean characterizing the economist and their work to accurately determine a donor list which is unaffected by the treatment. Take the case of the 2008 financial crisis on the work of Hyman Minsky. If we choose to view Minsky as a macroeconomist in general, then it is harder, and more subjective, to determine an appropriate list of possible economists on which to compare. We may be inclined to include names such as Paul Krugman or Oliver Blanchard who were macroeconomists but working on different topics and areas in macroeconomics. Some may argue these names fulfill the requirement for no interference but are not similar enough to meet the requirement as being acceptable comparisons, or potentially the other way around. With the breadth of impact of the 2008 financial crisis, it is difficult to determine if Krugman and Blanchard are reasonable comparisons. Were they impacted in the *same* way as Minsky? Likely not. Was the view or acceptance of their work impacted by the financial crisis, nonetheless? Most likely yes. In this case, one option of a more appropriate course of action would be to view and define Minsky amongst the other Keynesians (simply meaning following from the General Theory (1936)). By viewing Minsky as a Keynesian economist and narrowing the scope here, we ask the question of how the 2008 financial crisis impacted the work of Minsky as a Keynesian economist rather than a macroeconomist as a whole.

Thus, having a narrow or at least well-defined scope for the project creates a clear point of commonality to help balance the contextual requirements for an available comparison group and no interference. Moreover, a project which is too broad in scope will likely fail to create a donor list and find a data set which clearly maps to the question at hand. If there is not a clear link between the research question, donor pool and data, then there is space for holes and the chance to fail to meet the contextual requirements.

5.2.2) Corroboration of the limitations

The second modeling requirement is corroboration of the limitations which means directly acknowledging and then addressing any weaknesses and holes of the study. Specifically, corroborating the limitations means recognizing the quality limitations of your inputs including the data and the donor pool, and then taking actions to minimize the potential bias from these limitations. It is simply not enough to just acknowledge the limitations of a study. Especially with historical elements, this is particularly important where data quality is typically weaker. Data sources may not explicitly measure what we want them to, or the quality of the data may

not be strong. In either case, these limitations must be corroborated, meaning acknowledging and giving support to.

Take for one example data quality and consistency for citation analyses. Nowadays, there are several digital sources that can be useful for conducting synthetic control studies. This includes bibliometric databases like Google Scholar, Web of Science, Scopus, and economic specific sources such as IDEAS/RePEc. While these sources are all easily accessible, they do each come with their own limitations. For example, Andrada (2017) conducted a citation analysis on the work of Robert Lucas to determine what was most influential. Andrada (2017) measured Lucas's citations across Google Scholar, Web of Science, and IDEAS RePEc. Andrada found that each source recorded significant differences ranging from 20-55% in the number of citations from database to database (Andrada, 2017). So, while there is the availability of data, it may not be consistent.

In addition, for synthetic control methods which are forms of bibliometric studies acknowledging limitations may be crucial around citation data. As one point, take cases of measuring influence. The term and idea of influence can have many definitions to it and in many cases is difficult to quantify. As such, practitioners in HET may be inclined to use the mentions or citations of an economist's work or name as a proxy for influence. This is okay if this is clearly explained and established. However, there are nuanced differences between mentions and citations that suggests to what extent an idea or the work of an economist has been engaged with, whether it be shallower or more in depth. The limitation of using mentions or citations as a proxy for influence would have to be acknowledged and supported throughout the study to make a justified conclusion at the end.

Moreover, if someone is conducting a citation analysis, it needs to be recognized that any citation can be a positive or negative reference to an economist's work. A citation database cannot so quickly determine whether the citation of a work is a positive or negative engagement which could significantly impact the causal conclusions a practitioner may draw. For example, say that an economist's work is frequently cited but in a negative or critical way. A blanket concluding statement that the influence of said economist grew following one event does not capture the nuance of the criticism said economist had received. These distinct differences between influence, citations, and mentions are an example of a limitation which must be acknowledged and accounted for.

The inconsistency of citation numbers between databases and the case of proxying influence with citations represents that there will be limitations to each study which employs a synthetic control in HET. However, this does not mean that the model will be automatically invalid. On the contrary, such limitations are natural and simply need to be acknowledged and addressed. Corroboration of potential limitations, and particularly surrounding the data, is crucial in supporting and reinforcing the frame of each synthetic control model.

5.2.3) *Reflective conclusions*

Following adherence to the first two implementation requirements, then crafting reflective conclusions should help create a justified concluding claim. With the need for so many contextual requirements in synthetic controls, there are enough nuances and qualitative elements that must be considered when drawing the final causal conclusion. Being reflective means considering the detail and narrow scope of the defined research project in requirement one and the limitations and nuances in requirement two. By taking these requirements into account, it should be much more difficult to make large and sweeping conclusions with holes in the argumentation.

Being reflective is a matter of putting all the pieces together and then taking a step back and thinking beyond the numbers: does this conclusion match the qualitative history? If not, why might it not? Is there a modeling limitation? Or does there need to be a reassessment of the qualitative history? One thing, it should be remembered that negative or null results *are results*. There does not need to be a clear distinction or difference in the synthetic control output for the conclusion to have meaning. Rather it is better to ask, “what could the place of null results mean?”.

