is to speak a very particular language. Political inquiry is multilingual. The customary tendency at the disciplinary-administrative level is for the standardizing terms of empiricism-positivism to dominate conversation and for hermeneutics not to be read with the relevance to explanation that it understands itself as having.

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Reflections on Analytic Transparency in Process Tracing Research

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While the aims of APSA's Data Access and Research Transparency (DA-RT) initiative are incontrovertible, it is not yet clear how to best operationalize the task force's recommendations in the context of process tracing research. In this essay, I link the question of how to improve analytic transparency to current debates in the methodological literature on how to establish process tracing as a rigorous analytical tool. There are tremendous gaps between recommendations and actual practice when it comes to improving and elucidating causal inferences and facilitating accumulation of knowledge. In order to narrow these gaps, we need to carefully consider the challenges inherent in these recommendations alongside the potential benefits. We must also take into account feasibility constraints so that we do not inadvertently create strong disincentives for conducting process tracing.

Process tracing would certainly benefit from greater analytic transparency. As others have noted,[1] practitioners do not always clearly present the evidence that substantiates their arguments or adequately explain the reasoning through which they reached casual inferences. These shortcomings can make it very difficult for scholars to interpret and evaluate an author's conclusions. At worst, such narratives may read as little more than potentially plausible hypothetical accounts.

Researchers can make significant strides toward improving analytic transparency and the overall quality of process tracing by (a) showcasing evidence in the main text as much as possible, including quotations from interviews and documents wherever relevant, (b) identifying and discussing background information that plays a central role in how we interpret evidence, (c) illustrating causal mechanisms, (d) assessing salient alternative explanations, and (e) including enough description of context and case details beyond our key pieces of evidence for readers to evaluate additional alternative hypotheses that may not have occurred to the author. Wood's research on democratization from below is a frequently lauded example that illustrates many of these virtues.[2] Wood clearly articulates the causal process through which mobilization by poor and working-class groups led to democratization in El

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[1] Elman and Kapiszewski 2014; Moravcsik 2014.

[2] Wood 2000; Wood 2001.

Salvador and South Africa, provides extensive and diverse case evidence to establish each step in the causal process, carefully considers alternative explanations, and explains why they are inconsistent with the evidence. Wood's use of interview evidence is particularly compelling. For example, in the South African case, she provides three extended quotations from business leaders that illustrate the mechanism through which mobilization led economic elites to change their regime preferences in favor of democratization: they came to view democracy as the only way to end the massive economic disruption created by strikes and protests.[3]

Beyond these sensible if potentially demanding steps, can we do more to improve analytic transparency and causal inference in process tracing? Recent methodological literature has suggested two possible approaches: explicit application of Van Evera's (1997) process tracing tests, and the use of Bayesian logic to guide inference. As a practitioner who has experimented with both approaches and compared them to traditional narrative-based process tracing, I would like to share some reflections from my own experience that I hope will contribute to the conversation about the extent to which these approaches may or may not enhance analytic transparency.

I became interested in the issue of analytic transparency after submitting an article manuscript on strategies for taxing economic elites in unequal democracies, which included four Latin American case studies. The case narratives employed process tracing to illustrate the causal impact of reform strategies on the fate of proposed tax-reform initiatives. I marshaled key pieces of evidence from in-depth fieldwork, including interviews, congressional records, and newspaper reports to substantiate my arguments. However, several of the reviews that I received upon initial submission questioned the contribution of qualitative evidence to the article's causal argument. For example, a reviewer who favored large-n, frequentist hypothesis-testing objected that the case evidence was anecdotal and could not establish causality. Another reviewer was skeptical of the hypothesis that presidential appeals invoking widely shared values like equity could create space for reforms that might not otherwise be feasible—a key component of my explanation of how the center-left Lagos administration in Chile was able to eliminate a regressive tax benefit—and felt that the case study did not provide enough evidence to substantiate the argument.

These reviews motivated me to write what I believe is the first published step-by-step account that explicitly illustrates how process-tracing tests underpin inferences drawn in a case narrative.[4] I chose one of the four case studies and systematically identified each piece of evidence in the case narrative. I also included several additional pieces of evidence beyond those present in the text to further substantiate my argument. Applying state-of-the-art methods literature, I explained the logical steps that allowed me to draw causal inferences from each piece of evidence and evaluated how strongly each piece of evidence supported my argument with reference to particular types of tests. For example, I explained that specific statements from opposition politicians indicating that President Lagos' equity appeal compelled the right-party coalition to reluctantly accept the tax reform provide very strong evidence in favor of my explanation, not only because these statements affirm that explanation and illustrate the underlying causal mechanism, but also because it would be extremely surprising to uncover such evidence if the equity appeal had no causal effect.[5] Based on these observations, the equity appeal hypothesis can be said to pass "smoking gun" tests: this evidence is not *necessary* to establish the hypothesis, but it can be taken as *sufficient* to affirm the hypothesis.[6] Stated in slightly different terms, the evidence is not *certain*—hearing right-wing sources confess that the government's strategy forced their hand is not an ineluctable prediction of the equity-appeal hypothesis, but it is *unique* to that hypothesis—these observations would not be predicted if the equity hypothesis were incorrect.[7] Other types of tests (hoop, straw-in-the-wind, doubly decisive) entail different combinations of these criteria.

