Who Learns from What in Policy Diffusion Processes?

Fabrizio Gilardi University of Zurich

The idea that policy makers in different states or countries may learn from one another has fascinated scholars for a long time, but little systematic evidence has been produced so far. This article improves our understanding of this elusive argument by distinguishing between the policy *and* political *consequences of reforms and by emphasizing the conditional nature of learning processes. Using a directed dyadic approach and multilevel methods, the analysis of unemployment benefits retrenchment in OECD countries demonstrates that policy makers learn selectively from the experience of others. Right governments tend to be more sensitive to information on the electoral consequences of reforms, while left governments are more likely to be influenced by their policy effects.*

Interdependence is a defining feature of politics. Fundamental political phenomena such as conflict, cooperation, collective action, and decision making are characterized by the fact that the goals, strategies, and decisions of political actors are shaped by the goals, strategies, and decisions of other political actors. This idea is also the cornerstone of game-theoretical accounts of politics, which are constructed on the premise that actors are engaged in strategic behavior.

This article addresses this basic question by studying how policy makers in one country are influenced by prior choices in other countries or, in other words, how policies diffuse from one country to another. This classic argument, known in comparative research as "Galton's problem" (Ross and Homer 1976), has attracted considerable interest in recent years. Policy diffusion has been a major topic in the study of American federalism for a long time,[1] but a new wave of studies has made significant theoretical and empirical advancements (see, e.g., Shipan and Volden 2006, 2008; Volden 2006). In parallel, this question has been addressed at the cross-national level, where scholars have examined the spread of economic and social policies in particular (Brooks 2007; Elkins, Guzman, and Simmons 2006; Franzese and Hays 2008; Gilardi, Füglister, and Luyet 2009; Lee and Strang 2006; Meseguer 2009; Meseguer and Gilardi 2009; Simmons, Dobbin, and Garrett 2006, 2008; Simmons and Elkins 2004; Swank 2006). These two streams of research have improved significantly our understanding of diffusion processes. They have enhanced the conceptualization and operationalization of diffusion mechanisms, they have raised the standards of empirical analyses, and above all, they have provided strong evidence that policies do diffuse within and across countries.

On the other hand, the literature has been less successful in unpacking diffusion empirically, that is, in identifying specific diffusion mechanisms. Policies diffuse, but why? There is agreement that competition, learning, and social emulation are the main drivers of diffusion, but empirical evidence usually is ambiguous and unable to discriminate convincingly among these different explanations. Learning has been a particularly elusive hypothesis. In a recent article, Volden, Ting, and Carpenter affirmed that "[d]espite decades of study, systematic evidence that governments learn from one another has been limited" (2008, 319). While this assessment may be excessively gloomy, it is true that the literature, notwithstanding several promising works (see in particular Elkins, Guzman, and Simmons 2006; Lee and Strang 2006; Meseguer 2009; Volden 2006), has

Fabrizio Gilardi is Associate Professor at the Department of Political Science and at the Center for Comparative and International Studies, University of Zurich, Affolternstrasse 56, 8050 Zurich, Switzerland (gilardi@ipz.uzh.ch).

Previous versions of this article were presented at the 2008 MPSA Annual Conference, the 2008 APSA Annual Meeting, and seminars at Harvard University, the University of Zurich, and the University of Exeter. I thank the participants as well as Christian Bjørnskov, Ben Goodrich, Katerina Linos, Covadonga Meseguer, Beth Simmons, Duane Swank, Fabio Wasserfallen, and the *AJPS* editor and reviewers for helpful feedback. The bulk of this research was carried out while I was a visiting scholar at the Weatherhead Center for International Affairs, Harvard University, which I thank for its support. The financial help of the Swiss National Science Foundation (grant no. PA001–115307/1) is also gratefully acknowledged. Replication material is available on the author's website (www.fabriziogilardi.org).

[1]See, for example, Walker (1969), Gray (1973), and Berry and Berry (1990).

American Journal of Political Science, Vol. 54, No. 3, July 2010, Pp. 650–666

 ISSN 0092-5853

fallen short of providing compelling support for learning hypotheses.

I argue that findings have been mixed because most studies assume that the object of learning is the *policy* consequences of policy change, although the *political* effects are likely to be as important, if not more so. In addition, most studies assume that learning matters in the same way in all countries (or states), while in fact, learning processes are likely to be conditional: all policy makers need not be equally sensitive to the experience of others. In other words, who learns, and from what?

Building on recent theoretical work on learning and diffusion, I show that ideological positions and prior beliefs regarding the likely consequences of reforms are a powerful prism introducing significant variations in how policy makers take into account the experience of others. Depending on their preferences and prior beliefs, policy makers may be more or less sensitive to the cues coming from other countries. Furthermore, information about the *policy* and *political* consequences of policy change also may be taken into consideration differently by different policy makers.

Empirically, this article focuses on retrenchment in unemployment benefits in 18 OECD countries. This policy area is characterized by relatively clear partisan differences, which help us study the relationship between ideology and learning, and is an electorally salient domain, which is useful in investigating the political dimensions of learning. Unemployment policy also has a relatively straightforward goal, namely the reduction of unemployment, which makes it easier to identify and measure policy outcomes and thus to examine the policy side of learning.

The results of the analysis, which uses a dyadic approach (Volden 2006) and multilevel methods, show that information on the political and policy consequences of curtailing unemployment benefits is taken into account differently by different governments. Indications that a cut in benefits is compatible with electoral success makes the imitation of this policy more likely if the government is controlled by right parties, while signs that it leads to lower unemployment rates increases the probability of imitation if left parties are in power. Further, right governments are more likely than left governments to imitate cuts in unemployment benefits if the experience of other countries suggests that they are compatible with reelection, while left governments are less likely than right governments to imitate a reduction in benefits if it appears that this policy is associated with an increase in the unemployment rate. In sum, the analysis demonstrates that all policy makers do not learn equally and that there are significant differences between learning from *policy* and from *political* outcomes. This helps explain why previous studies have failed to provide strong evidence of learning and opens new questions for future diffusion research.

The rest of this article is structured as follows. The second section discusses how ideology and prior beliefs shape the influence of learning on policy choices in general, while the following section applies these ideas to the specific case of unemployment benefits retrenchment. The fourth section discusses data and methods, the fifth presents the results of the statistical analysis, and the conclusion sums up the main arguments and discusses its broader implications.

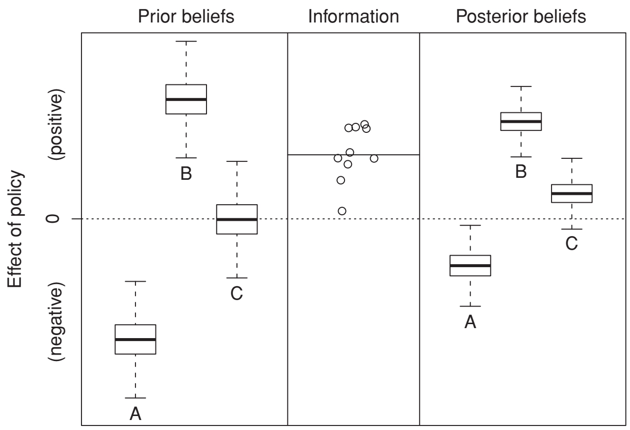
Who Learns, and from What?

Learning can be defined as a process whereby policy makers change their beliefs about the effects of policies (Dobbin, Simmons, and Garrett 2007, 460). When these beliefs are adapted by taking into account the experience of others, learning can be understood as a mechanism of diffusion, that is, an explanation of why and how policy choices in one country (or other relevant unit) are influenced by prior decisions in other countries (or other relevant units). However, do all policy makers learn equally? While this is the implicit assumption of most empirical analyses, recent theoretical work has suggested instead that ideology and prior beliefs constrain the influence of new information on policy change.

The Bayesian analogy frequently has been used in the study of learning (see, e.g., Meseguer 2006a, 2009; Simmons, Dobbin, and Garrett 2006) and is useful to understand why the experience of others is likely to have differential effects across countries. In the Bayesian account, policy makers have prior beliefs regarding the effects of policies, which are updated after observing their consequences in other countries. This leads to posterior beliefs, which determine the choices of policy makers. However, the weight of new information depends on prior beliefs. This logic is illustrated in Figure 1 , which shows how the beliefs of three policy makers (A, B, and C) change after taking into account new evidence.[2] The three actors hold different prior beliefs on the effects of a given policy. Tax policy is a case in point: some think that lower tax rates increase revenue collection, while others are more skeptical (Basinger and Hallerberg 2004; Swank 2006). Following this illustration, Figure 1 shows that

[2]The figure has been computed on the basis of Gelman et al. (2004, 78–80).