Synthetic controls are flexible models, as argued in chapter 4. This is one of the benefits of them as it means they can be widely applied. However, it also leaves them more susceptible to unjustified claims and conclusions. This plea for reflective conclusions is meant to act as a barrier against unjustified conclusions. In addition, the expectation is that adherence to the first two requirements- a narrow or at least well-defined research question and corroboration of the limitations- sets up the analysis for a justified conclusion through a reflective conclusion.

To conclude, the goal of this chapter was to provide a framework for *how* to apply synthetic controls in HET. Abadie (2021a) already provides a list of six contextual requirements which must be met for a valid synthetic control. Three of these six requirements, no anticipation, the need for an available comparison group and no interference, are the most relevant for cases in HET. Nonetheless, just mentioning these contextual requirements is not enough because they are difficult assumptions to hold and can easily lead to unjustified causal conclusions. Thus because of the difficulty of meeting them, I outline three additional implementation requirements which should be met on top of the contextual requirements for the causal conclusions to be fully justifiable for cases in HET. These three additional requirements should help guide practitioners in making sure the conclusions are not unreasonable, sweeping statements, as done by Magness and Makovi (2023). And hence we bridge to the next section where we will use this framework of the contextual and implementation requirements to criticize the primary case of synthetic controls in HET thus far: Magness and Makovi’s *Mainstreaming on Marx* (2023).

6) The how, part 2: applying the requirements to Magness and Makovi (2023)

The goal of this chapter is to take the requirements outlined in the previous chapter and apply it to the case of Magness and Makovi's "The Mainstreaming of Marx: Measuring the Effect of the Russian Revolution on Karl Marx's Influence". Magness and Makovi (2023) make sweeping and large conclusions that leave their argument and claim up to substantial criticism. This chapter will walk through Magness and Makovi's paper while criticizing it through the lens of the contextual and implementation requirements of the previous chapter. To draw justified conclusions, the models must have 1) a narrow or at least well-defined research question; 2) corroboration of the limitations; and 3) reflective conclusions. These implementation requirements should be present in any good research project. However, given the flexibility of synthetic controls, these points are especially crucial; and something which Magness and Makovi fail to meet.

6.1) The creation of the model, failing implementation requirement one

Magness and Makovi's paper is a good example of how *not* to engage synthetic controls in HET. What their analysis lacks is specific and detailed direction. They rely too heavily on statistical assumptions and not enough on the contextual history around Marx in the Russian Revolution. Thus, they fail to fulfill the first requirement: a narrow or at least defined research project.

In their paper, Magness and Makovi investigate "the academic *mainstreaming* of Marx's ideas, following his early rejection within the economics profession" (Magness and Makovi 2023, p. 2). They suspect that following the Soviet movement in Russia, Marx's "economic theories subsequently entered the academic mainstream as they began to reshape non-economic disciplines" (Magness and Makovi, 2023, p. 2). Magness and Makovi believe it was these historical events in Russia beginning in 1917 that pushed Marx's economic ideas to be some of the most widely read today. Magness and Makovi do acknowledge that if the Russian Revolution had not occurred, it does not mean Marx would not have ended up with the popularity he faces today. However, they do argue that it was the revolution that brought him out of his relative obscurity in the late 19th to early 20th centuries.

Magness and Makovi start by walking the reader through the stance of Marx in the early 20th century. They argue his economic work was largely in decline as the labor theory of value and surplus value were being tossed aside to make room for the marginal revolution, work from William Stanley Jevons and Carl Menger (Magness and Makovi, 2023, p. 5). As Magness and Makovi quote from Paul Samuelson in his presidential address to the American Economic Association in 1962, "From the viewpoint of pure economic theory, Karl Marx can be regarded as a minor post-Ricardian (Magness and Makovi, 2023, p. 8)." This leads Magness and Makovi to question, if Marx's economic work was no longer holding validity nor esteem, then why is he so well read today?

Moreover, Magness and Makovi suggest Marx's ideas were also less popular in socialist circles until the Russian Revolution. They suggest that relative to other socialist thinkers, there was nothing particularly special that set Marx apart. These two observations on Marx's position in economics and socialist thinkers lead Magness and Makovi to hypothesize that it was the Russian Revolution that nudged Marx to be as known today as he is. For them, the Russian Revolution adopted Marx almost as their revolutionary symbol which brought him out of relative obscurity (Magness and Makovi, 2023, p. 9).

Magness and Makovi suggest two primary hypotheses:

1. The Russian Revolution increased the relevance of Marx's economic ideas within the mainstream of academia.
2. The Russian Revolution allowed Marx to crowd out other political and socialist thinkers.

Immediately there is a concern. Magness and Makovi are trying to tackle two separate questions with one synthetic control model. At the beginning of their study, they characterize Marx in both this view of an economist and as a political and socialist thinker but then create the model and make conclusions which merge these two characterizations. This fails the first point of our framework to have a narrow or at least defined project and research question. On one side, they want to understand Marx's position amongst academia and amongst economics. Whereas on the other side, Magness and Makovi want to understand Marx's position amongst political and socialist thinkers. When it comes to creating the synthetic control model, these two questions should be represented by two different donor lists and even two separate data sources. There are differences between Marx as an economist and Marx as a political and socialist figure. An attempt to merge his two sides would be overstepping and oversimplifying the nuances and complexities of Marx himself along with his ideas. For Magness and Makovi, they immediately start off on bad footing as the scope of their research question(s) is far too broad. They fail the first implementation requirement.

