# Judicial Influence and the Importance of Intersecting Identities

## *Research & Politics* Online Appendices

Abigail A. Matthews
University at Buffalo, SUNY

Rachael K. Hinkle
University at Buffalo, SUNY

## A. Supplemental Data Information

### Data Collection

To compile the dataset we gathered all published circuit opinions that cite the Fourth Amendment (and use the words "search" or "seizure" at least once) from 1995 to 2010. Cases were obtained from the eleven numbered geographical circuits and the D.C. Circuit. Each of these cases is available as a possible precedent for all subsequent opinions and we paired each with all later cases in the dataset from 2000 to 2010.[1] This selection method is likely to be over-inclusive. Not every case that references the Fourth Amendment is relevant to every other such case. However, our objective is to build a choice set of all potential precedents that may be cited with respect to a search and seizure issue. In this context, the primary concern is under-inclusion, and that danger has been ameliorated. It is difficult to imagine a federal court ruling on a search and seizure issue (or even discussing it) without citing the Fourth Amendment. En banc cases are excluded from the data

[1] We exclude dyads in which the opinion or precedent were written by a judge sitting by designation.

because they are rare and substantially different.

**Variable Coding Details**

The outcome variable is constructed using *Shepard's Citations* which provides data on the citation and treatment of precedents. Using *Shepard's* reports for each case, we extracted data on whether an opinion cited each particular precedent. Because our theory is focused on citation as an indicator of influence, we do not count citations that are exclusively negative in nature. The *Shepard's* treatments that are negative in nature are 'Distinguished,' 'Criticized,' 'Limited,' 'Questioned,' 'Overruled,' 'Superseded,' and 'Disapproved' (Spriggs and Hansford 2000). Negative discussion of a precedent is not particularly common. Only nine percent of citations in the data were negative.

The primary explanatory variable, *Number of Shared Identities*, was coded using information on each judge's race/ethnicity, gender, and appointing president provided by the Federal Judicial Center.[2] Each judge's race/ethnicity is listed as one the following categories: African American, Asian American, Hispanic, or White. Two judges are coded as sharing the same race only if they are identified in the same category in the FJC data. In our data, the only gender identification categories are male and female. There are a total of 313 judges. While this might seem like a somewhat large group for members to be aware of others' demographic characteristics, federal circuit judges are an elite group likely to know or be aware of their peers for several reasons. Judges interact together with those from other circuits in a variety of ways including training, conferences, and committee work. Gender is often cued by names even if not known through personal experience. All but 41 judges in our data are white, which makes the race of colleagues easier to track. Finally, party is often known because of the highly political and televised nature of Article III judicial appointments.

Table 1 illustrates the distribution of precedent authors in our dataset. While most of the

[2]The Federal Judicial Center's Biographical Directory is available at https://www.fjc.gov/history/judges.

possible combinations have at least some data, there are no Asian American women in this time frame and some of the other categories are sparsely populated. This context is important to understanding our results. The patterns we uncover may well be a function of the relative lack of intersectional diversity and may be different in environments with greater demographic variation.

| | Republican | | Democrat | |
|---|---|---|---|---|
| | Male | Female | Male | Female |
| African American | 16,559 | 25,541 | 248,342 | 61,231 |
| Asian American | 2,516 | 0 | 20,803 | 0 |
| Hispanic | 88,132 | 3,445 | 120,002 | 8,491 |
| White | 2,750,186 | 341,370 | 995,562 | 533,379 |

Table 1: Distribution of Precedent Author Characteristics

We control for a variety of factors that reflect aspects of the relationship between the opinion and precedent, as well as aspects of each individually, that affect the likelihood of citation and may be correlated with our main explanatory variable. One concern is that two judges born in the same generation will have shared historical perspectives that shape their views in ways that transcend shared identities. Because of the increasing diversity of the federal judiciary over time, such shared major life events may be correlated with the number of identities two judges share. To account for this, we code each judge's generation based on their birth year and the Pew Research Center's definition of the relevant generations: the Greatest Generation (1900 - 1928), the Silent Generation (1928-1945), Baby Boomers (1946-1964), and Generation X (1965-1980).[3] Then we use these variables to create a variable, *Same Generation*, that equals one if the opinion and precedent authors are from the same generation, and zero otherwise.