FIGURE 1 Bayesian Learning



Note: The left panel shows the prior beliefs of three actors on the effects of a policy; the middle panel shows 10 data points constituting new information on these effects (the horizontal line is the mean); the right panel shows the posterior beliefs of the same actors.

A is quite sure that tax cuts reduce revenue, B is confident that they increase it, and C's views are not well defined.

When new information (in the example, 10 data points) reveals that the effect of tax cuts is likely to be markedly positive, the three actors update their beliefs. The information is identical for all actors, but their posteriors are quite different. A is still of the view that the effect is negative, albeit smaller than previously thought; B finds that its standpoint is comforted by the evidence and corrects it only marginally; and C now tends to think that tax cuts increase revenue, but only slightly and without much conviction. Thus, on the basis of these posterior beliefs, B would be much more likely than A to cut tax rates, and C would be more likely to do so than in the previous period, but still significantly less likely than B. These differences exist despite the fact that all actors were exposed to exactly the same information about the likely consequences of the policy. This result is interesting because the model assumes perfect rationality; even actors who make the best possible use of new information will not reach the same conclusion if they have different prior beliefs. Intuitively, this makes sense. In light of new evidence, policy makers who strongly believe that tax cuts have negative (or positive) consequences on revenue collection will change their minds less easily than those who hold less clear-cut opinions, and at the same time, the former will be keener to incorporate new evidence if it is consistent with their views and it does not require a sharp departure from entrenched beliefs.

Complementary insights on the conditional impact of learning come from the formal model developed by Volden, Ting, and Carpenter (2008). The model assumes that policy makers' utility is a function of both the perceived effectiveness of a policy and its proximity to policy makers' ideal points. This means that policy makers evaluate the attractiveness of, say, the death penalty on the basis of both the estimated consequences on a relevant outcome such as the crime rate ("effectiveness") and broader considerations such as the compatibility of this punishment with respect for human rights ("ideology").

As in the Bayesian approach, learning means that policy makers update their beliefs about the likely consequences of policies. They can learn either through experimentation or by observing the experience of others. The model predicts that the impact of effectiveness—and, therefore, learning—on policy change varies as a function of ideology. Policy makers with extreme ideal points will change policy (or, conversely, keep the status quo) regardless of the relative effectiveness of the alternatives, which, by contrast, will have a decisive impact on policy makers with more moderate positions. The experience of others does not affect all policy makers equally *not* because they have different prior beliefs—by assumption, in this model all actors share the same priors (Volden, Ting, and Carpenter 2008, 321)—but because ideology may offset evidence that an alternative policy is more effective. Again, this makes intuitive sense: some conservative policy makers would not be willing to regulate access to firearms strictly even if there were conclusive evidence that gun control saves lives, and some liberal policy makers would not support the death penalty even if it were proved that it helps reduce crime.

Therefore, recent theoretical work on learning suggests that ideological positions and prior beliefs on the effectiveness of policy alternatives limit the influence of new information and tie policy makers more or less firmly to their original policy stance. However, what is this new information about? In other words, what do policy makers learn from?

The literature assumes that the relevant effects of policies are those on *policy* outcomes. For instance, scholars have asked whether countries are more likely to sign bilateral investment treaties if these appear to increase investment flows (Elkins, Guzman, and Simmons 2006), whether public-sector downsizing (Lee and Strang 2006) and other market-oriented reforms (Meseguer 2006a, 2009) are more likely to be adopted if they seem to be linked to higher economic growth, and whether specific Children's Health Insurance Programs are more likely to spread if they are successful in reducing the uninsured rate among poor children (Volden 2006). Such policy outcomes are undoubtedly important. However, *political* outcomes also are likely to matter. If a given policy is passed, what will be the political fallout? Will it help or hurt electoral prospects? Policy makers care about these questions, and one way for them to find answers is to look at the experience of others, which can help them assess the political feasibility of a given policy change. Despite its plausibility, this point has not been addressed in the literature so far.

These arguments suggest an account of learning processes in which prior beliefs and ideology shape the impact of the policy and political consequences of reforms, as inferred from the experience of others, on policy change. Thus, the general hypothesis is that new information on the likely consequences of a policy matters more if it is not at odds with the preferences and prior beliefs of policy makers. Conversely, policy makers favoring a given policy will be more likely to adopt it if the experience of others indicates that it does lead to the desired policy and political outcomes. The next section discusses how these arguments play out in the specific case of unemployment benefits retrenchment.

Learning and Unemployment Policy

Unemployment policy is a particularly interesting area for the empirical analysis of learning for three reasons. First, there are fairly clear partisan differences that permit study of the interplay between ideology and learning. Second, unemployment reform is highly politicized and constitutes electorally dangerous ground, which is useful for investigating the political dimensions of learning. Finally, in comparison to other domains, the identification and measurement of relevant policy outcomes is relatively simple.

I focus on a specific aspect of unemployment policy, namely replacement rates, which indicate what share of the salary workers receive through unemployment insurance when they lose their jobs. Allan and Scruggs (2004) have developed a measure that does not rely simply on spending and which, therefore, is both more relevant for the study of unemployment policy and more directly linked to explicit policy choices than traditional spending measures. Using this indicator, Allan and Scruggs (2004) have documented substantial retrenchment in unemployment benefits. With respect to their post-1975 peak, replacement rates have decreased in 15 of the 18 OECD countries covered by their study,[3] and among these 15 countries, seven cut replacement rates by more than 10 points, and four others cut them by more than five points (Allan and Scruggs 2004, 499–500). These authors also demonstrated that partisan politics has been a significant driver of retrenchment: governments controlled by right parties have been more likely to cut replacement rates and, when cuts have occurred, they have been larger under right governments.

At the same time, cutting benefits is dangerous. A cross-national survey carried out by the International Social Survey Program in 1996 (ISSP 1999) showed that in all the 13 OECD countries covered by the study, a majority of respondents opposed reductions in unemployment benefit spending. On average, only 22.5% answered that the state should spend "less" or "much less" on these programs. This is a well-known fact: voters tend to oppose cuts in social policies. Therefore, unemployment benefits retrenchment lends itself well to an investigation of how *political* outcomes matter in learning processes.

This area also has desirable characteristics for the study of learning from *policy* outcomes. In some cases, the empirical analysis of learning is unfeasible because the identification and measurement of the relevant effects of policies is extremely difficult, while in many others researchers have to rely on rough proxies. For instance, in their study of public-sector reforms, Lee and Strang (2006) used economic growth, budgetary health, and trade balance as relevant outcomes. While these indicators are plausible, whether they are the main goals of public-sector reforms is debatable. By contrast, although unemployment policy does not have a single objective, reducing the unemployment rate is certainly a major goal.[4] Data on unemployment are widely available and are regularly reported in the media, often in the context of international comparisons. Policy makers and indeed the general public are aware not only of the unemployment rate in their own country but also abroad, and they have

[3]Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, United Kingdom, United States.

[4]The reduction of budget deficits can be another objective of cuts in unemployment policy. As Swank (2002) has shown, fiscal stress, in conjunction with international capital mobility, is linked to welfare state retrenchment. However, deficits are not a very relevant dimension for the study of learning because their connection with retrenchment is mechanical: all else being equal, if spending goes down, deficits also go down. This is straightforward, and the experience of others does not supply much additional information. By contrast, the link between the generosity of unemployment policy and the unemployment rate is much more uncertain, and the experience of others can help estimate it.

some sense of where their country stands in comparison to other countries.

What hypotheses can be developed regarding learning and unemployment benefits retrenchment? I start from the assumption, supported by empirical evidence (Allan and Scruggs 2004), that right governments prefer greater cuts than left governments. I also consider that policy makers have prior beliefs on the effects of cuts on both unemployment and reelection prospects and that they update them by looking at the experience of other countries. Because I am unable to measure priors empirically, I assume that they are correlated with ideology, especially with respect to *policy* outcomes. In other words, the assumption is that right governments tend to think that reducing unemployment benefits helps reduce the unemployment rate, while left governments are more skeptical. By contrast, the correlation between ideology and prior beliefs on *political* outcomes could be weaker: all policy makers have clear incentives to pay close attention to the electoral consequences of their choices, and they are less likely to be in denial about them than about policy consequences.

Building on the arguments developed in the second section, then, the first hypothesis is that right governments are more likely to imitate a reduction in benefits if the experience of others suggests that the reform is associated with a decrease in the unemployment rate, while left governments are less likely to imitate a cut in benefits if information coming from other countries suggests that it does not help to curb unemployment. The same hypothesis can be formulated also for political outcomes, although the difference between right and left governments is expected to be smaller than for policy outcomes. The second hypothesis stems from the other side of the reasoning, namely that evidence that cutting unemployment benefits leads to the desired policy and political outcomes should make imitation more likely, but the effect should vary with the partisan composition of governments. These hypotheses are different facets of the same argument, namely that learning is conditional on the prior beliefs and ideological positions of policy makers.