By failing to start with a defined and narrow project, we can see the ramifications in the donor pool and final list of individuals in the synthetic control which I argue fail to meet Abadie's contextual requirement for an available comparison group. To create their synthetic Marx, Magness and Makovi compile a donor list of 227 authors. They compile their donor list from 4 sources. First, they brainstormed relevant economic, socio-political, and socialist thinkers. Second, they consulted two sources in political philosophy: Rosen et al. (1999) and Cohen (2018). Third, they added almost all authors in the first 39 volumes from *Harvard University Classics* (Eliot, 1909). Last, they consulted several German language anthologies. Like the research question and hypothesis, this donor list is incredibly broad in scope and has no clear point of commonality between the research question, donor pool and variable of outcome.

Magness and Makovi essentially compile a list of all relevant figures at the time of Marx, despite their similarity to Marx nor whether they were unaffected by the Russian Revolution. There are concerns with this donor list as it fails both the contextual requirement for no interference and on the availability of an appropriate comparison control group. As mentioned

earlier, one of the main requirements to meet for synthetic controls to be reliable is that the units in the donor list are unaffected by the intervention. In this case, the intervention being the Russian Revolution is quite a significant event and so it can be hard to determine whether the other units were truly unaffected. Intuitively how can we be certain that each individual in the donor list of 227 people were all unaffected by the Russian Revolution? For example, one of the names is Pierre-Joseph Proudhon who was a French socialist thinker and an academic sparring partner of Marx. Assuming that those who engaged with Marx more following the revolution chose not to look at other socialist thinkers of his time such as Proudhon can be difficult to assume. Moreover, the contextual requirement for an available comparison requires the units in the donor list to be similar to Marx. Could we argue that thinkers such as Homer or Abraham Lincoln are sufficiently similar? Potentially, but it would be a stretch. The validity of the comparison between the real Marx and the synthetic Marx rests on these two contextual requirements which Magness and Makovi fail to meet with their donor list. Like their research question and hypothesis, the donor list is far too broad in scope to produce any reliable inferences.

Nonetheless, we can be more critical of the synthetic control. Fortunately, synthetic controls are transparent models so we can know exactly what authors and individuals compose the synthetic control which is then compared to Marx. We can thus look specifically at the names to see if the qualitative history of the individuals aligns with the story being told by the synthetic model. Magness and Makovi's synthetic Marx ends up consisting of 52.0% Ferdinand Lassalle, 28.8% Johann Karl Rodbertus, 12.0% Oscar Wilde, 0.2% Pierre-Joseph Proudhon, and miniscule amounts of Abraham Lincoln, Louis Pasteur, and Lord Kelvin. A list of primarily socialist and political thinkers aside from Rodbertus who was a proponent of the labor theory of value. This Marx replica acts as a control to compare to the actual Marx. However, as mentioned, this replica bridges two sides: Marx as economist and Marx as socialist figure. This makes any inferences wobbly as we cannot reliably look at one detail or thread. With the lack of a defined and narrow research project, there is no point nor thread of commonality connecting the pieces.

As we have argued, Magness and Makovi are too broad in scope with the design of their synthetic control. Magness and Makovi's research goal was to understand the academic influence of Marx and so Magness and Makovi lay out two primary hypotheses. The two hypotheses are relatively similar but distinct as one thinks about Marx as an economist and the other views him as a socialist thinker and political figure. However, the model they create does not represent the hypothesis and claims they conclude with.

6.2) The limitations, requirement two

The next implementation requirement, the need to corroborate potential limitations, is something Magness and Makovi also fail to fulfill. Let's continue further into the model created by Magness and Makovi and take a specific look at their data.

Magness and Makovi's treatment is the Russian Revolution in 1917 with the treated unit being mentions of "Marx" and the synthetic unit an optimally weighted fake (i.e., synthetic) Marx. The outcome variable of interest is the citations of an author in the Google Ngram books database. Magness and Makovi run their primary analysis on the English language database and run robustness checks for mentions in the French and German languages. The Google Ngram database "approximates the frequency that a specific phrase or author name is referenced in printed books over time" (Magness and Makovi, 2023, p. 2). The database logs mention of a phrase or name.

First, to criticize their understanding and interpretation of their data. Magness and Makovi argue that Google Ngram books allows them to test citations of an author. However, their data does not necessarily reflect a true citation and thus academic influence. Their data source is relatively limited. It only has 4% of books at the time and does not include periodicals.

More striking though, is what Google Ngram measures. In the set-up of their project, Magness and Makovi suggest they want to understand how the academic *influence* of Karl Marx changed due to the Russian Revolution. However, in their analysis, Magness and Makovi are actually measuring mentions of a name and not citation of a published work. Magness and Makovi question why Marx is so popular nowadays if his economic ideas were weak. I would venture to say it is because Marx had a clear and strong ideology which guided his work. This would explain why Marx became a revolutionary mascot and thus mentions of his name increased in books following the Russian Revolution in 1917. However, this does not suggest his academic influence increased. For example, one current ideological figure whose name has appeared more frequently in academic literature over the last few years is Donald Trump. This is not due to any academic influence he holds, but rather represents his political and ideological standing in society. So, it's possible that the increase in the mention of "Marx" relative to the synthetic unit is due to Karl Marx's ideological influence rather than his academic influence. Which is something Magness and Makovi fail to corroborate.

