Balancing the Scales of Justice: Public Defender and District Attorney Value-Added *

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Abstract

The adversarial nature of the American criminal justice system presumes that competition between public defenders (PDs) and district attorneys (DAs) yields fair outcomes, yet disparities in attorney skill may distort this process. This paper exploits the random assignment of attorneys in 15 years of administrative data from Bexar County, Texas, to estimate the value-added of attorneys on case outcomes. Attorney value-added has large effects on the probability of incarceration which are symmetric and additive such that having an above median DA (PD) and a below median PD (DA) increases (decreases) the probability of incarceration by approximately 10 percentage points. When attorneys have equal value-added, their effects cancel out, but imbalances in attorney value-added generate substantial variation in case outcomes. Even when PD and DA value-added are balanced, differences in attorney value-added affect the composition of released defendants: higher value-added pairs are more likely to release younger, first-time defendants, who subsequently exhibit higher rates of recidivism.

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1 INTRODUCTION

The American criminal justice system relies on adversarial competition between prosecution and defense to produce fair outcomes. The majority of defense services (80%, (Harlow, 2001)) are provided by public defenders (PDs) who represent defendants, while district attorneys (DAs) prosecute on behalf of the state. Attorneys on both sides present evidence and arguments to judges and juries, shaping case outcomes. Since attorneys influence how information is framed and interpreted, disparities in attorney skill may affect a case's results (Shem-Tov, 2022; Agan et al., 2021, 2023). If PDs are more skilled than DAs, they may secure acquittals for defendants who would otherwise be incarcerated. Conversely, more skilled DAs may overreach, leading to disproportionately harsh outcomes. Additionally, the overall skill level within an equally skilled PD-DA combination—whether both attorneys are highly skilled or both are less skilled—may influence the quality of justice outcomes.

This paper examines how attorney value-added and the composition of a PD-DA combination shapes criminal case outcomes in an adversarial legal system. Using rich administrative data from Bexar County, Texas, and leveraging the as-good-as-random assignment of attorneys to cases, I study whether it is the absolute value-added of each attorney or the relative value-added between opposing attorneys that determines case outcomes. To examine how value-added influences outcomes within balanced attorney combinations, I analyze how the composition of these combinations—holding relative skill fixed—shapes which defendants are released and their likelihood of recidivism.

Bexar County provides a unique setting to examine the effects of attorney value-added in adversarial competition by addressing challenges related to endogenous PD–DA matching. First, it has a large criminal justice system, with hundreds of attorneys handling tens of thousands of cases each year resulting in repeated observations of attorneys to estimate attorney value-added. Second, PDs and DAs are assigned to cases through independent and effectively random processes.[1] This assignment structure eliminates selection bias in attorney–case matching and generates exogenous variation in the value-added composition of PD–DA pairings, which I use to identify the causal effect of attorney combinations on case outcomes.

I estimate attorney value-added using felony court records from Bexar County spanning 2005–2019, covering roughly 70,000 cases. I define value-added by positioning each PD and DA within a distribution of effectiveness relative to peers, where high value-added PDs avoid incarceration at higher rates and high value-added DAs impose incarceration at higher rates, consistent with the mandates of their respective roles.[2] To improve mea-

[1] DAs are assigned to courtrooms such that the effect of a DA may include the effect of a judge even when controlling for courtroom.

[2] Value-added need not reflect legal skill alone, and I do not interpret it as such. The estimates may also capture bargaining strategies, relationships with judges, case triage, or institutional knowledge. Value-

surement where small samples of opposing attorneys could lead to mismeasurement of a given attorney's value added, I design a two-sided value-added approach that controls for the opposing attorney through the inclusion of a value-added term for both the PD and DA in the value added specification. I also use a leave-one-out procedure to avoid overfitting to any single case and apply an empirical Bayes shrinkage procedure to value-added estimates. The 15-year panel further enables construction of defendants' criminal histories and post-case recidivism outcomes which I use to estimate how PD-DA combinations relate to recidivism. I also link attorneys to demographic and educational information from the Texas State Bar to explore heterogeneity in value-added by characteristics such as experience and law school. Out-of-sample, shrunken value-added estimates closely match predictions from the linear model, supporting these measures' validity. Attorney and attorney-pair value-added are balanced across case characteristics, consistent with quasi-random assignment and enabling credible estimation.