Methods and Data

The analysis adopts a directed dyadic setup in which each country is in turn the potential "receiver" and the potential "sender" of policy changes. This approach is common in the international relations literature, where dependent variables are often dyadic—for instance, conflicts (e.g., Gartzke 2007; Maoz and Russett 1993), trade flows (e.g., Morrow, Siverson, and Tabares 1998), and bilateral investment treaties (Elkins, Guzman, and Simmons 2006). Recently, Volden (2006) has suggested that the dyadic approach can be employed usefully also for the study of policy diffusion (see also Gilardi and Füglister 2008). Using this framework, this author has studied the diffusion of Children's Health Insurance Programs across U.S. states and has shown that policies that are successful in one state are more likely to be adopted in other states. In this case, the dependent variable cannot be measured at the dyadic level because the phenomenon of interest (mutual influence) is unobservable. Thus, Volden (2006) defined the dependent variable in terms of increased similarity. The detection of systematic patterns of increased similarity permits us to make inferences about the underlying diffusion process.[5]

In this article, the dependent variable is coded 1 if, in a given year, country$_i$ cuts the unemployment replacement rate *and* country$_j$ did the same in the previous period,[6] and 0 otherwise. Plainly, if the dependent variable is coded 1, it means that "country$_i$ does what country$_j$ has already done," where the action of interest is retrenchment, namely a reduction in unemployment replacement rates. As a shortcut, in the rest of the article I refer to the dependent variable as "imitation." However, it is important to stress that a positive outcome for the dependent variable merely indicates *potential* imitation. Imitation itself is essentially unobservable: what we can do is simply try to detect systematic patterns in potential imitation, which then allow us to draw inferences on the existence and nature of interdependence.[7] The main analysis takes all reductions into account (that is, all negative changes), but I consider also other thresholds, namely cuts greater than 0.25, 0.5, 0.75, and 1 point, bearing in mind that the distribution is highly skewed toward smaller changes (see Appendix A1).

[5] An alternative way to model policy diffusion is a monadic event-history analysis where interdependence is taken into account through spatial lags. This would solve some of the complications of the dyadic approach discussed below, but it also would open a whole new series of methodological complications, as recent research has shown (Franzese and Hays 2009).

[6] The relevant "previous period" corresponds to the latest completed electoral term. This is because one of the key independent variables, namely the electoral performance of the incumbent party in country$_j$, is of course not measured yearly but only when an election is held (details shortly).

[7] To clarify further, this approach does not require the assumption that any policy adoption after the first is an imitation event. The only assumption is that the dependent variable defined in these terms (that is, country$_i$ adopts a policy which country$_j$ has already adopted) is a meaningful quantity that allows one to make inferences about the diffusion process (or absence thereof).

The dyadic approach has come under intense scrutiny in the international relations literature. A first problem is that cross-sectional heterogeneity cannot be dealt with through fixed effects if the dependent variable is binary and the event is relatively rare, since in this context many country or dyad dummies perfectly predict nonoccurence, and these cases must be dropped (Beck and Katz 2001; Bennett and Stam 2000; Green, Kim, and Yoon 2001; King 2001; Oneal and Russett 2001). A related issue is the complex dependencies that exist among observations. A given country appears multiple times in the dataset on both sides of the dyad. Therefore, dyads sharing the same country are by construction not independent. Bennett and Stam acknowledged the complication but concluded that "there is no obvious fix for the problem" (2000, 660). De facto, virtually all studies deal with this problem by computing robust standard errors for clustering on dyads (that is, by treating observations as independent across, but not within, dyads). However, observations are clustered not only on dyads but also on country$_i$ (the first country in the dyad) and on country$_j$ (the second country in the dyad). In other words, it is certainly not the case that, say, France–Germany is independent from France–Italy and from Britain–Germany, but this is what is usually assumed.

In this article, I adopt a better approach. The starting point is to recognize that dyadic datasets have a nonnested multilevel structure; observations are at the dyad-year level and grouped by year, country$_i$, and country$_j$. Extending the multilevel time-series cross-section model developed by Shor et al. (2007), I write the multilevel dyadic model as follows (see also Gelman and Hill 2007, 279–98):

$$
\begin{aligned}
y_{ijt} &\sim Bern(\alpha_i + \alpha_j + \alpha_t + X\beta)\\
\alpha_i &\sim N(\mu_{\alpha_i}, \sigma^2_{\alpha_i})\\
\alpha_j &\sim N(\mu_{\alpha_j}, \sigma^2_{\alpha_j})\\
\alpha_t &\sim N(\mu_{\alpha_t}, \sigma^2_{\alpha_t})
\end{aligned}
$$

The dependent variable is a probability, and the stochastic component at the first level is therefore assumed to follow a Bernoulli distribution. The systematic component includes a set of predictors as well as three intercepts—at the country$_i$, country$_j$, and year levels—that are themselves modeled as being drawn from a normal distribution. These random effects permit us to model cross-sectional and longitudinal heterogeneity, as well as the complex dependencies among observations, reasonably well.[8] In any case, this setup is superior to the default approach found in the literature of simply correcting the standard errors for clustering on dyads or, as in Volden (2006), on country$_i$. As a robustness check, I substitute the random effects for years (α_t) with t, t^2, and t^3, which is a convenient and reliable way to account for time dependence (Carter and Signorino 2009). I also estimate a standard logit model, which can serve as a point of reference for the multilevel model.

Another complication of dyadic analyses, which is specific to their application to policy diffusion, is that, by construction, country$_j$ can be imitated only to the extent that it already has adopted the policy (Boehmke 2009). In our case, country$_j$ can be imitated only if its unemployment replacement rate was cut in the previous period. If it was not, the probability of imitation is exactly 0. Thus, including such dyads merely inflates the number of negative cases without adding any information; it is analogous to keeping observations not in the risk set in a standard event history analysis (Boehmke 2009, 12). Accordingly, the analysis excludes dyad-years where, by construction, imitation is impossible.[9] However, as a robustness check, one model comprises all observations.

The three main independent variables are partisanship in country$_i$ and *political* and *policy* outcomes in country$_j$. First, partisanship is measured as the difference between right party and left party cabinet portfolios as a percent of all cabinet portfolios, with data taken from Swank (2003). The advantage of this measure is that it permits one to capture simultaneously the strength of both right and left parties in government: a value of −100 means that all portfolios are controlled by left parties, a value of 100 means that they all are controlled by right parties, and intermediate values reflect different mixes of left and right parties. On the other hand, a simpler measure (percent of right or percent of left party cabinet portfolios) necessarily captures only one of the two. For instance, if right parties control 60% of portfolios, the left can control any share between 40% and 0%. The two scenarios are obviously very different with respect to

[8]I acknowledge that the interdependencies that characterize dyadic datasets are almost certainly more complex than assumed here and that the multilevel model, while it is an improvement, may not be fully adequate. Unfortunately, no better solutions exist. In a recent article, Plümper and Neumayer (2010) developed several specifications for spatial dependence in dyadic data, but they assumed that the dependent variable is truly dyadic (as is the case in many applications in international relations), which makes their approach inapplicable in this project. Network analysis might lead to superior solutions, but its application to the study of diffusion is still in its infancy (see Hays, Kachi, and Franzese 2009).

[9]That is, $Pr(y_{i,t} = 1 | p_{j,t-1} = 0) = 0$, where y is imitation as defined earlier, and p is the policy to be imitated. Again, this occurs because of how the dependent variable is constructed. The claim is empirically verifiable and, in this dataset, it is indeed verified, as it should be.

the balance of power in government, but the difference would not be captured in the partisanship measure. I take centrist parties into account in two alternative measures. The first adds the share of centrist party cabinet portfolios to that of right parties, while the second subtracts it.[10] In addition, I also consider the share of governing party seats as a percent of all legislative seats (instead of the share of portfolios).

Second, for *political* outcomes, I focus on electoral performance. I have constructed four versions of this variable. The first is the difference in the share of votes received by the incumbent head of the government's party between the current and previous elections; the second computes the difference in the share of votes as a percent of the share in the previous election; and the third and fourth weigh the first two measures by the distance from the latest election, the idea being that closer successes or failures may carry greater weight than more distant ones.[11] Data come from Hellwig and Samuels (2007, 2008).