Magness and Makovi do acknowledge this limitation on the difference between mentions and citations. They state, "Our measures do not include citations in magazines, newspapers, and so on. Second, it does not measure citations per se, but only occurrences of specific phrases (Magness and Makovi, 2023, p. 20)." However, they do not adjust their project to this limitation of their data set. They simply acknowledge the limitation but do not fully corroborate it and thus leave the hole of this weakness wide open. They do not reinforce anything to take action against these limitations. Citations can be a strong proxy for measuring academic influence but mentions may not. Magness and Makovi's inability to properly corroborate the limitations of their data cause them to fail implementation requirement two and leave room for unjustified causal claims.

6.3) Lack of reflective conclusions, failing implementation requirement three

We have yet to get to the output of Magness and Makovi and have already outlined how their broad approach to the research question at hand and failure to corroborate the limitations

creates holes. Nonetheless, let's view the output. In Figure 1, we see a comparison of “citations” of actual Marx to synthetic Marx shows the Bolshevik Revolution in 1917, actual Marx (the solid line) has an increase in mentions relative to the “fake” synthetic Marx (the dashed line). Magness and Makovi argue the spike in 1921 and following decline until 1923 is because of the course of the Revolution itself and the possibility that some believed the Revolution could still fail in the early years. Whereas then the steady climb following 1923 is what solidified Marx out of obscurity.

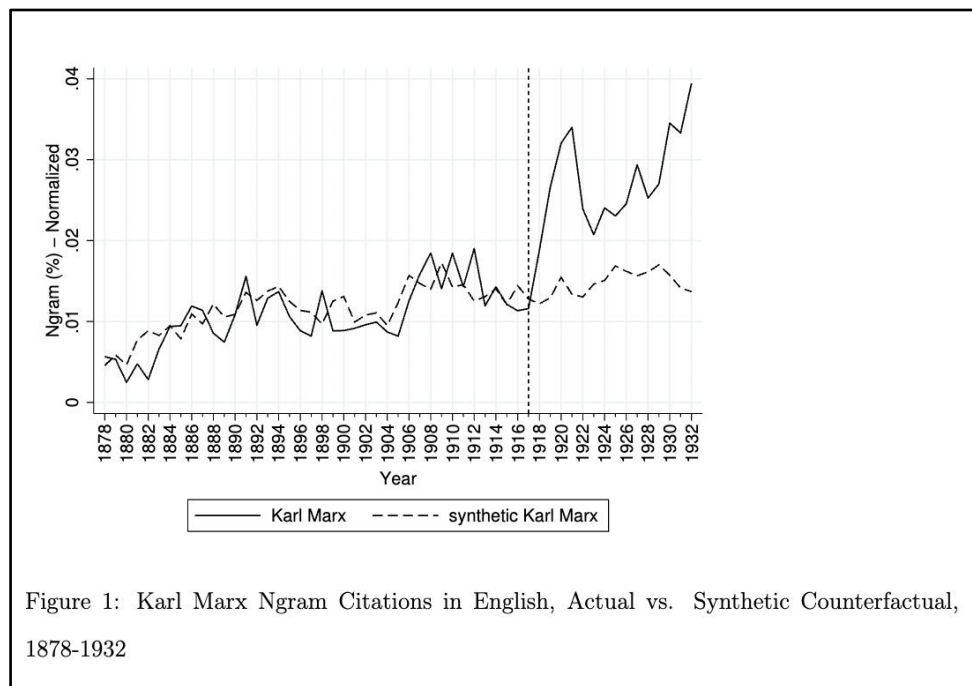


Figure 1: Karl Marx Ngram Citations in English, Actual vs. Synthetic Counterfactual, 1878-1932

Figure 1: Ngram mentions of actual Marx versus synthetic Marx (1878 - 1932) from Magness and Makovi (2023).

Based on this graph and a few robustness tests, Magness and Makovi conclude, “Our findings provide clear empirical evidence that the scholarly mainstreaming of Karl Marx is intimately connected to the events of the Russian Revolution of 1917” (Magness and Makovi, 2023, p. 29). Magness and Makovi believe both their hypotheses hold: the Russian Revolution increased the academic mainstreaming of Marx. However, they fail to accurately distinguish between these two hypotheses when crafting their model and drawing their conclusions. Their project is too broad in scope to craft a narrow and defined synthetic control model.

What Magness and Makovi must be more attuned to is the exact wording in their conclusion or in their research question. The creation of their model and the use of mentions rather than citations and the high number of socialist figures in their donor list suggests they are more concerned about Marx’s standing amongst other socialist and progressive writers as a societal figure and not against other academics as a whole. None of this is to say that the Russian Revolution had no effect on the academic influence and acceptance of Marx. Rather, the point I want to make is the synthetic control model created by Magness and Makovi does not match the causal claims they draw. Magness and Makovi leap to their conclusions and are not cautious enough with the inference they make.

For Magness and Makovi, their research question is about the academic influence of Marx, but they create a list of donors that is also based on societal and progressive ideas. For example, Abraham Lincoln fills a portion of the synthetic Marx unit. They may be similar political figures, but likely have no similar academic influence. When creating their donor list, Magness and Makovi blend their two hypotheses by adding both economists along with socialist, political, and ideological figures. However, the conclusions they draw are broadly about academia as a whole and do not align with the donor pool they selected. This is not to say that this donor list is entirely invalid, rather it does not fit with the goal of their research question and thus leads them to make a leap with their causal claim that Marx had an increase in his academic influence.