I find that the PD-DA effects are additive, such that only the relative value-added matters for incarceration. When both attorneys have similar value-added—whether above or below the median—their effects largely offset, resulting in comparable incarceration rates. In contrast, in mixed-value-added pairings, the higher value-added attorney shifts outcomes in favor of their side: an above-median public defender reduces incarceration probability by 9.8 percentage points, while an above-median prosecutor increases it by 9.9 points. These patterns extend to sentence length, where stronger prosecutors lengthen incarceration by 114 days and stronger defenders reduce it by 159 days, consistent with the adversarial nature of the courtroom. These findings demonstrate that courtroom personnel assignment moves criminal justice outcomes by meaningful magnitudes, yet is largely unmeasured and unmanaged. To verify that attorney value-added effects are additive, I test the assumption of my model that PD and DA effects enter linearly and additively by augmenting the model with interaction terms and conducting simulation exercises. The estimated PD and DA value-added remain stable when non-linear interactions are included, and the interaction effects are an order of magnitude smaller than the main effects. Simulations further show that, even under a linear additive specification, non-linearities of meaningful size would be detectable, providing additional support for the validity of the modeling assumptions.

While balanced PD-DA combinations have similar likelihoods of incarceration, absolute attorney value-added affects the composition of released defendants. I develop a method to characterize how the composition of released defendants varies conditional on relative skill. Conditional on relative skill, however, pairings of two high-skill attorneys are less likely to secure release for Black defendants, defendants charged with felonies, and those accused of the most severe offenses, but more likely to release defendants with higher

added is informative as a reduced-form summary of an attorney's average effectiveness in advancing their party's objectives.

predicted recidivism. This pattern suggests that higher-skilled attorneys impose harsher outcomes on defendants with more severe criminal profiles, potentially relying more on observable case characteristics—such as offense severity and prior convictions—rather than on unobserved recidivism risk. Recent evidence shows that prosecutors tend to overestimate the predictive value of prior offenses while underestimating declines in criminal behavior with age (Harrington and Shaffer, 2025). Consequently, high value-added prosecutors' reluctance to release older or previously convicted defendants may inadvertently increase recidivism rates. These results show that relative value-added determines case outcomes in an adversarial system, while higher absolute value-added reshuffles which defendants are released.

To link the PD and DA value-added distributions, I leverage a subsample of 22 attorneys who served in both roles. By comparing their value-added across roles, I align the PD and DA distributions to assess whether value-added as a PD is comparable to value-added as a DA. I find suggestive evidence of substantial overlap in skill distributions between PDs and DAs, indicating comparable effectiveness on both sides of the courtroom.

Attorney value-added correlates with measures of professional experiences, including case duration, law school rank, and experience. Among PDs, higher value-added is associated with longer case durations, suggesting greater investment in negotiations, whereas higher value-added DAs resolve cases more quickly, potentially reflecting efficiency in securing plea deals. I find suggestive evidence that attorneys from higher-ranked law schools exhibit greater value-added. PD performance improves with tenure while DA performance remains stable.

PD–DA combinations with similar relative value-added produce comparable incarceration rates, indicating that adversarial justice is preserved when attorneys are evenly matched, even at lower levels of skill. These findings highlight the importance of balanced adversarial representation for fairer justice outcomes. Balanced representation improves fairness, but even within balanced PD-DA pairs, the composition of those incarcerated varies according to absolute attorney skill. This underscores the critical role of attorney skill in shaping case outcomes and the limits of balance alone in achieving comparable outcomes for similar cases.

I make contributions to three literatures. First, I contribute to the literature on the effect of courtroom personnel on court outcomes. These papers show that judge, PD, and DA attributes impact case outcomes. Work using evaluator-assignment designs show that judge and DA leniency affects the probability of incarceration and subsequent outcomes such as recidivism and employment (Kling, 2006; Norris et al., 2021; Agan et al., 2023). Other work shows that PD quality varies leading to disparate impacts in otherwise similar cases (Abrams and Yoon, 2007). There is also empirical evidence that matched characteristics of attorneys and defendants leads to reductions in conviction rates (Sloan, 2019; Mikdash and Oh, 2019). While this literature shows that courtroom personnel

and client pairings are important, this is the first paper to study the effects of PD-DA personnel combinations in courtrooms. I show that value-added composition of PD-DA pairs affects incarceration rates.

Second, I contribute to the literature on adversarial legal systems—where judges rely on attorney-presented information—by studying the effects of attorney value-added on justice outcomes. In theory, competition between attorneys could lead to better justice outcomes (Dewatripont and Tirole, 1999; Zorro Medina et al., 2016; Kaplow, 2011). There is little empirical evidence of how competition, particularly in the presence of imbalances, affects case outcomes. In addition, existing work evaluates ways in which various institutional aspects of adversarial legal systems such as the method of public defense provision and payment schemes affect the quality of defense (Agan et al., 2021; Shem-Tov, 2022; Lee, 2021). This paper also studies the importance of court institutions by evaluating the potential importance of attorney assignment. I find that attorney value-added imbalances can lead to disparities in the probability of incarceration for otherwise similar cases and that these effects could be mitigated by better matching of PDs and DAs.