Third, for *policy* outcomes, I focus on the evolution of the unemployment rate in country$_j$. For comparability with political outcomes, I look at changes during electoral terms. This variable is computed as the difference between the rate at the end and at the beginning of the term. I also construct three alternative measures following the same logic as for political outcomes.

The analysis includes a series of controls. We could expect that policy makers are more likely to follow the example of others if they share similar partisan affiliations; therefore, I control for the difference in government partisanship between country$_i$ and country$_j$ (for the latter, measured during the relevant electoral term). Policy makers also may pay more attention to countries whose replacement rates are closer to their own; accordingly, I control for the difference in replacement rates between country$_i$ and country$_j$ (for the latter, again considering the relevant electoral term). Because policy makers in countries with higher replacement rates may be more likely to cut them, I include the lagged unemployment replacement rate for country$_i$. The unemployment rate in country$_i$ also may influence the decision to cut benefits and is controlled for. Since countries that have already cut replacement rates several times may be less likely to do it again, I include the number of previous cuts in country$_i$. As a general measure of the institutional context, I use the "political constraints" index developed by Henisz (2000). Finally, I control the difference in population between country$_i$ and country$_j$ and whether the two countries are in the same region (Europe, North America, Oceania).

Statistical Analysis

The results of the statistical analysis are displayed in Table 1. The first model includes only the main variables of interest, namely government partisanship in country$_i$ and policy and political outcomes in country$_j$. Right governments are more likely to imitate cuts in benefits, while policy and political outcomes in other countries do not appear to matter. The second model adds interactions between partisanship and outcomes, and we see that their standard errors are small; the effect of partisanship seems to depend on policy and political outcomes in other countries and, conversely, the effects of these outcomes on the probability that cuts are imitated are conditional on partisanship. The third model adds the controls discussed in the fourth section, which do not affect the main coefficients significantly, nor their standard errors. The positive coefficient of political constraints (with a small standard error) is puzzling, but it is actually not very stable across specifications.[12] We also can notice that the coefficient for the previous number of cuts is negative and its standard error is very small, which indicates that, as expected, the probability of cutting benefits decreases as the number of prior reductions increases. The fourth model controls for time dependence in a different way (namely, by including t, t^2, and t^3—rescaled to avoid computational problems—instead of random effects for years), which does not affect the results. The fifth model takes all observations into account, including those for which imitation is impossible, given how the dependent variable is constructed (see the fourth section). The results do not change, although, as one would expect, the coefficients tend to be smaller because of the addition of many observations for which the dependent variable must be 0. Finally, the sixth model is a common logit, with standard errors corrected for clustering on country$_i$ and again with time dependence modeled by t, t^2, and t^3. The key coefficients remain very similar to those estimated in the other models.

Given that, so far, the standard logit has been the model of choice for dyadic analyses, it is useful to consider how it compares with the multilevel approach.

[10] In analyses not shown but available upon request, I also use the share of centrist parties and the share of centrist minus that of right and left parties to see whether learning has stronger effects for policy makers with less extreme positions. I find that it is not the case. See also the discussion in the fifth section.

[11] The weight is $1/n$, where n is the number of years since the last election.

[12] However, one explanation for the positive coefficient could be that countries with few veto players are the first to adopt the reform, which makes them less likely to imitate others and, conversely, increases the share of countries with many veto players in the "imitators" set (Gilardi, Füglister, and Luyet 2009).

TABLE 1 Determinants of the Probability of Imitating Unemployment Benefits Cuts

	(1)	(2)	(3)	(4)	(5)	(6)
Partisanship$_i$	0.180***	0.238***	0.207***	0.136*	0.110**	0.129
	(0.063)	(0.066)	(0.072)	(0.069)	(0.054)	(0.132)
Unempl. change$_j$	−1.722	−2.113	−1.779	−4.094*	−2.301	−4.310
	(2.268	(2.295)	(2.396)	(2.094)	(1.900)	(2.716)
Vote change$_j$	−0.240	−0.361	−0.223	−0.398	0.175	−0.734
	(0.715)	(0.720)	(0.743)	(0.687)	(0.617)	(0.721)
Unempl. change$_j \times$ Part.$_i$	–	7.579***	8.053***	8.696***	5.944***	7.477**
	–	(2.724)	(2.854)	(2.750)	(2.287)	(3.750)
Vote change$_j \times$ Part.$_i$	–	3.058***	2.817***	2.849***	1.624**	2.640***
	–	(0.941)	(0.969)	(0.941)	(0.766)	(1.004)
$\lvert$Part.$_{i,t}$ − Part.$_j \rvert$	–	–	−0.097	−0.095	0.038	−0.068*
	–	–	(0.065)	(0.063)	(0.051)	(0.040)
Repl. rate$_{i,t-1}$	–	–	0.006	0.004	0.013**	0.015***
	–	–	(0.007)	(0.007)	(0.005)	(0.005)
$\lvert$Repl. rate$_{i,t-1}$ − repl. rate$_j \rvert$	–	–	0.000	(0.001)	0.003	0.001
	–	–	(0.003)	(0.003)	(0.003)	(0.002)
Same region	–	–	−0.048	−0.031	0.068	0.254
	–	–	(0.135)	(0.131)	(0.130)	(0.178)
Population$_i$−Population$_j$	–	–	−0.000	0.000	−0.001	−0.000
	–	–	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment$_i$	–	–	−1.250	−4.900**	0.103	−0.319
	–	–	(2.101)	(1.915)	(1.536)	(2.932)
Political constraints$_i$	–	–	1.657**	0.882	0.642	−1.775*
	–	–	(0.803)	(0.770)	(0.592)	(0.931)
Number of prior cuts$_i$	–	–	−0.391***	−0.465***	−0.152***	0.030
	–	–	(0.040)	(0.043)	(0.027)	(0.054)
Time/10	–	–	–	0.352	–	−1.622
	–	–	–	(0.720)	–	(1.911)
Time^2/10^2	–	–	–	2.481***	–	1.843
	–	–	–	(0.642)	–	(1.666)
Time^3/10^5	–	–	–	−6.995***	–	−5.311
	–	–	–	(1.719)	–	(4.394)
Intercept	0.206	0.197	2.216**	0.768	−1.114*	−0.005
	(0.186)	(0.187)	(0.899)	(0.731)	(0.602)	(0.739)
$\sigma^2_{\alpha_i}$	0.295	0.295	1.571	1.758	0.746	–
$\sigma^2_{\alpha_j}$	0.000	0.000	0.000	0.000	0.266	–
$\sigma^2_{\alpha_t}$	0.384	0.388	2.955	–	0.746	–
Deviance	4,255	4,241	4,150	4,268	7,189	4,480
N	3,332	3,332	3,332	3,332	6,409	3,332

Note: Multilevel logistic regression coefficients with standard errors (Models 1–5) and logistic regression coefficients with standard errors adjusted for clustering on country$_i$ (Model 6).

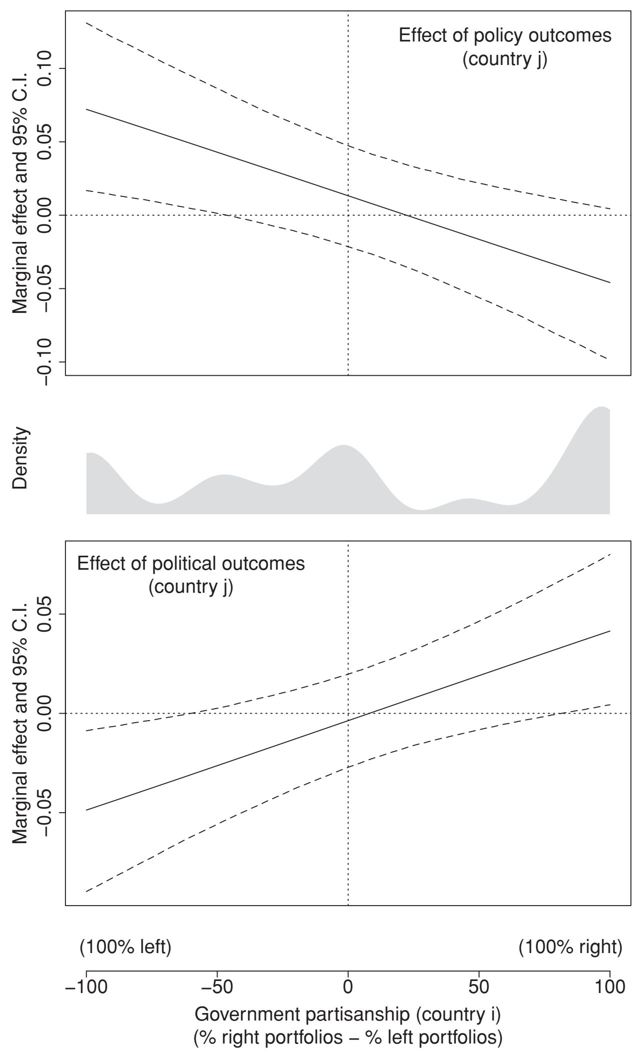
The deviance statistic shows that the multilevel model fits the data better than the standard logit. This can be seen also in the receiver-operating characteristic (ROC) plot in Appendix A2: the curve for the multilevel model is consistently greater than that for the logit, which indicates a better fit (King and Zeng 2001, 640–41). The random effects do help to capture significant unobserved heterogeneity, especially at the country$_i$ and year levels. On the other hand, as we see in Models 1–4 in Table 1, there is almost no variance left at the country$_j$ level, which means that the estimated intercepts for this group are very similar. This is due to the choice of conditioning on the "opportunity to imitate" (Boehmke 2009). If all observations are included in the analysis, as in Model 5, then there is some variance also at the country$_j$ level.