As a whole, Magness and Makovi build their model to test the second hypothesis but draw and state their conclusions based on the first hypothesis. This is not to say that neither hypothesis is inaccurate, but rather they cannot use their synthetic control to make claims on their first hypothesis because their data and donor list do not lend themselves to answering this question. They design their model with too broad a scope and so the inferences they make are invalid based on the narrowness of the model which they created.

Magness and Makovi fail requirements one by setting up a project with two relatively distinct hypotheses. This mistake is represented by their broad and large donor list which has no clear point of commonality aside from being big names or popular figures at the time. Then if we look at requirement two, Magness and Makovi do not fully corroborate their limitations. The data Magness and Makovi use is limited to representing mentions of a figure and not citations. This is not necessarily a problem, except Magness and Makovi fail to account for this limitation when trying to measure influence. Rather, it is as if simply mentioning the limitations is enough. Lastly, when we take the way Magness and Makovi approach the two prior requirements, it is no surprise they also fail to make a reflective conclusion. The conclusions Magness and Makovi draw overstep what their model can tell; they fail requirement three. Rather Magness and Makovi make conclusions which are based on the project they desired to put out from the beginning, but which does not map to the synthetic control model they have.

Synthetic controls in HET must be built on detailed historical foundations and must meet the implementation requirements outlined in the previous chapter to make justified and worthy causal conclusions. Not only do Magness and Makovi fail to meet the three implementation requirements, but they also fail to meet the contextual requirements of an available comparison group and no interference. Magness and Makovi's study is a great example of how the application of synthetic controls in HET can go poorly. This is not to say that all use of synthetic controls in HET are pointless. Rather, we must have standards and guidelines to set our expectations such as these three implementation requirements.

7) The who: non-epistemic implications for employing synthetic controls

The goal of this last chapter is to consider the non-epistemic points on the place of synthetic control methods in HET and specifically through the lens of *who* should be considered when thinking about the potential consequences of introducing an empirical, causal model into what is largely a qualitative field of study. Most of this thesis has focused on the epistemic points of synthetic controls, but there are non-epistemic points to consider. These non-epistemic considerations are meant to be potential political or sociological points. The chapter will be structured by evaluating three cases: journal editors and referees given the role of journal impact factors, young economics students, and practitioners of HET more generally by echoing the question asked by Cherrier and Svorenčik (2018) about the potential of a civil war and whether synthetic controls may or may not contribute.

It should be briefly noted why this discussion is valuable. It is worthwhile to consider these non-epistemic points because the introduction of new methodologies is not always straightforward. A common example is Alfred Marshall's use of mathematics in his textbook *Principles of Economics* (Marshall, 1890). Marshall was worried about the way the mathematical explanations would be received and so placed the mathematical reasoning in the appendix of the textbook. The introduction-- and adoption-- of new methodologies is not always a linear progression. And so, exploring the potential political and sociological implications of a new method is desired apart from the epistemic based value.

7.1) Journal editors and referees given journal impact factors⁵

The first case I am going to consider is with journal editors and referees. Within the HET community, one primary group who may be inclined to approve of projects employing synthetic controls for reasons aside their intellectual value are journal editors and referees due to the controversy of journal impact factors. When it comes to impact factors, practitioners in HET are automatically at a disadvantage relative to other areas of study in economics because of the way impact factors are calculated which favor papers that cite literature in the previous 2 years; a relatively short time-window for those engaging with historical material.

In 2018, controversy arose surrounding the case of Clarivate's Web of Science Journal Impact Factors for four HET journals. Journal Impact Factors (JIFs) are a measurement used to understand the impact of a paper or journal. A more technical definition is that JIFs are the ratio between citations in all indexed literature in a given year to items published in the journal of the prior two years to the number of citable items in the journal of the previous two years. The controversy arose because Clarivate argued that the citations of two HET journals were distorted and skewed by a third and thus biasing the impact factors. This decision from Clarivate led to practitioners in HET to question the situation and for *Æconomia* to release a special issue on the place of impact factors in HET in 2021 (Edwards and Meardon, 2021).

⁵ Thank you to Erwin Dekker for the suggestion to explore the implication of journal impact factors.

The value of impact factors is debated. Nonetheless, Hurtado and Pinzon-Fuchs (2021) conducted a survey of practitioners in HET in 2019 to understand their views on impact factors. They found that while practitioners don't all believe that impact factors influence their careers, many practitioners felt impact factors had more to say about the status of journals. This suggests those who lead journals, referees, and editors, are the ones who may be particularly susceptible.

The introduction of synthetic controls is directly relevant to the case of JIFs because the method itself is so recent and there are so many papers coming up in it across policy evaluation and economic history which could be cited as support. In addition, there are more and more statistical advances to the model that come out every year. This 2-year window may be a relatively significant short period for practitioners in HET who pursue the standard qualitative framework. Thus, the methodology of synthetic controls and the recent literature associated with it, may be attractive to journal editors or referees despite the quality of the analyses. Journal editors and referees may have an incentive to accept papers which engage with synthetic controls even if they do not reach a high standard of expectation. Thus, this makes it even more important for practitioners in HET to engage with synthetic controls to set the expected standards.

I think no matter the clear answer on the importance of JIFs, there is some general view that impact factors play a role. There are some practitioners in HET who do not care for what the impact factors represent and do not believe they provide useful information (see Cardoso, 2021). However, the fact that there is not a clear and resounding "no" in response to the question on the value of impact factors is a sign that they do carry some weight, even if practitioners would prefer to admit they do not.