While this exercise was most immediately an effort to convince scholars from diverse research traditions of the soundness of the article's findings, this type of procedure also advances analytic transparency by helping readers understand and assess the research. Scholars cannot evaluate process tracing if they are not familiar with the method's logic of causal inference, if they are unable to identify the evidence deployed, or if they cannot assess the probative weight of the evidence with respect to the explanation. While I believe that well-written case narratives can effectively convey all of this information to readers who are familiar with process tracing, explicit pedagogical appendices may help make process tracing more accessible and more intelligible for a broad audience.

However, there are drawbacks inherent in the process-tracing tests approach. For example, evidence rarely falls into the extreme categories of necessity and sufficiency that are generally used to classify the four tests. For that reason, I found it difficult to cast inferences in these terms; the pieces of evidence I discussed in my appendix did not all map clearly onto the process-tracing tests typology. Furthermore, it is not clear how the results of multiple process-tracing tests should be aggregated to assess the strength of the overall inferences in cases where the evidence does not line up neatly in favor of a single explanation.

These problems with process-tracing tests motivated me to redo my appendix using Bayesian analysis. This endeavor is part of a cross-disciplinary collaboration that aims to apply insights from Bayesian analysis in physics to advance the growing methodological literature on the Bayesian underpinnings of process tracing.[8] We believe the literature on process-tracing tests has rightly made a major contribution to qualitative methods. Yet Bayesian analysis offers a more pow-

[3] Wood 2001, 880.

[4] Fairfield 2013.

[5] See Fairfield 2013, 56 (observations 2a-e).

[6] Collier 2011; Mahoney 2012.

[7] Van Evera 1997; Bennett 2010.

[8] Fairfield and Charman 2015.

erful and more fundamental basis for understanding process tracing. Instead of asking whether a single hypothesis passes or fails a series of tests, which is very close to a frequentist approach, Bayesian analysis asks whether our evidence makes a given hypothesis more or less plausible compared to rivals, taking into account our prior degree of belief in each hypothesis and relevant background information that helps us interpret the evidence. While process-tracing tests can be incorporated within a Bayesian framework as special cases,[9] Bayesian analysis allows us to avoid the restrictive language of necessity and sufficiency by focusing on the degree to which a given piece of evidence alters our confidence in a hypothesis relative to rivals. Moreover, Bayesian probability provides clear procedures for aggregating inferences from distinct pieces of evidence.

Literature on *informal* Bayesianism in process tracing has elucidated various best practices that enhance analytic transparency.[10] One key lesson is that what matters most for inference is not the amount of evidence but rather how decisive the evidence is relative to the hypotheses at hand. In some cases, one or two highly probative pieces of evidence may give us a high level of confidence in an explanation. However, the available evidence does not always allow us to draw definitive conclusions about which hypothesis provides the best explanation, in which case we should openly acknowledge that uncertainty remains, while working hard to obtain more probative evidence where possible.[11]

Recently, several scholars have taken a step further by advocating that Bayesian analysis in process tracing should be *formalized* in order to make causal inferences more systematic, more explicit, and more transparent.[12] By revising my tax-reform appendix with direct applications of Bayes' theorem—the first such exercise of its kind—my collaborator and I aim to illustrate what formalization would entail for qualitative research that draws on extensive case evidence and to assess the advantages and disadvantages of this approach. I begin with an overview of the substantial challenges we encountered and then discuss situations in which formalization might nevertheless play a useful role in advancing analytic transparency.