Across these models, the robust finding is that policy and political outcomes in country$_j$ do not matter per se, but only in interaction with the partisan composition of government in country$_i$. Conversely, it seems that right governments in country$_i$ are generally more likely to imitate cuts, but this also depends on the signals coming from country$_j$ concerning the possible consequences of reducing unemployment benefits. Table 1 shows that this result is not affected by the inclusion of controls, nor by how time dependence is accounted for, nor by the specific model used (multilevel or standard logistic regression). Further robustness checks are presented in Appendix A3, which shows the results of 10 additional models using different measures of the dependent and key independent variables, as discussed in the fourth section. Despite some weakening for more extreme thresholds in the identification of relevant cuts, the results withstand these tests, and we can therefore be confident that they are not driven by specific methodological choices.

To understand the findings better, we now turn to a graphical interpretation showing how political and policy outcomes in country$_j$ affect the probability that country$_i$ imitates country$_j$ conditional on partisanship in country$_i$ and, conversely, how the effect of partisanship on the probability of imitation depends on political and policy outcomes in country$_j$. These are two sides of the same argument, namely that learning is conditional on the preferences and/or prior beliefs of policy makers.

Figure 2 shows how the effects of "good" policy (top panel) and political (bottom panel) outcomes in country$_j$[13] vary conditional upon government partisanship in country$_i$, whose distribution in the dataset is shown in the middle panel. The top panel shows how the effect of *policy* outcomes in country$_j$ depend upon the partisan composition of government in country$_i$. Better unemployment trends in country$_j$ increase the probability that country$_i$ imitates the cuts in benefits in country$_j$ only if most cabinet portfolios are controlled by left parties; otherwise, good policy outcomes in country$_j$ do not make country$_i$ more likely to imitate. This suggests that given their preferences and/or priors, right governments are willing to reduce unemployment benefits regardless of the evidence coming from other countries, while left governments are more likely to cut them if this seems to give positive results in other countries, and less likely to cut them in the case of apparent negative results. We will examine this point below. The effect of good

FIGURE 2 Learning from *Policy* and from *Political* Outcomes



Note: The top panel shows the marginal effect of good *policy* outcomes in country$_j$ on the expected probability that country$_i$ imitates country$_j$, conditional on the partisan composition of the government in country$_i$. The bottom panel does the same but for *political* outcomes. The middle panel shows the distribution of the conditioning variable, namely the partisan composition of government. The figure is based on Model 3 in Table 1.

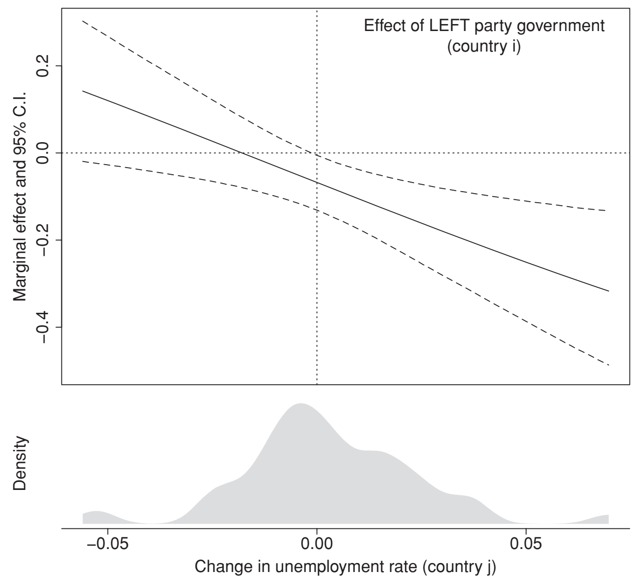
[13]For policy outcomes, the difference in the expected probability of imitation when the difference in the unemployment rate in country$_j$ goes from the 20th to the 80th percentile, i.e., from a decrease to an increase; for political outcomes, the difference in the expected probability of imitation when electoral results in country$_j$ go from the 80th to the 20th percentile, i.e., from gains to losses.

policy outcomes is quite sizable; the point estimate for a government fully controlled by left parties is 0.073, which means that conditional on left party government, a decrease in unemployment in country$_j$ increases the probability of imitation by about 7%.

Turning to *political* outcomes, the bottom panel in Figure 2 shows that the impact of electoral outcomes in country$_j$ is not distinguishable from zero when government portfolios in country$_i$ are not concentrated clearly in the hands of left or right parties. However, when the right controls all portfolios, an electoral success of the incumbent in country$_j$ makes it more likely that policy makers in country$_i$ imitate the cuts in unemployment benefits enacted in country$_j$. In Figure 2, the effect may seem only marginally significant, but the distribution of partisanship in country$_i$ (shown in the middle panel) indicates that governments where right parties control all portfolios are the modal category in the dataset; precisely, they constitute 29.7% of observations. Moreover, we can note that the point estimate for the effect of "good" political outcomes in country$_j$ conditional on right partisanship in country$_i$ is 0.041, meaning that positive electoral outcomes in country$_j$ increase the probability that country$_i$ imitates the cuts in benefits made in country$_j$ by about 4% if the government is controlled by right parties, which is fairly substantial.

The other point highlighted by the bottom panel in Figure 2 is less straightforward. We see that when the government in country$_i$ is dominated by left parties, good political outcomes in country$_j$ *decrease* the probability that cuts in unemployment benefits are imitated. This result could be driven by the fact that, in the dataset, there is a certain trade-off between good *policy* and good *political* outcomes. On the one hand, change in unemployment and change in electoral support for the incumbent are correlated negatively, as one would expect; incumbents tend to fare better if unemployment has decreased. At the same time, in a regression (using the country-year dataset) of incumbent vote change on unemployment change, the coefficient of unemployment change is negative but with a large standard error.[14] Furthermore, it turns out that only 18.7% of the observations have a positive outcome for both unemployment and incumbent votes, which means that a given country, in a given year, is not likely to send "good" signals on both dimensions. Hence, in the majority of cases, policy makers in country$_i$ have to focus either on the positive electoral results of country$_j$ and discount the negative unemployment outcomes, or on the positive unemployment results and overlook the negative electoral scores.

FIGURE 3 Learning from *Policy* Outcomes



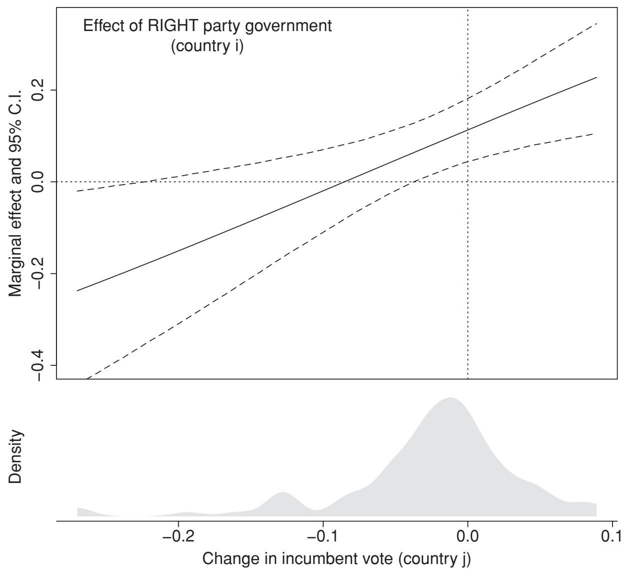
Note: The top panel shows the marginal effect of *left* party government in country$_i$ on the expected probability that country$_i$ imitates country$_j$, conditional on *policy* outcomes in country$_j$, whose distribution is shown in the bottom panel. The figure is based on Model 3 in Table 1.