Thus, one potential consequence of introducing this novel quantitative methodology given these impact factors is that it may create an incentive for referees, editors and even researchers themselves to approve and pursue, respectively, projects which employ a synthetic control despite the quality. However, these incentives cannot cloud out the quality of synthetic controls.

7.2) A bridge for young students in economics into HET

Another group who may be especially likely to employ synthetic controls is young students in economics. The logic is that synthetic controls may serve as a bridge for economics students who would like to pursue a thesis or other project under HET but need to fulfill the empirical and quantitative expectations of their economics program. Thus, synthetic controls could act as a bridge between the modern, heavily quantitative economic programs and topics in HET for curious young students.

Many acknowledge there is a difference between researched economics and taught economics. The "textbook" material which many bachelor's students learn typically have a neoclassical trend to them. Despite this trend, many students are interested in topics outside of this textbook core. This is evident by the rise of groups such as Rethinking Economics which aims to spread

awareness on pluralist economic ideas. Rethinking Economics is an international initiative with university and regional chapters across the world.

Initiatives such as Rethinking Economics represent how some young economists are unsatisfied with the core curriculum they receive and their curiosity and desire to understand more. This is where the value of synthetic controls can come in. As a methodology, synthetic controls are widely accepted by many economists as a valid quantitative tool. Such an accepted methodology could thus serve as a bridge for young economics students who are curious to expand into topics outside their textbook core, such as the history of economic thought.

Moreover, Robert Skidelsky has suggested that many of these curious young economics students can find the answers they're looking for in HET (Skidelsky, 2020). Skidelsky has suggested that young economists can find answers to the concerns of our generation, such as inequality or climate change, by looking at the history of economics. Skidelsky suggests that these curious students will "recognise oneself in great thinkers of the past" (Skidelsky, 2020, p. 147). For students interested in learning about the dissenting history of the field, synthetic controls can offer an acceptable methodology for pursuing these topics or research questions which may not fit the standard nor expected economics curriculum. In addition, from a practical standpoint, the model is fairly accessible, as outlined in chapter 4, and there are ample materials available for students interested in learning the model, such as Cunningham (2020).

Thus, another potential consequence of the introduction of synthetic control models into HET is that they can act as a bridge to curious young economic students. If practitioners in HET choose to pursue synthetic controls, then they could open this bridge and define this path for these curious economic students who want to pursue more in the history of economic thought. In addition, the contextual requirements of synthetic controls, and specifically the ones for an available comparison group and no interference, will require these students to engage deeply with the qualitative side of their research. Even though these students may not create the strongest of synthetic control models, their choice to engage with these models will mean they still have an opportunity to explore the qualitative sides of their questions given the place of the contextual requirements in the model. So, if practitioners in HET choose to engage more with synthetic controls and build out the research agenda, it could form a bridge for economics students to access and explore HET.

7.3) Concerns of a divide⁶

The last group to consider when thinking about the non-epistemic considerations is practitioners in HET more generally. I'll start this section by echoing one of the questions raised by Cherrier and Svorenčík (2018) about the potential for a significant divide or even

⁶ It should be noted that I come at this discussion from the point of view of a young graduate student who has training in economics, history of economics, and economic methodology. I thus see the way ideas and methods can mix between the areas of economics and the history of economic thought, and actively choose to approach the two from an interdisciplinary perspective.

civil war amongst practitioners in HET. Simply, could synthetic controls cause a divide, or worse a civil war?

For the case of Cherrier and Svorenčik (2018), the discussion is primarily focused on the potential concern for a divide in HET down a quantitative versus qualitative line. They look to fields such as political science, sociology, and history to see how qualitative and quantitative methods sit within each discipline. Cherrier and Svorenčik show that amongst the social sciences and humanities, the mixing of qualitative and quantitative methods take several forms from creating two separate camps to cohabitating with little interaction (Cherrier and Svorenčik 2018, p. 368-369). Cherrier and Svorenčik (2018, p. 368) use this to argue that practitioners in HET must use this time to “reflexively engineer the intellectual and institutional standards of our nascent ‘quantitative turn’”. So, while they are wary of a potential divide, Cherrier and Svorenčik (2018) rather conclude that what is most important is attention to the topic through educating doctoral students and urging journal editors to engage with the material.

If we focus on the specific case of synthetic controls, some practitioners may be particularly wary of their potential to cause a divide after the discontent following Magness and Makovi (2023). In November 2022, Magness and Makovi announced their forthcoming paper in the *Journal of Political Economy* by sharing a thread of their results on Twitter (Magness, 2022). Their study quickly drew attention and led many other economists to engage in discussion around the contents of their paper. It was a contentious debate that eclipsed #EconTwitter for a 2-3 day period and led economists from different subfields, including some historians of economics, to either criticize or praise Magness and Makovi (Cherrier, 2022; Dekker, 2022; Milanovik, 2022; Johnson, 2022).⁷ The debates were quite contentious and left little room for discussion which is not the way synthetic controls should proceed in HET.

So, what is the impact of introducing synth to HET? Well, some people won't like it. It is a causal econometric model which is a newer and potentially uncomfortable introduction. Nonetheless, as far as causal models go, synthetic controls may be the one to cause the least amount of problems given their dependency on qualitative knowledge. As mentioned in chapter 5, synthetic controls must meet contextual requirements about the case at hand to form a valid causal conclusion. The most challenging contextual requirement is the expectation to have no interference and an available comparison or control group on which the units are unaffected and untreated by the event at hand. In Magness and Makovi, this means that individuals which compose the synthetic Marx must be unaffected by the Russian Revolution. This requirement is fairly difficult to meet and relies on specific qualitative information. For this case of the synthetic Marx, feeling certain that there is no impact on the other individuals may mean turning to primary sources such as letters, archived notes, or other qualitative methods which practitioners in HET are best trained for.