I lastly contribute to the literature measuring the value-added of agents within multiagent production functions. Value-added methods have been applied to estimate the effects of agents on outcomes, including teachers, health insurance, and prisons (Chetty et al., 2014a; Abaluck et al., 2021; Bravo, 2024). Related work has decomposed value-added across institutions such as schools and neighborhoods or tax collector teams (Chetty et al., 2014b; Bergeron et al., 2022). Other studies develop methodologies to estimate an individual's contributions in collaborative team settings (Weidmann and Deming, 2021; Bonhomme, 2021). In contrast, I develop two-sided value added, a new method to estimate the contribution of each agent in adversarial settings. I consider the adversarial setting where PDs and DAs operate in opposition on the same case. A PD defends her client from incarceration while a DA prosecutes with intent to incarcerate. This paper studies a context of pair production in which agents in pairs have opposite aims.

The rest of the paper is structured as follows: Section 2 describes the institutional context and setting. Section 3 presents the data. Section 4 discusses the empirical methodology. Section 5 discusses the results regarding the effect of PD-DA value-added on criminal justice outcomes and estimates the role of each attorney's value-added within a case on the composition and recidivism of the released. Section 6 shows the relationship between attorney value-added and attributes. Section 7 concludes.

2 INSTITUTIONAL CONTEXT AND SETTING

I study felony cases in Bexar County, Texas, where PDs and DAs are effectively randomly assigned to defendants. Randomized assignment mechanisms for both PDs and DAs create quasi-experimental variation in attorney combinations, independent of case or attorney

characteristics. This institutional setting, combined with a large and diverse caseload, provides an opportunity to evaluate the impact of attorneys on criminal justice outcomes.

2.1 Institutional Context

The criminal justice system in Bexar County follows the adversarial model, in which PDs and DAs present opposing arguments before judges and juries. PDs defend indigent defendants, while DAs prosecute on behalf of the state. The adversarial system is premised on the idea that balanced competition between attorneys produces fair and balanced outcomes. In practice, disparities in attorney skill may weaken this ideal, generating unequal representation or prosecution.

All felony defendants are entitled to a defense attorney. Defendants with resources may hire a private defense attorney, while indigent defendants receive publicly subsidized representation through defense attorneys serving as PDs. In Bexar County, PDs contract with the county at rates of \$50–\$150 per hour, compared with roughly \$200 per hour for private attorneys (Agan et al., 2021). At any given point, defense attorneys can work in both capacities. PDs represent defendants across all stages of the legal process, including bail hearings, investigations, plea negotiations, trial defense, and sentencing. Their skill may affect outcomes through multiple channels, such as the quality of evidence presented or the leniency of plea agreements.

Prosecution is handled by the Bexar County District Attorney's Office, which is headed by an elected District Attorney and staffed by salaried prosecutors. The office is divided into intake and outtake teams. Intake prosecutors are randomly assigned to cases conditional on case type and oversee the grand jury process, which determines whether charges are dismissed or indicted. Indicted cases are then transferred to outtake prosecutors, who handle all subsequent stages of the case. My analysis focuses on outtake prosecutors, whose decisions influence final case outcomes, including incarceration and sentence length.

2.2 Attorney Assignment Process

In Bexar County, PDs and DAs are assigned through independent court processes, ultimately forming PD-DA pairings. PDs represent indigent defendants, handling 60% of cases in Bexar County, while DAs prosecute cases on behalf of the county and operate within courtrooms. This assignment process enables me to assess the role of attorneys within an adversarial system, independent of potential biases that could arise from non-random PD-DA pairings.

With a population of 2 million, Bexar County generates a substantial volume of court cases, requiring extensive prosecution and defense services. This environment enables the observation of numerous attorneys each handling many cases. Furthermore, Bexar

County encompasses San Antonio, Texas, the seventh largest city in the United States, characterized by a highly diverse and rapidly growing population (US Census Bureau, 2023).

PDs are assigned to cases through a rotating "wheel" system intended to ensure random assignment of attorneys. Separate wheels exist by offense level, and cases are assigned sequentially to the attorney at the top of the relevant wheel, who then moves to the bottom of the list. Defendants cannot reject their assigned PD, and PDs are removed from the wheel if they decline cases. I restrict the analysis to felony cases with publicly provided defense and to the five of eight Bexar County courtrooms that use the wheel system.

DAs are allocated to cases through a courtroom-based system that yields effectively random assignments conditional on case type. DAs are permanently assigned to courtrooms. Each courtroom has three to four prosecutors, who divide cases by seniority: senior prosecutors handle more severe charges (such as homicide), while junior prosecutors handle less severe offenses (such as theft). Because felony cases are randomly distributed across courtrooms, the assignment of a DA to a given case is random, conditional on case type. Importantly, judges and DAs are linked to courtrooms, so the effect of the DA also may include the effect of the judge despite controlling for the courtroom. Together, these procedures generate PD–DA pairings that are determined by independent randomization. This setting provides a clean environment to study how attorney skill shapes criminal justice outcomes.