In sum, Figure 2 shows that information on the likely consequences of policy change is taken into account differently by policy makers with different prior beliefs and/or ideological orientations. Further, it suggests that there could be a trade-off between learning from political and from policy outcomes, which different policy makers solve in different ways. Signals coming from the experience of others can be contradictory, pointing to good political outcomes but bad policy outcomes, or vice versa. Left and right governments seem to resolve this contradiction differently, the former being more sensitive to policy outcomes (maybe at the expense of political fallout), and the latter being more responsive to political outcomes (possibly because of stronger priors on positive policy outcomes).

These points are illustrated in Figures 3 and 4 , which show the flip side of Figure 2, namely how the effects of government partisanship in country$_i$ change depending on policy and political outcomes in country$_j$. Figure 3 considers the former. We see that left and right party governments are equally likely to imitate a reduction in benefits from country$_j$ if the latter experienced a decrease in the unemployment rate, while left party governments are less likely than right party governments to imitate

[14]Vote change $= -0.023(0.005) - 0.655(0.453)\times$ Unemployment change (standard errors adjusted for clustering on countries in parentheses).

FIGURE 4 Learning from *Political* Outcomes



Note: The top panel shows the marginal effect of *right* party government in country$_i$ on the expected probability that country$_j$ imitates country$_j$, conditional on *political* outcomes in country$_j$, whose distribution is shown in the bottom panel. The figure is based on Model 3 in Table 1.

cuts from country$_j$ if the unemployment rate went up. The size of the effect is large, about 14% according to the point estimate.[15] The effects of partisanship conditional on *political* outcomes are displayed in Figure 4, which shows that right governments are more likely than left governments to imitate cuts in benefits if the incumbent government in country$_j$ was electorally successful, or at least did not lose too many votes.[16] Substantively, the effects are again large, namely about 13% according to the point estimate.[17] On the other hand, when incumbents in country$_j$ suffer major losses, right and left governments are equally likely (or unlikely) to imitate its policies.[18]

Taken together, Figures 2–4 indicate not only that learning is indeed conditional on the preferences and/or prior beliefs of policy makers, which was the main hypothesis, but also that information on policy and political outcomes is taken into account differently by different policy makers. Right governments tend to be more sensitive to information on the electoral consequences of reforms, while left governments are more likely to be influenced by their policy effects, especially when they are negative. In sum, the analysis shows that all policy makers do not learn equally, and it suggests that in the presence of multiple objectives, such as policy and political goals, trade-offs arise that different policy makers solve in different ways depending on whether the evidence contradicts their prior beliefs and/or ideological positions or it is consistent with them. These findings have several implications for the study of interdependence and policy diffusion, and I address them in the next, concluding section.

Conclusion

The idea that policy makers in one country (or state) are influenced by the decisions made in other countries (or states) is accepted widely. A large number of studies at the subnational and cross-national level have demonstrated that interdependence is a powerful force in policy making and that policy diffusion is a real phenomenon. However, what are the mechanisms driving diffusion processes? Many explanations have been suggested, but the evidence is inconclusive. Empirical studies have shown convincingly that policies do diffuse, but most have been unable to differentiate between alternative mechanisms. The disconnect between theories and empirical analysis is currently the main problem of this research program, and progress on this issue is essential to move beyond generic claims that interdependence matters and policies diffuse.

This article has focused on a particularly elusive argument, namely learning, or the idea that the experience of others is taken into account because it supplies useful information on the likely consequences of policy choices. Specifically, I have shown that all policy makers are not equally sensitive to new information about the likely effects of policy change and that the relevant outcomes from which policy makers learn include both the *policy* and the *political* consequences of reforms. Ideological positions and prior beliefs about the effectiveness of policies shape the interpretation of new evidence and make policy makers react differently to information coming from

[15]Evaluated at the 80th percentile of change in unemployment rate, namely 0.018.

[16]The distribution in the bottom panel of Figure 4 shows that incumbent governments tend to lose some votes, so moderate losses may be discounted as normal.

[17]Evaluated at the 80th percentile of change in incumbent vote, namely 0.014.

[18]The region where the difference between right and left parties is negative clearly corresponds to outlying cases in the distribution of change in incumbent vote and thus can be safely disregarded.

the experience of others, which helps them assess both the political and policy potential of alternatives. The statistical analysis of unemployment benefits retrenchment in 18 OECD countries shows that right governments are more likely to imitate cuts if the experience of others suggests that cutting benefits is not excessively prejudicial to reelection, while the same governments are more willing to dismiss evidence that retrenchment is not associated with better unemployment performance. On the other hand, left governments seem to pay more attention to the policy consequences of a reduction in benefits, possibly discounting information on the political fallout in case the two conflict. These differential responses are linked to the trade-offs that emerge when policy makers pursue multiple objectives and information is contradictory, pointing to good outcomes on one dimension (e.g., policy) but bad consequences on the other (e.g., politics). How the trade-off is solved depends on the alignment between the evidence and the preferences and prior beliefs of policy makers.

These findings help explain why the literature has not shown convincingly that learning is a significant driver of policy diffusion: learning processes are more complex than usually assumed. The dominant view is that either learning matters, or it does not; either evidence of success influences the adoption of policies, or it does not. Empirical tests of this argument have produced ambiguous results because, as this article has shown, all policy makers are not equally sensitive to the same information. Their preferences and prior beliefs limit the extent to which evidence of success is taken into account, and they may even determine whether policy or political outcomes are given priority.

The results also show that the distance between "rational" and "bounded" flavors of learning may be smaller than has been appreciated so far (Meseguer 2006b). Proponents of bounded learning argue that cognitive shortcuts drastically limit the efficiency with which new information is processed, so that learning is strongly biased (Weyland 2005, 2007). For instance, policy makers may give more attention to examples that are geographically closer, culturally more similar, or otherwise "available" and, through the "representativeness" heuristic, they may draw strong conclusions from suggestive but inconclusive evidence. However, this article has shown that prior beliefs and ideology can make even rational learners subject to something akin to confirmation bias (see, e.g., Taber and Lodge 2006). Thus, the opposition between different types of learning probably has been overstated.

A number of new questions and implications emerge from these findings. First, the connection between learning from policy and from political outcomes needs further consideration. This article has shown that a trade-off between policy and electoral goals can affect how policy makers learn, and which objective is given priority may depend on the prior beliefs and ideological position of policy makers. Nevertheless, exactly how learning is affected by this tension remains unclear. For instance, what is the net effect of an example that points to positive policy consequences but negative political fallout? More theoretical and empirical work on these issues would be welcome.

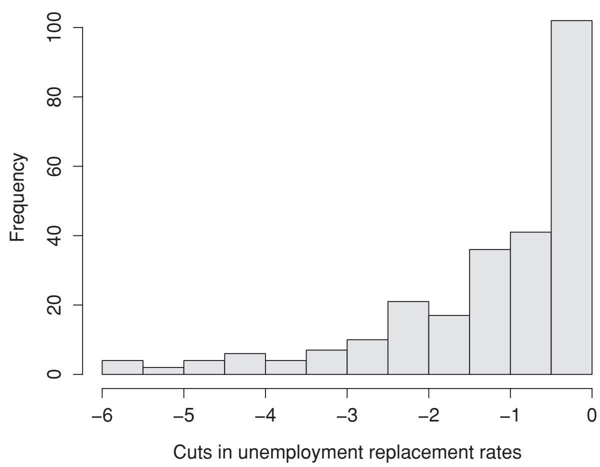
Second, what is the connection between ideology and prior beliefs? I have posited that policy makers with strong ideological orientations also are likely to hold well-defined prior beliefs on the effectiveness of a policy. For instance, if policy makers prefer low unemployment benefits because they trust market mechanisms more than state intervention, then they are also likely to believe that such a policy has beneficial consequences on the unemployment rate. However, I have been unable to disentangle the two dimensions empirically, and recent theoretical work has focused either on ideology at the expense of prior beliefs (Volden, Ting, and Carpenter 2008) or on prior beliefs but neglecting preferences (Meseguer 2006a). The interplay between these two factors needs to be examined in more detail.

Third, this article has focused on learning, but the literature has identified other diffusion mechanisms, such as competition and social emulation (Braun and Gilardi 2006; Simmons, Dobbin, and Garrett 2006). How do the arguments developed here apply to these mechanisms? For instance, competition means that policy makers are influenced by the choices of others because these affect their capacity to attract resources. Does this mechanism work equally for all policy makers, or are some more prone to give in to or, on the contrary, resist competitive pressures? Social emulation, on the other hand, means that some policies gain legitimacy and are socially constructed as appropriate solutions to given problems. Are all policy makers equally sensitive to this stimulus?