The similarity of a precedent to the case at hand is undoubtedly a major factor in whether a judge cites a precedent. We account for this in two ways. First, we calculate the cosine similarity

[3] See https://www.pewtrusts.org/en/research-and-analysis/data-visualizations/2019/defining-our-six-generations

between the opinion and the precedent.[4] This metric is commonly used to quantify how similar two texts are (Hinkle 2015). It is based on a formula that counts the number of words two documents share in common and weights particularly unusual, and therefore informative, words more highly. We scale these cosine similarity scores so that they range from zero to one hundred; higher scores indicate greater similarity.[5] Another potential point of similarity between two cases is their procedural background. While our dataset is limited to search and seizure cases, there are different case types within that broader topic. Each case is coded according to whether it is a criminal case, a civil rights case, or a habeas petition. We include a binary variable, *Same Sub Issue*, that equals one if the opinion and precedent are the same type and zero otherwise.

In addition to legal relevance, we also expect a judge's ideological preferences to influence their citation choices (Hinkle 2015). Given the multiplicity of precedents often available on a topic, we anticipate that authors will be less likely to cite precedents that noticeably depart from their own ideological preferences. To account for this important factor, albeit in a general fashion, we use a dichotomous indicator variable for whether the opinion author is ideologically opposed to the precedent. First, each precedent is coded as reaching a conservative outcome if it favors the government and a liberal outcome if it favors the accused.[6] For Republican-appointed judges, the

[4]Cosine scores are calculated using the majority opinion in each respective case after removing citations, words shorter than three letters, and stop words ("a", "and", and "the").

[5]It would be preferable to use text generated prior to the resolution of a case to measure the similarity to a precedent such as the decision being appealed or legal briefs. However, such sources of text are not readily available (Hinkle 2015). Appendix C demonstrates that neither omitting *Cosine Similarity* nor limiting analysis to precedents in the top half of the similarity metric undermines any of the substantive conclusions from either the main model or the alternative specifications discussed in Appendix B.

[6]Although these outcomes are mutually exclusive, they are not exhaustive. Some cases result

variable *Ideologically Opposed Precedent* equals one if the precedent outcome is liberal and zero otherwise. For Democrat-appointed judges, this variable equals one if the precedent outcome is conservative and zero otherwise.

The way in which we account for ideological motivations above and beyond any impact of shared partisanship required two key decisions. First, we use the direction in which a precedent is decided rather than the ideology of the judges who issued that ruling. The reason for this is simple; while outcomes are famously correlated with ideology, there are many cases in the federal circuit courts where the law leaves little room for ideology to operate. For example, in this dataset the ideological direction of the panel median matches the case outcome only 49% of the time. Second, we focus exclusively on the preferences of the opinion author. This is due to the reality created by the heavy workload faced by circuit court judges. They often have little time to make detailed recommendations about how opinions assigned to other judges are drafted, and, as a result, opinions are generally the exclusive product of the author's decisionmaking (Bowie, Songer and Szmer 2014).

Next, features of the opinion and precedent separately can influence citation. First, we account for whether the opinion author is the chief judge or new to the court because judges may exhibit different citation behaviors over the course of their career. We control for the length of the opinion as longer opinions generally contain more citations. The year of the opinion is included in the model to account for any general changes in citation over time (Fowler et al. 2007). Features of the precedent can also shape citation. A precedent being decided unanimously may indicate the kind of particularly strong legal arguments that will be cited more frequently down the road. Research has also shown that the age of a precedent plays an important role in citation patterns (Black and Spriggs 2013; Landes, Lessig and Solimine 1998).[7] The length of the precedent may

in split outcomes that are coded as neither conservative nor liberal.