3 DATA

I use administrative court records from Bexar County, Texas, containing the PD and DA assigned. To ensure clean identification of attorney effects, I restrict the sample to cases where the defense attorney is a PD, yielding randomly assigned PD–DA combinations. These cases cover a wide range of offenses and allow for construction of criminal histories and measurement of future recidivism.[3]

3.1 Data

The administrative data cover 114,164 felony cases between 2005 and 2019 (Bexar County, Texas, 2023). For each case, I observe offense type, offense level, courtroom, and sentence imposed, as well as outcomes at each stage of the criminal process. The analysis sample is limited to felony cases with randomly assigned PDs. Approximately 60% of cases are handled by a defense attorney acting as a PD and courtrooms using the wheel system, resulting in a sample of 70,438 cases. As an additional specification, I exclude roughly 22.5% of cases involving probation revocation in which the originally assigned PD may

[3]I thank Agan et al. (2021) for providing initial data and code describing the institutional context.

not be observed because the revocation PD is recorded as the acting PD. I find that attorneys value-added is similar when revoked cases are excluded.[4]

3.2 Summary Statistics

The sample includes 70,438 cases involving 694 PDs and 258 DAs (Table 1). Defendants are disproportionately Black (18%) and male (78%), with an average of 1.6 prior cases. Third-degree/state felonies are most common, accounting for 74% of cases. Most cases are resolved through plea deals (82%), with dismissals (12.7%) and trials (less than 1%) being rare. Approximately 48% of cases result in incarceration, while 12.7% involve probation and 26.4% involve deferred adjudication.

Table 2 reports attorney caseloads. Over the sample period, the average PD handles 99.2 cases in total (9.5 per year), while the average DA handles 258 cases (33.9 per year). The larger number of PDs reflects the county contract system. High caseloads for both PDs and DAs allow for estimation of attorney value-added.

4 EMPIRICAL STRATEGY

My specification for measuring attorney skill uses a value-added approach, where an attorney's value-added is defined by the outcomes of their cases. By comparing an attorney's average case outcomes to those of other attorneys, I measure their skill relative to their peers allowing me to place each attorney within the value-added distribution. This method leverages the high case volume to estimate attorney skill and can be used across multiple outcomes.

4.1 Empirical Framework

The criminal justice system can be viewed as a process in which PDs and DAs influence the probability of incarceration through their actions. PDs aim to defend clients and reduce the likelihood of incarceration, while DAs seek to secure convictions and impose sentences. The level of evidence presented in a case, along with attorney skill, shapes how judges and juries interpret the case and decide outcomes. Differences in attorney value-added can therefore change the observed presentation of evidence and, ultimately, the defendant's probability of incarceration.

To structure thinking about the role of attorney value-added, consider each case as having an underlying "true" level of evidence regarding guilt. Attorneys influence the observed evidence by advocating for or against incarceration: high value-added PDs can mitigate the apparent strength of evidence, while high value-added DAs can amplify it. Imbalances in skill can lead to errors in outcomes. For example, a relatively stronger

[4] In Figure D1, I show that attorney value-added estimates are highly correlated in the full sample and the sample of cases that are not revoked.

DA may result in incarceration even when evidence is weak (a Type I error), whereas a stronger PD may prevent incarceration even when evidence is strong (a Type II error).

Attorney value-added can be categorized in broad terms as "high" or "low." A high-value-added PD reduces the probability of incarceration, whereas a high-value-added DA increases it. Each case can then be understood as the interaction between a PD and DA, creating four possible combinations: both attorneys low-value-added, both high-value-added, PD high-DA low, or PD low-DA high. This framework highlights how outcomes in the adversarial system may be impacted by the value-added of each attorney in a PD-DA combination.

4.1.1 Methodology

To account for the skill of an adversary, I develop a two-sided value-added approach. This method mitigates mismeasurement that can arise from opponent skill in a finite sample. For example, a PD who randomly faces only highly skilled DAs may appear less effective because their outcomes are dominated by strong opponents. Appendix Section A shows that this source of mismeasurement diminishes as the number of PD–DA pairings increases.

Using this approach, I estimate PD and DA value-added across randomly assigned cases with the following fixed effects model:

$$Y_i = \lambda_{p(i)} + \gamma_{d(i)} + X_i'\nu + \epsilon_i \tag{1}$$

Here, Y_i is a criminal justice outcome, such as an indicator for incarceration or the number of days incarcerated. The PD fixed effect $\lambda_{p(i)}$ captures the contribution of PD p to case i, and the DA fixed effect $\gamma_{d(i)}$ captures the contribution of DA d. The vector X_i' includes case year, offense type, and offense level fixed effects, as well as demographic controls (age, sex, race) to account for factors relevant to attorney assignment. Standard errors are clustered at the case level.

I estimate two-sided-value-added using a leave-one-out procedure, whereby the estimate for a given case is constructed from all other cases handled by the attorney. This approach ensures that value-added is estimated out-of-sample and is not overfit to the outcome of any individual case. By construction, the procedure mitigates bias from mechanical correlation between an attorney's performance and the case outcomes used to evaluate it.