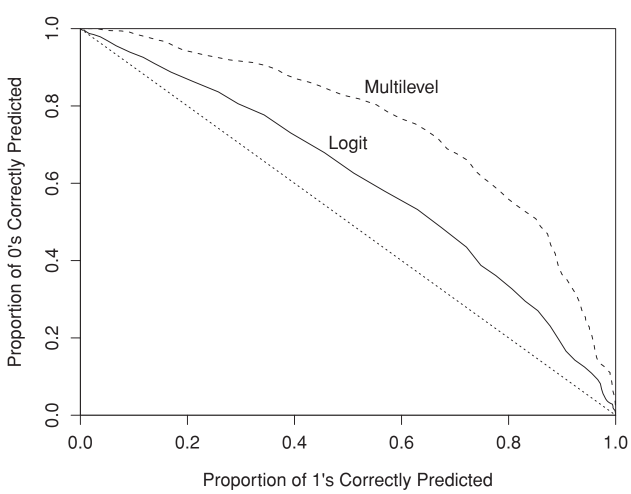
Finally, a normative question is whether evidence that policies diffuse because policy makers learn is good news. At first sight, yes, but this article has shown that some policy makers may pay more attention to the political consequences of reforms than to their policy outcomes, and this certainly is not very appealing from a normative standpoint. Learning does seem to be an important component of policy diffusion processes, but scholars need to look more closely at the conditions under which the experience of others has an influence on domestic policy choices.

Appendix

A1 Distribution of Cuts in Unemployment Replacement Rates



A2 ROC Curve



A3 Robustness Checks

Model A1 includes an alternative measure of partisanship where the share of cabinet portfolios controlled by centrist parties is added to that of portfolios controlled by right parties.

Model A2 includes an alternative measure of partisanship where the share of cabinet portfolios controlled by centrist parties is subtracted from that of portfolios controlled by right parties.

Model A3 includes an alternative measure of partisanship using the share of governing party seats as a percent of all legislative seats (instead of the share of cabinet portfolios).

Model A4 includes alternative measures of policy and political outcomes in country$_j$, which considers the percent change in, respectively, the unemployment rate and incumbent vote, instead of simple change.

Model A5 includes alternative measures of policy and political outcomes in country$_j$, which weights changes in, respectively, the unemployment rate and incumbent vote by the inverse of the distance from the relevant electoral term.

Model A6 includes alternative measures of policy and political outcomes in country$_j$, which weights percent (instead of simple) changes in, respectively, the unemployment rate and incumbent vote by the inverse of the distance from the relevant electoral term.

Model A7 considers only cuts in unemployment benefits greater than 0.25 points in the construction of the dependent variable.

Model A8 considers only cuts in unemployment benefits greater than 0.5 points in the construction of the dependent variable.

Model A9 considers only cuts in unemployment benefits greater than 0.75 points in the construction of the dependent variable.

Model A10 considers only cuts in unemployment benefits greater than 1 point in the construction of the dependent variable.

	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)
Partisanship$_i$	0.268***	0.124*	0.425***	0.130*	0.189***	0.185***
	(0.072)	(0.066)	(0.131)	(0.073)	(0.071)	(0.070)
Unempl. change$_j$	−3.082	−0.776	−1.730	−0.032	−1.475	−1.687
	(2.461)	(2.397)	(2.395)	(0.054)	(3.751)	(3.716)
Vote change$_j$	−0.693	0.118	−0.210	−0.026	0.124	−0.004
	(0.764)	(0.749)	(0.745)	(0.240)	(1.100)	(0.389)
Unempl. change$_j$ × Part.$_i$	8.219***	6.120**	15.644***	0.232***	9.955**	9.618**
	(2.712	(2.640)	(5.170)	(0.066)	(4.598)	(4.545)
Vote change$_j$ × Part.$_i$	2.618***	2.330***	5.235***	0.723**	3.226**	1.152**
	(0.905	(0.899)	(1.728)	(0.315)	(1.435)	(0.502)
|Part.$_{i,t}$− Part.$_j$|	−0.036	−0.083	−0.108	−0.083	−0.105	−0.094
	(0.061)	(0.059)	(0.096)	(0.065)	(0.065)	(0.065)
Repl. rate$_{i,t-1}$	0.007	0.006	0.006	0.006	0.007	0.007
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
|Repl. rate$_{i,t-1}$− repl. rate$_j$|	0.000	0.001	0.000	0.000	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Same region	−0.051	−0.061	−0.039	−0.044	−0.054	−0.054
	(0.136)	(0.135)	(0.135)	(0.134)	(0.134)	(0.134)
Population$_i$− Population$_j$	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment$_i$	−1.163	−0.887	−1.502	−1.365	−0.952	−0.988
	(2.086)	(2.111)	(2.107)	(2.103)	(2.093)	(2.094)
Political constraints$_i$	1.764**	1.533*	1.782**	1.669**	1.708**	1.701**
	(0.803)	(0.800)	(0.809)	(0.803)	(0.802)	(0.802)
Number of prior cuts$_i$	−0.389***	−0.392***	−0.395***	−0.395***	−0.386***	−0.386***
	(0.041)	(0.040)	(0.041)	(0.041)	(0.040)	(0.040)
Intercept	1.990**	2.303**	2.208**	2.244**	2.132**	2.116**
	(0.902)	(0.895)	(0.902)	(0.902)	(0.896)	(0.895)
$\sigma^2_{\alpha_i}$	1.586	1.552	1.605	1.595	1.553	1.550
$\sigma^2_{\alpha_j}$	0.000	0.000	0.000	0.000	0.000	0.000
$\sigma^2_{\alpha_t}$	2.939	2.941	3.005	3.017	2.923	2.918
Deviance	4,146	4,157	4,147	4,145	4,155	4,155
N	3,332	3,332	3,332	3,332	3,332	3,332

	(A7)	(A8)	(A9)	(A10)
Partisanship$_i$	0.269***	0.309***	0.597***	0.687***
	(0.079)	(0.087)	(0.103)	(0.117)
Unempl. change$_j$	−1.579	−1.965	−2.781	−2.906
	(2.687)	(3.028)	(3.351)	(3.577)
Vote change$_j$	−0.258	−0.392	−0.480	−1.191
	(0.804)	(0.885)	(1.032)	(1.501)

	(A7)	(A8)	(A9)	(A10)
Unempl. change$_j$ × Part.$_i$	7.514**	6.848**	5.180	3.358
	(3.115)	(3.351)	(3.632)	(3.824)
Vote change$_j$ × Part.$_i$	1.970*	2.459**	3.078**	3.550**
	(1.047)	(1.141)	(1.293)	(1.799)
$\lvert$Part.$_{i,t}$ − Part.$_j\rvert$	−0.044	−0.023	0.048	0.050
	(0.072)	(0.079)	(0.088)	(0.098)
Repl. rate$_{i,t-1}$	0.013*	0.003	−0.001	0.017*
	(0.008)	(0.008)	(0.010)	(0.010)
$\lvert$Repl. rate$_{i,t-1}$ − repl. rate$_j\rvert$	0.002	0.002	0.006	0.003
	(0.003)	(0.004)	(0.004)	(0.005)
Same region	0.070	0.011	−0.065	−0.097
	(0.159)	(0.186)	(0.203)	(0.243)
Population$_i$ − Population$_j$	−0.001	−0.002	−0.001	−0.002
	(0.001)	(0.002)	(0.002)	(0.002)
Unemployment$_i$	−0.566	−1.887	−1.495	−1.082
	(2.347)	(2.539)	(2.848)	(3.072)
Political constraints$_i$	3.248***	4.544***	3.196***	2.229*
	(0.893)	(1.032)	(1.135)	(1.226)
Number of prior cuts$_i$	−0.362***	−0.378***	−0.475***	−0.326***
	(0.041)	(0.043)	(0.054)	(0.055)
Intercept	−0.682	−1.327	−0.777	−2.398**
	(0.889)	(0.952)	(1.044)	(1.026)
$\sigma^2_{\alpha_i}$	2.577	2.720	3.267	2.659
$\sigma^2_{\alpha_j}$	0.000	0.000	0.000	0.000
$\sigma^2_{\alpha_t}$	1.694	1.216	1.290	0.742
Deviance	3,432	2,863	2,270	1,788
N	2,822	2,550	2,210	1,836

References

Allan, James P., and Lyle Scruggs. 2004. "Political Partisanship and Welfare State Reform in Advanced Industrial Societies." *American Journal of Political Science* 48(3): 496–512.

Basinger, Scott, and Mark Hallerberg. 2004. "Remodeling the Competition for Capital: How Domestic Politics Erases the Race to the Bottom." *American Political Science Review* 98(2): 261–76.