First, formalizing Bayesian analysis requires assigning numerical values to all probabilities of interest, including our prior degree of belief in each rival hypothesis under consideration and the likelihood of observing each piece of evidence if a given hypothesis is correct. This task is problematic when the data are inherently qualitative. We found that our numerical likelihood assignments required multiple rounds of revision before they became reasonably stable, and there is no guarantee that we would have arrived at similar values had we approached the problem from a different yet equally valid starting point.[13] We view these issues as fundamental problems for advocates of quantification that cannot easily be resolved either through efforts at standardization of practice or by specifying a range of probabilities rather than a precise value. The latter approach relocates rather than eliminates the arbitrariness of quantification.[14]

Second, highly formalized and fine-grained analysis ironically may obscure rather than clarify causal inference. Disaggregating the analysis to consider evidence piece-by-piece risks compromising the level on which our intuitions can confidently function. In the tax reform case we examine, it strikes us as intuitively obvious that the total body of evidence overwhelmingly favors a single explanation; however, reasoning about the contribution of each piece of evidence to the overall conclusion is much more difficult, all the more so if we are trying to quantify our reasoning. If we disaggregate the evidence too finely and explicitly unpack our analysis into too many steps, we may become lost in minutiae. As such, calls for authors to "detail the micro-connections between their data and claims… and discuss how evidence was aggregated to support claims,"[15] which seem entirely reasonable on their face, could actually lead to less clarity if taken to extremes.

Third, formal Bayesian analysis becomes intractable in practice as we move beyond very simple causal models, which in our view are rarely appropriate for the social sciences. Whereas frequentists consider a single null hypothesis and its negation, applying Bayes' theorem requires elaborating a complete set of mutually exclusive hypotheses. We need to explicitly state the alternatives before we can reason meaningfully about the likelihood of observing the evidence if the author's hypothesis does not hold. Ensuring that alternative hypotheses are mutually exclusive is nontrivial and may entail significant simplification. For example, some of the hypotheses we assess against my original explanation in the revised appendix involve causal mechanisms that—in the real world—could potentially operate in interaction with one another. Assessing such possibilities would require carefully elaborating additional, more complex, yet mutually exclusive hypotheses and would aggravate the challenges of assigning likelihoods to the evidence uncovered. By contrast, in the natural sciences, Bayesian analysis is most often applied to very simple hypothesis spaces (even if the underlying theory and experiments are highly complex); for example: H_1 = the mass of the Higgs boson is between 124 and 126 GeV/c^2, H_2 = the mass falls between 126 and 128 GeV/c^2, and so forth.

[9] Humphreys and Jacobs forthcoming.

[10] Bennett and Checkel 2015.

[11] Bennett and Checkel 2015a, 30f.

[12] Bennett and Checkel 2015b, 267; Bennett 2015, 297; Humphreys and Jacobs forthcoming; Rohlfing 2013.

[13] Bayes' theorem implies that we must reach the same conclusions regardless of the order in which we incorporate each piece of evidence into our analysis. Literature in the subjective Bayesian tradition has sometimes maintained that the order in which the evidence is incorporated does matter, but we view that approach as misguided and that particular conclusion as contrary to the laws of probability. These points are further elaborated in Fairfield and Charman 2015.

[14] In their work on critical junctures, Capoccia and Kelemen (2007, 362) likewise note: "While historical arguments relied on assessments of the likelihood of various outcomes, it is obviously problematic to assign precise probabilities to predictions in historical explanations…."

[15] DA-RT Ad Hoc Committee 2014, 33.

Numerous other practical considerations make formal Bayesian analysis infeasible beyond very simple cases. The Chilean tax reform example I chose for the original appendix is a particularly clear-cut case in which a small number of key pieces of evidence establish the causal importance of the reform strategy employed. The original case narrative was 583 words; the more extensive case narrative in my book, *Private Wealth and Public Revenue in Latin America: Business Power and Tax Politics*, is 1,255 words. By comparison, the original process-tracing tests appendix was 1,324 words; our Bayesian version is presently roughly 10,000 words. My book includes 33 additional case studies of tax reform initiatives. If scholars were expected to explicitly disaggregate and elaborate process tracing to the extent that we have done in our Bayesian appendix, it would be a death knell for qualitative research. Hardly anyone would undertake the task; the timeline for producing publishable research—which is already long for case-based qualitative work—would become prohibitive.

To be sure, no one has suggested such stringent standards. Advocates of Bayesian process tracing have been clear that they do not recommend full quantification in all cases. Yet we fear that there may be little productive middle ground between qualitative process tracing underpinned by informal Bayesian reasoning and full quantification in order to apply Bayes' theorem. Attempts to find a middle ground risk disrupting clear and cogent narratives without providing added rigor, since they would not be able to employ the mathematical apparatus of Bayesian probability. We are therefore skeptical of even "minimal" recommendations for scholars to identify their priors and likelihood ratios for the most probative pieces of evidence.[16] The question of how to make process tracing more analytically explicit without risking false precision is an important problem for methodologists and practitioners to grapple with moving forward.