I then apply an empirical Bayes shrinkage procedure to the leave-one-out estimates to correct for noise in measurements of attorney value-added arising from limited case counts. Estimated fixed effects of $\hat{\lambda}$ and $\hat{\gamma}$ tend to be noisy due to the relatively low case counts. The empirical Bayes correction adjusts each value-added estimate by its relia-

bility as outlined in Appendix Section B (Kane and Staiger, 2008). Noisier, less reliable value-added estimates are shrunk towards zero giving corrected PD and DA value-added estimates, $\hat{\lambda}^{EB}$ and $\hat{\gamma}^{EB}$. The resulting out-of-sample, shrunken value-added measures closely align with predictions from the linear model, supporting their validity for subsequent analysis. In Table E1, I find that shrunken estimates have coefficients close to one. This suggests that the controls included account for the variance structure of the data.

This model relies on two key assumptions of balance of attorney assignment and linearity of attorney effects. Balance assumes that attorney assignment is independent of case characteristics, so that variation in outcomes reflects attorney skill rather than case selection. Linearity assumes that attorney skill enters additively, meaning the combined effects of PD and DA value-added are the sum of their individual contributions. Violations of these assumptions could bias estimates, either by confounding case characteristics with skill or by misrepresenting interactions between attorney skill. I validate these assumptions empirically below.

5 RESULTS

I find that attorneys have meaningful impacts on case outcomes and that attorney value-added is balanced across pre-attorney assignment case characteristics. I then demonstrate that the composition of attorney value-added within a PD–DA pairing has large, symmetric, and additive effects on incarceration such that outcomes are determined by the relative rather than the absolute value-added of the two attorneys. I then show that, despite similar rates of incarceration conditional on relative value-added, higher value-added attorneys are less likely to release Black defendants, older defendants, and defendants with prior criminal histories, and that defendants released by higher value-added attorneys are more likely to recidivate.

5.1 Estimates of Value-Added

Figure 1 presents estimates of attorney value-added. Figure 1a shows DA fixed effects $\hat{\gamma}$ and $\hat{\gamma}^{EB}$ for each of the 258 DAs. Figure 1b shows PD value-added $\hat{\lambda}$ and $\hat{\lambda}^{EB}$ for each of the 694 PDs.[5] Figure 1 includes summary statistics showing that a 1 standard deviation increase in PD (DA) skill leads to a 6.2 ppt decrease (8.2 ppt increase) in the probability of incarceration. Equivalently, a 1 standard deviation increase in PD (DA) skill reduces (increase) incarceration rates by 12.9% and 17%.

As an initial investigation of the interaction of PD and DA value-added, I plot the relationship between PD value-added, DA value-added, and incarceration outcomes. The probability of incarceration increases with relative DA skill (Figure D2). The incarceration

[5]For PDs and DAs, I find that value-added and empirical Bayes shrunk value-added have correlations of 0.96 and 0.98, respectively.

probability is the highest when the highest value-added DAs are paired with the lowest value-added PDs. Analogously, the incarceration probability is the lowest when the lowest value-added DAs are paired with the highest value-added PDs.

5.2 Validating Assumptions behind PD and DA Value-Added

My specification assumes that attorney value-added enters linearly and that attorney value-added is balanced across cases. I assess these assumptions by testing for non-linear interaction terms and examining whether attorney value-added measures are correlated with pre-assignment case characteristics. The results support the validity of these assumptions.

Table 3 tests for the presence of match effects by including a battery of PD-DA skill interaction terms in the specification testing for the effect of PD and DA effects on incarceration. The effects of PD and DA skill are stable across the inclusion of many forms of PD-DA match effects and are an order of magnitude smaller than the effects of PDs and DAs. This test provides some verification that incarceration outcomes are primarily driven by each attorney's skill, not particular PD-DA combination match effects. This may be due to the adversarial nature of the criminal justice system where attorneys do not work together with the same objective. In addition, Figure D3 and Figure D4 present the relationship between attorney value-added and attorney value-added with match terms. I find that attorney-value added is primarily driven by the linear terms, not the match terms.[6]

In Figure 2a, I find that the skill composition of a defendant's PD-DA combination is independent of case characteristics and defendant demographics. I calculate an omnibus measure of the probability of incarceration by predicting the probability of incarceration using only case characteristics and defendant demographics. I then regress this omnibus prediction of incarceration against PD-DA combination type to verify that attorney skill is independent of defendant and case characteristics. I observe a precise near-null relationship between PD-DA combination type and the omnibus measure for each PD-DA combination type at the 5% level. Additionally, the balance results are robust to controlling for omnibus measures of case characteristics and defendant demographics, as well as to design controls for offense level, crime type, and offense year, indicating that the observed effects are driven by attorney combination type rather than underlying case or defendant attributes.