Beck, Nathaniel, and Jonathan N. Katz. 2001. "Throwing Out the Baby with the Bath Water: A Comment on Green, Kim, and Yoon." *International Organization* 55(2): 487–95.

Bennett, D. Scott, and Allan C. Stam. 2000. "Research Design and Estimator Choices in the Analysis of Interstate Dyads." *Journal of Conflict Resolution* 44(5): 653–85.

Berry, Frances Stokes, and William D. Berry. 1990. "State Lottery Adoptions as Policy Innovations: An Event History Analysis." *American Political Science Review* 84(2): 395–415.

Boehmke, Frederick J. 2009. "Policy Emulation or Policy Convergence? Potential Ambiguities in the Dyadic Event History Approach to State Policy Emulation." *Journal of Politics* 71(3): 1125–40.

Braun, Dietmar, and Fabrizio Gilardi. 2006. "Taking 'Galton's Problem' Seriously: Towards a Theory of Policy Diffusion." *Journal of Theoretical Politics* 18(3): 298–322.

Brooks, Sarah M. 2007. "When Does Diffusion Matter? Explaining the Spread of Structural Pension Reforms across Nations." *Journal of Politics* 69(3): 701–15.

Carter, David B., and Curtis S. Signorino. 2009. "Back to the Future: Modeling Time Dependence in Binary Data." Pennsylvania State University and University of Rochester.

Dobbin, Frank, Beth Simmons, and Geoffrey Garrett. 2007. "The Global Diffusion of Public Policies: Social Construction, Coercion, Competition, or Learning?" *Annual Review of Sociology* 33: 449–72.

Elkins, Zachary, Andrew Guzman, and Beth Simmons. 2006. "Competing for Capital: The Diffusion of Bilateral Investment Treaties, 1960–2000." *International Organization* 60(4): 811–46.

Franzese, Robert J., and Jude C. Hays. 2008. "Interdependence in Comparative Politics: Substance, Theory, Empirics, Substance." *Comparative Political Studies* 41(4/5): 742–80.

Franzese, Robert J., and Jude C. Hays. 2009. "The Spatial Probit Model of Interdependent Binary Outcomes: Estimation, Interpretation, and Presentation." University of Illinois, Urbana-Champaign and University of Michigan.

Gartzke, Erik. 2007. "The Capitalist Peace." *American Journal of Political Science* 51(1): 166–91.

Gelman, Andrew, John B. Carlin, Hal S. Stern, and Donald B. Rubin. 2004. *Bayesian Data Analysis*. 2nd ed. New York: Chapman & Hall/CRC.

Gelman, Andrew, and Jennifer Hill. 2007. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge: Cambridge University Press.

Gilardi, Fabrizio, and Katharina Füglister. 2008. "Empirical Modeling of Policy Diffusion in Federal States: The Dyadic Approach." *Swiss Political Science Review* 14(3): 413–50.

Gilardi, Fabrizio, Katharina Füglister, and Stéphane Luyet. 2009. "Learning from Others: The Diffusion of Hospital Financing Reforms in OECD Countries." *Comparative Political Studies* 42(4): 549–73.

Gray, Virginia. 1973. "Innovation in the States: A Diffusion Study." *American Political Science Review* 67(4): 1174–85.

Green, Donald P., Soo Yeon Kim, and David H. Yoon. 2001. "Dirty Pool." *International Organization* 55(2): 441–68.

Hays, Jude C., Aya Kachi, and Robert J. Franzese. 2009. "The m-STAR Model of Dynamic, Endogenous Interdependence and Network-Behavior Coevolution in Comparative and International Political Economy." University of Illinois, Urbana-Champaign and University of Michigan.

Hellwig, Timothy, and David Samuels. 2007. "Voting in Open Economies: The Electoral Consequences of Globalization." *Comparative Political Studies* 40(3): 283–306.

Hellwig, Timothy, and David Samuels. 2008. "Electoral Accountability and the Variety of Democratic Regimes." *British Journal of Political Science* 38: 65–90.

Henisz, Witold J. 2000. "The Institutional Environment for Multinational Investment." *Journal of Law, Economics, and Organization* 16(2): 334–64.

ISSP. 1999. "International Social Survey Program: Role of Government III, 1996." hdl:1902.2/2808, Inter-university Consortium for Political and Social Research [Distributor].

King, Gary. 2001. "Proper Nouns and Methodological Propriety: Pooling Dyads in International Relations Data." *International Organization* 55(2): 497–507.

King, Gary, and Langche Zeng. 2001. "Improving Forecasts of State Failure." *World Politics* 53: 623–58.

Lee, Chang Kil, and David Strang. 2006. "The International Diffusion of Public-Sector Downsizing: Network Emulation and Theory-Driven Learning." *International Organization* 60(4): 883–909.

Maoz, Zeev, and Bruce Russett. 1993. "Normative and Structural Causes of Democratic Peace, 1946–1986." *American Political Science Review* 87(3): 624–38.

Meseguer, Covadonga. 2006a. "Learning and Economic Policy Choices." *European Journal of Political Economy* 22: 156–78.

Meseguer, Covadonga. 2006b. "Rational Learning and Bounded Learning in the Diffusion of Policy Innovations." *Rationality and Society* 18(1): 35–66.

Meseguer, Covadonga. 2009. *Learning, Policy Making, and Market Reforms*. Cambridge: Cambridge University Press.

Meseguer, Covadonga, and Fabrizio Gilardi. 2009. "What Is New in the Study of Policy Diffusion?" *Review of International Political Economy* 16(3): 527–43.

Morrow, James D., Randolph M. Siverson, and Tressa E. Tabares. 1998. "The Political Determinants of International Trade: The Major Powers, 1907–90." *American Political Science Review* 92(3): 649–61.

Oneal, John R., and Bruce Russett. 2001. "Clear and Clean: The Fixed Effects of Liberal Peace." *International Organization* 55(2): 469–85.

Plümper, Thomas, and Eric Neumayer. 2010. "Spatial Effects in Dyadic Data." *International Organization* 64(1): 145–66.

Ross, Marc Howard, and Elizabeth Homer. 1976. "Galton's Problem in Cross-National Research." *World Politics* 29(1): 1–28.

Shipan, Charles R., and Craig Volden. 2006. "Bottom-Up Federalism: The Diffusion of Antismoking Policies from U.S. Cities to States." *American Journal of Political Science* 50(4): 825–43.

Shipan, Charles R., and Craig Volden. 2008. "The Mechanisms of Policy Diffusion." *American Journal of Political Science* 52(4): 840–57.

Shor, Boris, Joseph Bafumi, Luke Keele, and David Park. 2007. "A Bayesian Multilevel Modeling Approach to Time-Series Cross-Sectional Data." *Political Analysis* 15(2): 165–81.

Simmons, Beth A., Frank Dobbin, and Geoffrey Garrett, eds. 2008. *The Global Diffusion of Markets and Democracy*. Cambridge: Cambridge University Press.

Simmons, Beth A., and Zachary Elkins. 2004. "The Globalization of Liberalization: Policy Diffusion in the International Political Economy." *American Political Science Review* 98(1): 171–89.

Simmons, Beth, Frank Dobbin, and Geoffrey Garrett. 2006. "Introduction: The International Diffusion of Liberalism." *International Organization* 60(4): 781–810.

Swank, Duane. 2002. *Global Capital, Political Institutions, and Policy Change in Developed Welfare States*. Cambridge: Cambridge University Press.

Swank, Duane. 2003. "Comparative Political Parties Data Set." http://www.mu.edu/polisci/Swank.htm.

Swank, Duane. 2006. "Tax Policy in an Era of Internationalization: Explaining the Spread of Neoliberalism." *International Organization* 60(4): 847–82.

Taber, Charles S., and Milton Lodge. 2006. "Motivated Skepticism in the Evaluation of Political Beliefs." *American Journal of Political Science* 50(3): 755–69.

Volden, Craig. 2006. "States as Policy Laboratories: Emulating Success in the Children's Health Insurance Program." *American Journal of Political Science* 50(2): 294–312.

Volden, Craig, Michael M. Ting, and Daniel P. Carpenter. 2008. "A Formal Model of Learning and Policy Diffusion." *American Political Science Review* 102(3): 319–32.

Walker, Jack L. 1969. "The Diffusion of Innovations Among the American States." *American Political Science Review* 63(3): 880–99.

Weyland, Kurt. 2005. "Theories of Policy Diffusion: Lessons from Latin American Pension Reform." *World Politics* 57(2): 262–95.

Weyland, Kurt. 2007. *Bounded Rationality and Policy Diffusion: Social Sector Reform in Latin America*. Princeton, NJ: Princeton University Press.