⁷ For anyone who questions the value of Twitter for tracking the progression of ideas and debates, see Cherrier (2018) on why practitioners in HET should engage on Twitter.

So, could synthetic controls cause a divide within HET? My intuition is no. Specifically, it is the dependent nature of synthetic controls to qualitative knowledge that should help prevent a clear divide between quantitative and qualitative methods. As has been emphasized throughout this project: a strong qualitative foundation is necessary for a justified synthetic control to meet the contextual and implementation requirements. Since the core of a good synthetic control is a qualitative foundation, I see it unlikely that the model can create a serious divide if the requirements and framework outlined in chapter 5 are upheld and proper standards and expectations are set. So based on the standards and expectations laid out in this thesis, the qualitative and quantitative methods must cohabit for synthetic controls to offer any epistemic value to the field. Essentially, the standards and expectations on the place of synthetic controls in HET can be made in such a way to prevent a divide and encourage cohabitation.

This chapter has aimed to explore potential non-epistemic considerations on the place of synthetic controls in HET by considering journal editors and referees, young economic students, and the practitioners of HET more generally. Despite the speculative nature of this chapter, I urge practitioners to not turn away from synthetic controls regardless of their outlook on the value of them. Like the introduction of quantitative methods broadly, the introduction of synthetic controls into HET is likely to continue. A publication of synthetic controls in a top five journal will likely make ripples and lead to other studies employing the same methodology, whether practitioners in HET want to see it or not. It is possible the method could be a passing fad, but even then, it should not be ignored. There is a concern that a method such as synthetic controls which is accepted by traditional economics could open a door to HET for individuals with insufficient training in the history of economics. Through this door, econometricians, and other individuals with no training in HET could begin to publish more and voice opinions and arguments on HET topics to the larger field which are unjustified claims and conclusions. The best way to shield against these unjustified causal claims in HET is for practitioners to engage in the material on synthetic controls, as similarly suggested by Cherrier and Svorenčik (2018) for quantitative methods generally. Standards and expectations on how to appropriately employ the methodology in HET should be set by practitioners in HET and not econometricians or others. The importance of the contextual requirements in leading to a just causal claim creates a space where the expertise of practitioners in HET is necessary for the validity of the model. The best way to determine these expectations and guidelines is to engage with the research and discuss.

8) Conclusion

This thesis has aimed to show the value of synthetic control models for HET. In the introduction, I suggested there were three primary reasons to consider adopting synthetic control models as a new methodology. First, that the methodology can offer epistemic value for a few reasons, but also because practitioners in HET already tend towards making causal generalizations (see chapter 3). Second, the methodology can offer non-epistemic advantages as outlined in chapter 7. The third point, that the introduction of these models will likely persist, at least throughout the near future, is what was echoed throughout the piece.

Chapter 5 presented a framework on how synthetic controls in HET should be approached, and chapter 6 applied it to the existing case of Magness and Makovi (2023) to show why their study falls short. The contextual requirements of synthetic controls, and specifically the requirements for an available comparison group and no interference, are simultaneously one of its strengths as it makes the empirical model more applicable to cases in HET, but these requirements are also one of the model's greatest weaknesses as it is easier to extrapolate and scrutinize. Thus, I suggested three implementation requirements to help practitioners in HET meet these contextual requirements as a means to properly approach synthetic controls.

It is this point on which this thesis aims to conclude: practitioners in HET must be the ones to set the standards about how to engage synthetic control models in HET related topics because of the qualitative nature of these contextual requirements. Synthetic control models are not as complicated and out of reach as many practitioners in HET may feel. In reality these models are quite accessible, as argued in chapter 4. But with the continuation of quantitative methods and empirical studies throughout the whole of economics, it is only a matter of time before these methods are forcefully knocking at the doorstep to the history of economic thought. Before synthetic controls are applied haphazardly to case studies in HET, practitioners must open a space for discussion to set the expectations and standards. This thesis has hoped to be the foot in the door and the spark to ignite such conversation.