[6]In addition, Table E2 presents simulation evidence that demonstrates that non-linear effects would be detectable even when value-added is estimated using a linear additive specification, providing further support for the validity of the modeling assumptions. I simulate case outcomes where case outcomes are determined by attorney value added and the interactions of attorney value added. I then estimate value added on these simulated case outcomes. Repeating the test for non-linearities, I find that the non-linearities of a meaningful magnitude.

5.3 Effects of PD-DA Combinations on Incarceration and Sentence Length

Both attorneys in a PD–DA pairing influence the probability and length of incarceration. In unbalanced pairings where one attorney has higher value-added than the other, the higher value-added attorney drives outcomes toward their party's preferred result, whereas in balanced pairings where attorneys have similar value-added, the effects largely offset each other. I also find heterogeneity in these effects by case type and defendant history.

To analyze the effects of the composition of PD-DA value-added on case outcomes, I organize attorneys into low or high value-added using their value added estimates. PD p is defined as a high value-added type if her fixed effect is greater than the median PD fixed effect, $1[\hat{\lambda}_p^{EB} > \text{median}(\hat{\lambda}_p^{EB})]$. DA d is defined as a high value-added type if her fixed effect is greater than the median DA fixed effect, $1[\hat{\gamma}_d^{EB} > \text{median}(\hat{\gamma}_d^{EB})]$. For both attorney types, low value-added types are those whose fixed effects are below median.

Figure 2b shows that the value-added composition of a PD–DA pairing meaningfully affects incarceration. In unbalanced pairings, a high value-added DA facing a low value-added PD increases the probability of incarceration by 10 percentage points, whereas a high value-added PD facing a low value-added DA reduces the probability by 10.1 percentage points. In balanced pairings, these effects are muted, as the attorneys counterbalance each other.[7]

5.4 Effect of Absolute versus Relative Attorney Value-Added on Defendant Release

To further characterize the role of attorney value-added in PD-DA combinations, I estimate its effects along two dimensions. The first is relative value-added, defined as the difference between PD and DA value-added, which captures the gap in attorney value-added. The second is absolute value-added, which reflects each attorney's individual contribution within a combination. Importantly, absolute value-added can vary even when relative value-added is held constant.

I find that case outcomes depend on relative value-added such that PD and DA value-added combine linearly to determine incarceration rates. PD-DA combinations with similar relative value-added generate comparable incarceration rates, even when their absolute value-added differs. Thus, conditional on a fixed relative value-added, low value-added attorneys can produce similar outcomes to high value-added attorneys.[8]

[7] Figure D6 shows analogous patterns for sentence length: high value-added DAs lengthen incarceration by 114.2 days, whereas high value-added PDs shorten it by 159.1 days.

[8] This result follows from Table 3, Column (3), since Equation 2 is a reorganization of that specification. Let the Column (3) specification be

$$Y_i = \psi\gamma_{d(i)} + \kappa\lambda_{p(i)} + \eta X_i + \epsilon_i.$$

Rewriting yields

$$Y_i = [\kappa](\gamma_{d(i)} - \lambda_{p(i)}) + [\psi + \kappa]\lambda_{p(i)} + \eta X_i + \epsilon_i.$$

It follows that $\delta = -\kappa$ and $\beta = \psi + \kappa$, so the values of coefficients δ and β in Equation 2 and presented

To test the roles of relative and absolute value-added, I estimate

$$Y_i = \delta\left(\gamma_{d(i)} - \lambda_{p(i)}\right) + \beta\gamma_{d(i)} + \Omega\left[\left(\gamma_{d(i)} - \lambda_{p(i)}\right) \times \lambda_{d(i)}\right] + \eta X_i + \epsilon_i \tag{2}$$

where Y_i is an indicator for incarceration in case i. Relative value-added is defined as the difference between DA and PD value-added, $(\gamma_{d(i)} - \lambda_{p(i)})$, while $\lambda_{d(i)}$ captures the DA's absolute value-added. The coefficient δ measures the effect of relative value-added, β the effect of absolute value-added, and Ω the interaction between relative and absolute value-added. X_i includes design and demographic controls as in Equation 1.

Table 4 shows that incarceration is driven by relative rather than absolute value-added. The estimated effect of relative value-added is large and precisely estimated, $\hat{\delta} = 0.86\,(0.04)$, while the effect of absolute value-added is small and imprecisely estimated, $\hat{\beta} = 0.051\,(0.05)$. Results are robust to including the interaction term of absolute and relative skill. These findings imply incarceration is driven by the relative balance of a PD-DA combination's value-added within a case, not the absolute levels. Incarceration rates are similar across the PD–DA value-added distribution when relative value-added is constant, suggesting that balanced adversarial representation produces similar incarceration rates along the value-added distribution and even when attorney value-added is low.