[7]When examining a sufficiently long time span, Black and Spriggs (2013) show that it is important to include a squared term for precedent age in order to best model its decaying influence.

matter as well. More extensive legal analysis in a precedent provides more opportunity for things to cite. Summary statistics are provided in Table 2 and the full regression results are in Table 3.

| **Continuous Variables** | **Min.** | **25%** | **50%** | **75%** | **Max.** |
|---|---|---|---|---|---|
| Number of Shared Identities | 0 | 1 | 2 | 3 | 3 |
| Cosine Similarity | 1.29 | 4.13 | 5.44 | 7.20 | 83.16 |
| Logged Word Count, Opinion | 5.81 | 7.87 | 8.28 | 8.66 | 10.64 |
| Opinion Year | 2000 | 2004 | 2007 | 2009 | 2010 |
| Precedent Age | 0 | 2 | 5 | 8 | 15 |
| Logged Word Count, Precedent | 5.81 | 7.87 | 8.30 | 8.71 | 10.64 |
| **Dichotomous Variables** | **0** | **1** | | | |
| Precedent Cited | 99.9% | 0.1% | | | |
| Same Gender | 32% | 68% | | | |
| Same Race | 22% | 78% | | | |
| Same Party | 47% | 53% | | | |
| Same Generation | 60% | 40% | | | |
| Same Sub Issue | 37% | 63% | | | |
| Ideologically Opposed Precedent | 70% | 30% | | | |
| Chief Judge | 98% | 2% | | | |
| New Judge (< 2 years) | 98% | 2% | | | |
| Precedent Not Unanimous | 84% | 16% | | | |

Table 2: Summary Statistics

However, such a term has little effect in our model so we exclude it in the interest of parsimony.

| | Cumulative Shared Identities | |
|---|---|---|
| | Coef. | S.E. |
| Number of Shared Identities | 0.026* | (0.008) |
| Same Generation | 0.031* | (0.012) |
| Cosine Similarity | 0.065* | (0.001) |
| Same Sub Issue | 0.353* | (0.021) |
| Ideologically Opposed Precedent | −0.010 | (0.012) |
| Chief Judge | −0.055 | (0.051) |
| New Judge (< 2 years) | −0.090 | (0.072) |
| Logged Word Count, Opinion | 0.168* | (0.015) |
| Opinion Year | −0.011* | (0.003) |
| Precedent Not Unanimous | 0.024 | (0.014) |
| Precedent Age | −0.018* | (0.002) |
| Logged Word Count, Precedent | 0.059* | (0.010) |
| Intercept | 16.172* | (6.318) |
| N | 5,215,559 | |
| AIC | 50059.5 | |
| BIC | 50234.5 | |

Table 3: Citation Model: Probit regression estimates of the effect of shared characteristics and a range of control variables on the probability an opinion will cite a precedent. The reported standard errors are robust standard errors that are clustered on the opinion and * denotes a p-value less than 0.05.

## B. Binary Specification of Shared Identities

For the sake of parsimony and theoretical clarity, our main analysis simply counts the number of shared identities and treats them each equally. Of course, that simplifying assumption may not be fully accurate. In this section, we elaborate by presenting and discussing model specifications using separate indicators for each type of shared identity. We also further emphasize the importance of an intersectional approach by contrasting a model in which we interact the three binary variables with a simpler model that treats each shared identity independently. The results of both models are provided in Table 4

The right-hand model in Table 4 shows that failing to consider how identities interact leads to the conclusion that shared party and race matter to the exclusion of shared gender. The literature often shows that a judge's gender and race only appear to impact their behavior in a subset of