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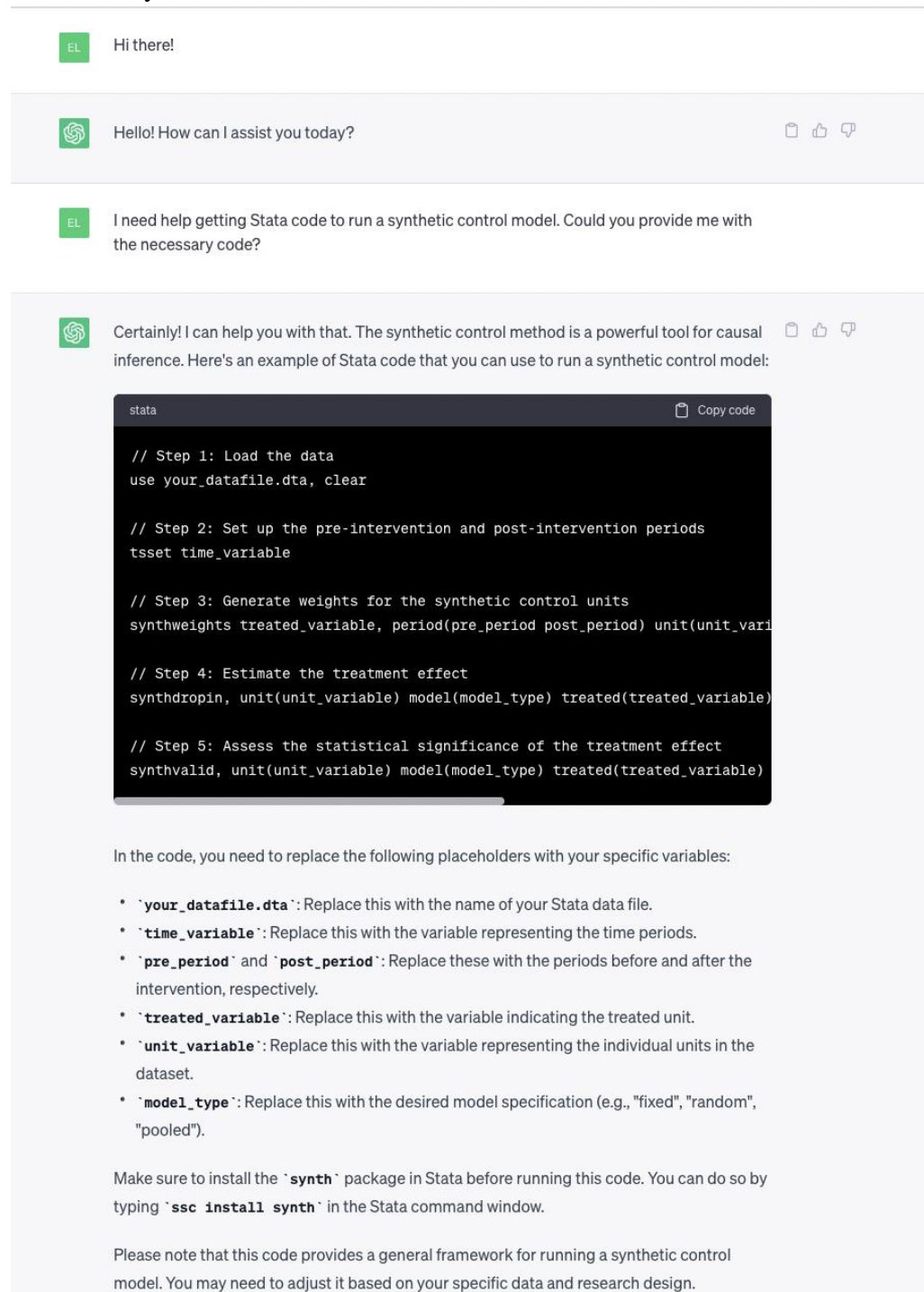
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A) Appendix

A.1) AI softwares for generating code

Below is an image from what happens when you ask ChatGPT, an Open AI, to help with the code for a synthetic control model in Stata:



The screenshot shows a chat interface with the following content:

EL: Hi there!

ChatGPT: Hello! How can I assist you today?

EL: I need help getting Stata code to run a synthetic control model. Could you provide me with the necessary code?

ChatGPT: Certainly! I can help you with that. The synthetic control method is a powerful tool for causal inference. Here's an example of Stata code that you can use to run a synthetic control model:

```
stata
Copy code

// Step 1: Load the data
use your_datafile.dta, clear

// Step 2: Set up the pre-intervention and post-intervention periods
tsset time_variable

// Step 3: Generate weights for the synthetic control units
synthweights treated_variable, period(pre_period post_period) unit(unit_vari

// Step 4: Estimate the treatment effect
synthdropin, unit(unit_variable) model(model_type) treated(treated_variable)

// Step 5: Assess the statistical significance of the treatment effect
synthvalid, unit(unit_variable) model(model_type) treated(treated_variable)
```

In the code, you need to replace the following placeholders with your specific variables:

- ``your_datafile.dta``: Replace this with the name of your Stata data file.
- ``time_variable``: Replace this with the variable representing the time periods.
- ``pre_period`` and ``post_period``: Replace these with the periods before and after the intervention, respectively.
- ``treated_variable``: Replace this with the variable indicating the treated unit.
- ``unit_variable``: Replace this with the variable representing the individual units in the dataset.
- ``model_type``: Replace this with the desired model specification (e.g., "fixed", "random", "pooled").

Make sure to install the ``synth`` package in Stata before running this code. You can do so by typing ``ssc install synth`` in the Stata command window.

Please note that this code provides a general framework for running a synthetic control model. You may need to adjust it based on your specific data and research design.

Below is the code which ChatGPT suggests implementing:

```
// Step 1: Load the data
use your_datafile.dta, clear
```

```
// Step 2: Set up the pre-intervention and post-intervention periods
tsset time_variable

// Step 3: Generate weights for the synthetic control units
synthweights treated_variable, period(pre_period post_period) unit(unit_variable)
model(model_type)

// Step 4: Estimate the treatment effect
synthdropin, unit(unit_variable) model(model_type) treated(treated_variable)
weights(synthweights) time(pre_period post_period)

// Step 5: Assess the statistical significance of the treatment effect
synthvalid, unit(unit_variable) model(model_type) treated(treated_variable)
weights(synthweights) time(pre_period post_period)
```