5.5 Effect of Relative versus Absolute Attorney Value-Added on the Composition and Recidivism of the Released Defendants

I next examine how absolute value-added shapes both the composition of released defendants and their subsequent recidivism. Higher value-added attorneys are less likely to secure release for defendants with prior felonies, more severe case types, or older defendants. In addition, defendants released by high value-added attorneys are more likely to recidivate. These patterns suggest that high value-added attorneys condition release decisions more heavily on observable case characteristics—such as offense severity, prior convictions, or age—without targeting or incorrectly estimating subsequent recidivism.

To estimate the role of absolute skill in shaping the composition of released defendants, I adapt Equation 2 by using $C_i(1 - D_i)$ as the outcome. This specification characterizes variation in release composition conditional on relative skill within each PD–DA pairing. Using $C_i(1 - D_i)$ as the outcome restricts the contribution to the relative value-added parameter, δ, to released defendants, since $C_i(1 - D_i) = 0$ when $D_i = 1$. This design allows the characteristics of defendants to be separately identified from the effect of each PD–DA combination type on incarceration by restricting comparisons to the released. It also accommodates analysis of C_i as well as outcomes defined only for defendants with $D_i = 0$, such as recidivism. Additional detail is provided in Appendix Section C.

in Table 4 Column (1) can be directly recovered from the coefficients in Table 3 Column (3).

$$C_i(1 - D_i) = \delta\left(\gamma_{d(i)} - \lambda_{p(i)}\right) + \beta\gamma_{d(i)} + \eta X_i + \epsilon_i, \tag{3}$$

where D_i is an indicator for incarceration. C_i is a demographic characteristic of the defendant or the subsequent recidivism outcomes. By using $C_i(1 - D_i)$ as an outcome, I study how PD-DA combinations with similar relative rates of incarceration vary in the composition in their decisions of who to release.

Within fixed relative skill, Table 5 shows that high value-added attorneys are systematically less likely to release older defendants, defendants with felony histories, and Black defendants. A one–standard deviation increase in absolute skill reduces the probability of releasing a felony defendant by 34 percentage points and lowers the average age of released defendants by 0.049 (0.018) years. I find no significant effects on the release probability for men, Latinos, misdemeanor defendants, or predicted recidivism risk. By contrast, a one–standard deviation increase in absolute skill decreases the probability of releasing a Black defendant by 6.1 percentage points. These results suggest that high value-added attorneys place disproportionate weight on observable characteristics—including criminal history, age, and race—in making release decisions.

Turning to how these release decisions relate to the probability of recidivism, I find that defendants released by high value-added attorneys are more likely to recidivate (Table 5). A one-standard deviation increase in absolute value-added conditional on relative value-added increases recidivism by 21 percentage points. These findings suggest that high value-added attorneys systematically use observable characteristics despite that leading to higher recidivism.

Taken together, these findings indicate that higher value-added PD-DA combinations release defendants with more severe criminal histories but that do not lead to the lowest rates of recidivism. The results align with recent work on prosecutorial biases and the limits of recidivism prediction. In particular, Harrington and Shaffer (2025) show that DAs systematically overweight prior convictions and underestimate the decline in offending with age. Consistent with this, the reluctance of high-skill DAs to release older or previously convicted defendants may inadvertently raise high value-added attorneys' recidivism rates.

6 ATTORNEY ATTRIBUTES AND VALUE-ADDED

I examine how attorney value-added relates to attorney attributes and how PD and DA distributions compare. High value-added is associated with experience, education, and case resolution speed. Exploiting attorneys who serve in both roles, I further show that PD and DA value-added overlap substantially, consistent with both groups being drawn from a common distribution.

6.1 Attorney Characteristics and Value-Added

I find that human capital through both education and experience relate to value-added. High value-added attorneys are more likely to have attended higher-ranked law schools. Regarding experience in the courtroom, I find that PD value-added rises with experience, while DA value-added remains relatively flat. In addition, high value-added DAs resolve cases more quickly, whereas high value-added PDs handle longer cases. Together, these patterns suggest that education and experience contribute to attorney value-added.

Figure 3 shows that attorneys who graduated from higher-ranked law schools have higher value-added (State Bar of Texas, 2025). Using U.S. News & World Report rankings, I calculate the average value-added for each law school and compare the average VA of attorneys from schools ranked above 100 to those from schools ranked below 100 (U.S. News & World Report, 2025). The results indicate a positive association between law school rank and attorney performance, suggesting that educational background is somewhat predictive of attorney value-added.

Figure 4 shows that experience matters for PDs but less for DAs. To isolate the effect of experience, I restrict the sample to attorneys whose first observed case occurs in 2006, the second year of my dataset. I include attorney fixed effects to control for time-invariant individual traits. This specification allows me to estimate how outcomes evolve as attorneys gain experience, holding constant unobserved attorney quality. As a result, the estimated returns to experience reflect the effect of tenure in the PD or DA role, rather than differences in individual ability. By their 100th case, a PD's defendant is approximately 13 percentage points less likely to receive an incarceration sentence. For DAs most levels of case experience, I find a mostly statistically insignificant relationship between case experience and likelihood of incarceration.