| | Interacted Shared Identities | | Individual Shared Identities Only | |
|---|---|---|---|---|
| | Coef. | S.E. | Coef. | S.E. |
| Same Gender | −0.017 | (0.033) | −0.004 | (0.016) |
| Same Race | 0.042 | (0.028) | 0.049* | (0.020) |
| Same Party | −0.007 | (0.038) | 0.036* | (0.011) |
| Same Gender × Same Race | 0.034 | (0.029) | | |
| Same Gender × Same Party | 0.028 | (0.038) | | |
| Same Race × Same Party | 0.069* | (0.028) | | |
| Same Race × Same Gender × Same Party | 0.071* | (0.027) | | |
| Same Generation | 0.030* | (0.012) | 0.031* | (0.012) |
| Cosine Similarity | 0.065* | (0.001) | 0.065* | (0.001) |
| Same Sub Issue | 0.353* | (0.021) | 0.353* | (0.021) |
| Ideologically Opposed Precedent | −0.008 | (0.012) | −0.009 | (0.012) |
| Precedent Author on Citing Panel | 0.414* | (0.196) | 0.416* | (0.196) |
| Chief Judge | −0.055 | (0.051) | −0.053 | (0.051) |
| New Judge (< 2 years) | −0.092 | (0.072) | −0.090 | (0.072) |
| Logged Word Count, Opinion | 0.169* | (0.015) | 0.168* | (0.015) |
| Opinion Year | −0.011* | (0.003) | −0.011* | (0.003) |
| Precedent Not Unanimous | 0.024 | (0.014) | 0.023 | (0.014) |
| Precedent Age | −0.018* | (0.002) | −0.018* | (0.002) |
| Logged Word Count, Precedent | 0.060* | (0.010) | 0.060* | (0.010) |
| Same Gender | | | −0.004 | (0.016) |
| Same Race | | | 0.049* | (0.020) |
| Same Party | | | 0.036* | (0.011) |
| Intercept | 16.077* | (6.294) | 16.079* | (6.301) |
| N | 5,215,559 | | 5,215,559 | |
| AIC | 50057.7 | | 50051.9 | |
| BIC | 50327.0 | | 50267.4 | |

Table 4: Citation Models with Binary Identity Variables: Probit regression estimates of the effect of shared characteristics and a range of control variables on the probability an opinion will cite a precedent. The reported standard errors are robust standard errors that are clustered on the opinion and * denotes a p-value less than 0.05.

cases in which the topic is explicitly related to those identities (e.g., Boyd, Epstein and Martin 2010; Kastellec 2013). Since this dataset is based on search and seizure law, which arguably implicates race more clearly than gender, it would be entirely in keeping with the existing literature to conclude that shared gender identities do not matter in such a domain. Yet the results from the model on the left that includes interaction terms suggest otherwise. When taking the nuance of how identities work together into account, there is no longer evidence that any single shared identity, even party, is sufficient to motivate increased citation. Neither are the combinations of shared gender and race or gender and party enough to significantly increase citation compared to a pair of judges who share none of the three characteristics. However, a judge is significantly more likely to cite a precedent written by a colleague of the same race and party or who shares all three identities. In short, shared gender does play a role in citation, but only emerges when also considered in conjunction with other shared characteristics.

A follow-up examination of which pairs of shared identity combinations are statistically different from each other, in the model with interactions, sheds further light on the nuances of citation decisions. Judges who share all three characteristics are more likely to cite each other than those who share the same gender and race ($p = 0.037$), only the same party ($p = 0.039$), or only the same gender ($p < 0.001$). Judges who share the same race and party cite each other more frequently than peers who are only the same gender ($p = 0.006$).

There are two important caveats to our analysis. First, the results must be understood in light of the reality of our data. Even though the dataset contains millions of dyads and each shared identity is present in more than half of those dyads, there are still several specific race/gender/party combinations that are represented sparsely or not at all. As a result, null findings may be limited to this time frame and institutional context. The second point is related to the first. While the robustness checks in this section parse the impact of each shared identity individually, the data do not contain enough variation to extend the analysis to consider the important issue of how judges with privileged or traditionally-excluded identities might make different citation choices, including how they might be influenced by in-group and out-group dynamics. That is a fascinating question in its own right, but it is beyond the scope of this article.