Given these caveats, when might formal Bayesian analysis contribute to improving causal inference and analytic transparency in qualitative research? First and foremost, we see an important pedagogical role. Reading examples and trying one's own hand at such exercises could help to familiarize students and established practitioners with the inferential logic that underpins process tracing. These exercises might also help train our intuition to follow the logic of Bayesian probability more systematically. Bayesianism is much closer than frequentism to how we intuitively reason in the face of uncertainty, but we need to learn to avoid biases and pitfalls that have been well documented by cognitive psychologists. As Bennett notes, "further research is warranted on whether scholars … reach different conclusions when they use Bayesian mathematics explicitly rather than implicitly, and whether explicit use of Bayesianism helps to counteract the cognitive biases identified in lab experiments."[17] We explore these questions with regard to our own reasoning about the Chilean tax reform case. On the one hand, we have not identified any inferential differences between the original case narrative and the formalization exercise. This consistency could indicate that informal Bayesian reasoning functioned very well in this instance, or that the intuition underpinning that informal analysis also strongly shaped the (necessarily somewhat ad-hoc) quantification process. On the other hand, we do note several differences between our Bayesian analysis and the process-tracing tests approach regarding the inferential weights assigned to distinct pieces of evidence. The lesson is that explicitly elaborating alternative hypotheses, rather than attempting to assess a single hypothesis (the equity appeal had an effect) against its negation (it had no effect), can help us better assess the probative value of our evidence.[18]

Second, these exercises could play a role in elucidating the precise locus of contention when scholars disagree on causal inferences drawn in a particular case study. We explore how this process might work in our revised appendix. We first assign three sets of priors corresponding to different initial probabilities for my equity-appeal hypothesis and three rival hypotheses. For each set of priors, we then calculate posterior probabilities across three scenarios in which we assign relatively larger or smaller likelihood ratios for the evidence. We find that in order to remain unconvinced by my explanation, a skeptical reader would need to have extremely strong priors against the equity-appeal hypothesis and/or contend that the evidence is far less discriminating (in terms of likelihood ratios) than we have argued. While identifying the precise points of disagreement could be inherently valuable for the knowledge accumulation process, formal Bayesian analysis may be less effective for resolving disputes in cases that are less clear-cut than the one we have examined. Scholars may well continue to disagree not only on prior probabilities for hypotheses, but more importantly on the probative weight of key pieces of evidence. Such disagreements may arise from differences in personal judgments as well as decisions about how to translate those judgments into numbers.

Third, elaborating a formal Bayesian appendix for an illustrative case from a scholar's own research might help establish the scholar's process tracing "credentials" and build trust among the academic community in the quality of the scholar's analytical judgments. As much as we try to make our analysis transparent, multiple analytical steps will inevitably remain implicit. Scholars who conduct qualitative research draw on vast amounts of data, often accumulated over multiple years of fieldwork. Scholars often conduct hundreds of interviews, to mention just one type of qualitative data. There is simply too much evidence and too much background information that informs how we evaluate the evidence to fully articulate or catalog. At some level, we must trust that the scholar has made sound judgments along the way; qualitative research is simply not replicable as per a laboratory science desideratum. But of

[16] See Bennett and Checkel 2015b, 267. We would further argue that the most probative pieces of evidence are precisely those for which quantification is least likely to provide added value. The author can explain why the evidence is highly decisive without need to invent numbers, and if the evidence is indeed highly decisive, readers should be able to recognize it as such on its face.

[17] Bennett 2015, 297.

[18] For a detailed discussion, see Fairfield and Charman 2015, 17f.

course trust in analytical judgment must be earned by demonstrating competence. Scholars might use a formalized illustration to demonstrate their care in reasoning about the evidence and the plausibility of the assumptions underlying their inferences. Again, however, further research is needed to ascertain whether the ability to formalize improves our skill at informal analysis, and to a significant extent, moreover, the quality of informal process tracing can be assessed without need for quantifying propositions.

To conclude, my experiments with explicit application of process-tracing tests and formal Bayesian analysis have been fascinating learning experiences, and I believe these approaches provide critical methodological grounding for process tracing. Yet I have become aware of limitations that restrict the utility and feasibility of formalization and fine-grained disaggregation of inferences in substantive process tracing. There is certainly plenty of scope to improve analytic transparency in process-tracing narratives—e.g. by highlighting the evidence and explaining the rationale behind nuanced inferences. Future methodological research may also provide more insights on how to make informal Bayesian reasoning more systematic and rigorous without recourse to quantification. Increasing analytic transparency in process tracing, in ways that are feasible for complex hypotheses and extensive qualitative evidence, will surely be a key focus of methodological development in years to come. In the meantime, further discussion about the practical implications of the DA-RT analytic transparency recommendations for qualitative research is merited.

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