## C. Considering Cosine Similarity

While cosine similarity is a useful way to account for which precedents are most relevant to the case at hand, as we point out above in Appendix A, there is a possibility for bias. We calculate *Cosine Similarity* using the text of an opinion, which is drafted contemporaneously with decisions about which precedent to cite. As a result, citation to a case—especially if accompanied by a direct quotation—can lead to words being included in an opinion that increase its cosine similarity to the cited precedent. The ideal approach would be to either use documents that precede the opinion (like the decision being appealed) or hand-code the relevant facts in each case. However, prior documents are not readily available and hand-coding is not logistically feasible since this dataset includes more than five thousand cases.

Nevertheless, we take steps to ensure the use of *Cosine Similarity* in our models is not driving our results. We do so by conducting two types of robustness checks, both for our main model and for the alternative specifications presented in Appendix B. The first check is to simply re-run the models without the cosine measure. The results in Table 5 show that none of the significant results we discussed previously were an artifact of including *Cosine Similarity*. In fact, two constituent terms in the model with the interacted shared identities are statistically significant that were not before. In this model, there is evidence that share race alone and shared race and gender together result in more citations than when no identities are shared.

Given the broad inclusion of all precedents that cite the Fourth Amendment and the importance of legal relevance to citation, some caution is warranted in interpreting the results of a model in which the only control for such relevance is whether two cases are both criminal, civil rights, or habeas cases. As a result, we conduct a second robustness check to provide yet another perspective. Here, we use *Cosine Similarity* not as a control, but to set a threshold for inclusion in the analysis. In practice, many cases that address search and seizure issues are not related to each other. Table 6 shows the results of our models when we only analyze cases in the top half of the

| | Cumulative Shared Identities | | Interacted Shared Identities | | Individual Shared Identities Only | |
|---|---|---|---|---|---|---|
| | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| Number of Shared Identities | $0.030^*$ | $(0.007)$ | | | | |
| Same Gender | | | $-0.011$ | $(0.030)$ | $-0.002$ | $(0.014)$ |
| Same Race | | | $0.047$ | $(0.025)$ | $0.066^*$ | $(0.018)$ |
| Same Party | | | $0.001$ | $(0.035)$ | $0.035^*$ | $(0.010)$ |
| Same Gender × Same Race | | | $0.055^*$ | $(0.026)$ | | |
| Same Gender × Same Party | | | $0.011$ | $(0.034)$ | | |
| Same Race × Same Party | | | $0.090^*$ | $(0.025)$ | | |
| Same Race × Gender × Party | | | $0.084^*$ | $(0.025)$ | | |
| Same Generation | $0.021^*$ | $(0.011)$ | $0.021$ | $(0.011)$ | $0.021$ | $(0.011)$ |
| Same Sub Issue | $0.438^*$ | $(0.020)$ | $0.438^*$ | $(0.020)$ | $0.438^*$ | $(0.020)$ |
| Ideologically Opposed Precedent | $-0.005$ | $(0.011)$ | $-0.003$ | $(0.011)$ | $-0.004$ | $(0.011)$ |
| Chief Judge | $0.006$ | $(0.052)$ | $0.005$ | $(0.052)$ | $0.008$ | $(0.052)$ |
| New Judge (< 2 years) | $-0.109$ | $(0.068)$ | $-0.111$ | $(0.068)$ | $-0.109$ | $(0.068)$ |
| Logged Word Count, Opinion | $0.206^*$ | $(0.014)$ | $0.207^*$ | $(0.014)$ | $0.206^*$ | $(0.014)$ |
| Opinion Year | $-0.013^*$ | $(0.003)$ | $-0.013^*$ | $(0.003)$ | $-0.013^*$ | $(0.003)$ |
| Precedent Not Unanimous | $0.051^*$ | $(0.013)$ | $0.051^*$ | $(0.013)$ | $0.051^*$ | $(0.013)$ |
| Precedent Age | $-0.021^*$ | $(0.002)$ | $-0.021^*$ | $(0.002)$ | $-0.021^*$ | $(0.002)$ |
| Logged Word Count, Precedent | $0.065^*$ | $(0.009)$ | $0.066^*$ | $(0.009)$ | $0.065^*$ | $(0.009)$ |
| Intercept | $20.028^*$ | $(5.839)$ | $19.746^*$ | $(5.822)$ | $19.838^*$ | $(5.826)$ |
| N | 5,215,559 | | 5,215,559 | | 5,215,559 | |
| AIC | 59329.1 | | 59318.9 | | 59314.3 | |
| BIC | 59490.8 | | 59561.3 | | 59502.8 | |

Table 5: Models without Cosine Similarity: Probit regression estimates of the effect of shared characteristics and professional experiences and a range of control variables, but not cosine similarity, on the probability an opinion will cite a precedent. The reported standard errors are robust standard errors that are clustered on the opinion and * denotes a p-value less than 0.05.

distribution of *Cosine Similarity*. This approach reduces the noise in the data created by dyads that are quite dissimilar. Here the results are remarkably similar to our primary models that include all data and control for *Cosine Similarity*.

| | Cumulative Shared Identities | | Interacted Shared Identities | | Individual Shared Identities Only | |
|---|---|---|---|---|---|---|
| | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| Number of Shared Identities | $0.030^*$ | $(0.008)$ | | | | |
| Same Gender | | | $-0.039$ | $(0.032)$ | $-0.006$ | $(0.015)$ |
| Same Race | | | $0.027$ | $(0.027)$ | $0.067^*$ | $(0.019)$ |
| Same Party | | | $-0.014$ | $(0.038)$ | $0.036^*$ | $(0.011)$ |
| Same Gender × Race | | | $0.041$ | $(0.029)$ | | |
| Same Gender × Party | | | $-0.012$ | $(0.037)$ | | |
| Same Race × Party | | | $0.078^*$ | $(0.028)$ | | |
| Same Race × Gender × Party | | | $0.066^*$ | $(0.027)$ | | |
| Same Generation | $0.028^*$ | $(0.012)$ | $0.027^*$ | $(0.012)$ | $0.028^*$ | $(0.012)$ |
| Same Sub Issue | $0.383^*$ | $(0.022)$ | $0.384^*$ | $(0.022)$ | $0.384^*$ | $(0.022)$ |
| Ideologically Opposed Precedent | $-0.001$ | $(0.012)$ | $0.001$ | $(0.012)$ | $0.000$ | $(0.012)$ |
| Chief Judge | $0.006$ | $(0.062)$ | $0.007$ | $(0.062)$ | $0.009$ | $(0.062)$ |
| New Judge (< 2 years) | $-0.111$ | $(0.074)$ | $-0.113$ | $(0.074)$ | $-0.112$ | $(0.074)$ |
| Logged Word Count, Opinion | $0.157^*$ | $(0.015)$ | $0.159^*$ | $(0.015)$ | $0.158^*$ | $(0.015)$ |
| Opinion Year | $-0.008^*$ | $(0.003)$ | $-0.008^*$ | $(0.003)$ | $-0.008^*$ | $(0.003)$ |
| Precedent Not Unanimous | $0.050^*$ | $(0.014)$ | $0.050^*$ | $(0.014)$ | $0.050^*$ | $(0.014)$ |
| Precedent Age | $-0.022^*$ | $(0.002)$ | $-0.022^*$ | $(0.002)$ | $-0.022^*$ | $(0.002)$ |
| Logged Word Count, Precedent | $0.054^*$ | $(0.009)$ | $0.055^*$ | $(0.009)$ | $0.054^*$ | $(0.009)$ |
| Intercept | $11.594$ | $(6.294)$ | $11.388$ | $(6.275)$ | $11.387$ | $(6.276)$ |
| N | 2,604,050 | | 2,604,050 | | 2,604,050 | |
| AIC | 51895.2 | | 51884.8 | | 51880.3 | |
| BIC | 52048.4 | | 52114.7 | | 52059.1 | |

Table 6: Models with Cosine Similarity in top 50%: Probit regression estimates of the effect of shared characteristics and professional experiences and a range of control variables, but not cosine similarity, on the probability an opinion will cite a precedent, using only data where the cosine similarity between the opinion and precedent is in the top half of values in this dataset. The reported standard errors are robust standard errors that are clustered on the opinion and * denotes a p-value less than 0.05.

## D. Shared Professional Experiences

While the primary focus of our research is the combined impact of shared identities on citation, one may wonder if shared professional experiences may also play a role. Even more importantly for our project here, there may be a concern that shared identities and professional backgrounds could overlap in ways that bias the results and undermine our conclusions. In order to allay such concerns, this section provides the regression results of a model that adds several components of shared professional experience to our main model. Specifically, we add five binary indicators that each equal one if the author of the opinion and precedent were both prosecutors, both attended the same law school, both have experience as an attorney general, both have experience as a solicitor general, or were both law professors. The results show that none of these shared backgrounds is statistically significant, and our key explanatory variable, *Number of Shared Identities*, continues to be statistically significant.

| | Coef. | S.E. |
|---|---|---|
| Number of Shared Identities | 0.025* | (0.008) |
| Same Generation | 0.031* | (0.012) |
| Cosine Similarity | 0.065* | (0.001) |
| Same Sub Issue | 0.353* | (0.021) |
| Ideologically Opposed Precedent | −0.010 | (0.012) |
| Precedent Author on Citing Panel | 0.415* | (0.196) |
| Chief Judge | −0.056 | (0.051) |
| New Judge ($<$ 2 years) | −0.091 | (0.072) |
| Logged Word Count, Opinion | 0.168* | (0.015) |
| Opinion Year | −0.011* | (0.003) |
| Precedent Not Unanimous | 0.024 | (0.014) |
| Precedent Age | −0.018* | (0.002) |
| Logged Word Count, Precedent | 0.059* | (0.010) |
| Both Former Prosecutors | 0.013 | (0.025) |
| Same Law School | 0.019 | (0.036) |
| Both Former AG | 0.036 | (0.032) |
| Both Former SG | 0.097 | (0.089) |
| Both Former Professors | 0.001 | (0.024) |
| Intercept | 16.230* | (6.319) |
| N | 5,215,559 | |
| AIC | 50065.2 | |
| BIC | 50321.1 | |

Table 7: Shared Professional Experience Model: Probit regression estimates of the effect of shared characteristics and professional experiences and a range of control variables on the probability an opinion will cite a precedent. The reported standard errors are robust standard errors that are clustered on the opinion and * denotes a p-value less than 0.05.

## References


Black, Ryan C. and James F. Spriggs. 2013. "The Citation and Depreciation of U.S. Supreme Court Precedent." *Journal of Empirical Legal Studies* 10(2):325–358.

Bowie, Jennifer Barnes, Donald R. Songer and John Szmer. 2014. *The View from the Bench and Chambers*. University of Virginia Press.

Boyd, Christina L., Lee Epstein and Andrew D. Martin. 2010. "Untangling the Causal Effects of Sex on Judging." *American Journal of Political Science* 54(2):389–411.

Fowler, James H., Timothy R. Johnson, James F. Spriggs, Sangick Jeon and Paul J. Wahlbeck. 2007. "Network Analysis and the Law: Measuring the Legal Importance of Precedents at the U.S. Supreme Court." *Political Analysis* 15(03):324–346.

Hinkle, Rachael K. 2015. "Legal Constraint in the US Courts of Appeals." *The Journal of Politics* 77(3):721–735.

Kastellec, Jonathan P. 2013. "Racial Diversity and Judicial Influence on Appellate Courts." *American Journal of Political Science* 57(1):167–183.

Landes, William M., Lawrence Lessig and Michael E. Solimine. 1998. "Judicial Influence: A Citation Analysis of Federal Courts of Appeals Judges." *Journal of Legal Studies* 27(2):271–332.

Spriggs, James F. and Thomas G. Hansford. 2000. "Measuring Legal Change: The Reliability and Validity of Shepard's Citations." *Political Research Quarterly* 53(2):327–341.