6.2 Relating Value-Added from PD and DA Distributions

To compare PD and DA value-added, I leverage a sample of 22 attorneys who serve in both roles. I use my estimates of value-added which places PDs and DAs within separate distributions. I then estimate the relationship between the two distributions using these switchers between the PD and DA role. The results indicate overlap in the skill distributions of PDs and DAs, suggesting comparable levels of underlying ability across both sides of the courtroom.

Figure 5 plots each attorney's value-added as a PD against their value-added as a DA. The distributions overlap such that an average DA is comparable to an average PD. Within this limited sample, I find a correlation of –0.2: attorneys with high PD value-added tend to have lower DA value-added. This negative correlation may reflect the selection of attorneys who switch roles, or it may capture genuine differences in the skills that translate into effectiveness for PDs versus DAs.

7 CONCLUSION

This paper shows that PD and DA value-added jointly determine case outcomes. Attorney value-added exerts large, symmetric, and linear effects, such that outcomes are primarily driven by relative attorney skill within a PD–DA pairing rather than the absolute skill of either attorney. The stronger attorney is able to shift cases toward their side's preferred outcome. Conditional on relative skill, however, I find that absolute value-added affects which defendants are released: higher-skill pairings disproportionately release younger defendants and those without felony histories, but these releases are associated with higher recidivism rates.

These results align with prior work demonstrating the importance of attorney quality, while providing new insight into how value-added operates in an adversarial system. While earlier research has studied PDs and DAs in isolation, I show that outcomes hinge on both attorneys within a court case. More broadly, my findings underscore the role of court institutions and personnel in shaping outcomes for otherwise similar cases. Methodologically, this paper also introduces a framework for estimating value-added in environments with multiple competing agents.

I further show that low value-added attorneys achieve outcomes similar to high value-added attorneys when matched against opponents of comparable skill. This suggests that the adversarial ideal—where attorney competition drives outcomes—can be realized even in a low-skill environment. One implication is that balancing attorney assignments could reduce variance in incarceration rates without requiring uniformly high attorney skill.

A limitation of this study is that I cannot observe case evidence or guilt. Thus, my estimates capture how attorney value-added affects outcomes, not whether those outcomes are "accurate." Recidivism analysis provides suggestive evidence on the composition of released defendants, but does not identify whether attorney competition improves the quality of adjudication.

Future research could extend this work by examining the mechanisms underlying attorney bargaining, the dynamics of repeated interactions between PDs and DAs, and the ways attorney value-added shapes the presentation of evidence. Together, these avenues would deepen our understanding of how legal institutions translate attorney ability into case outcomes.

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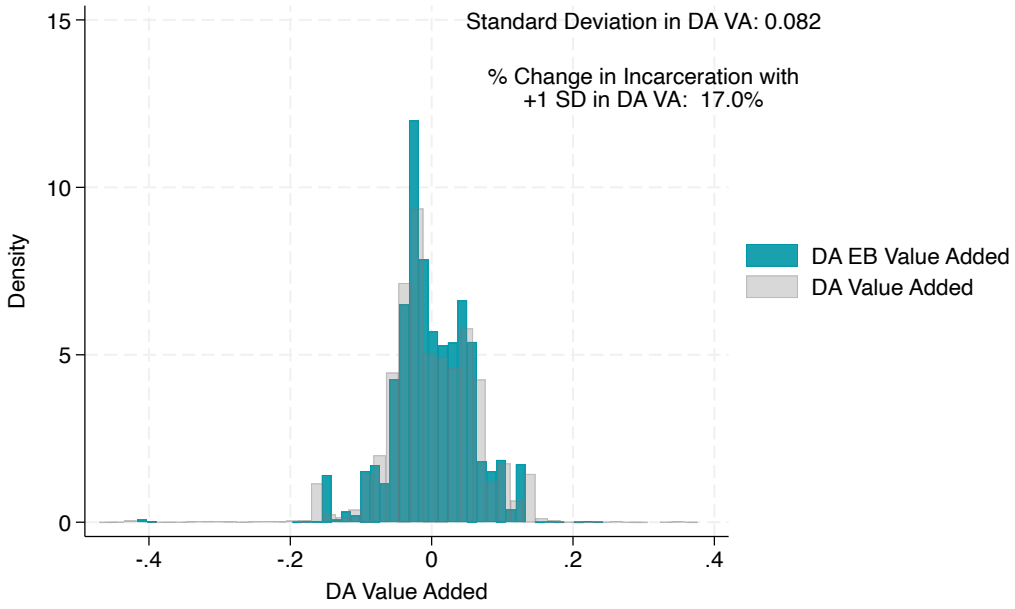
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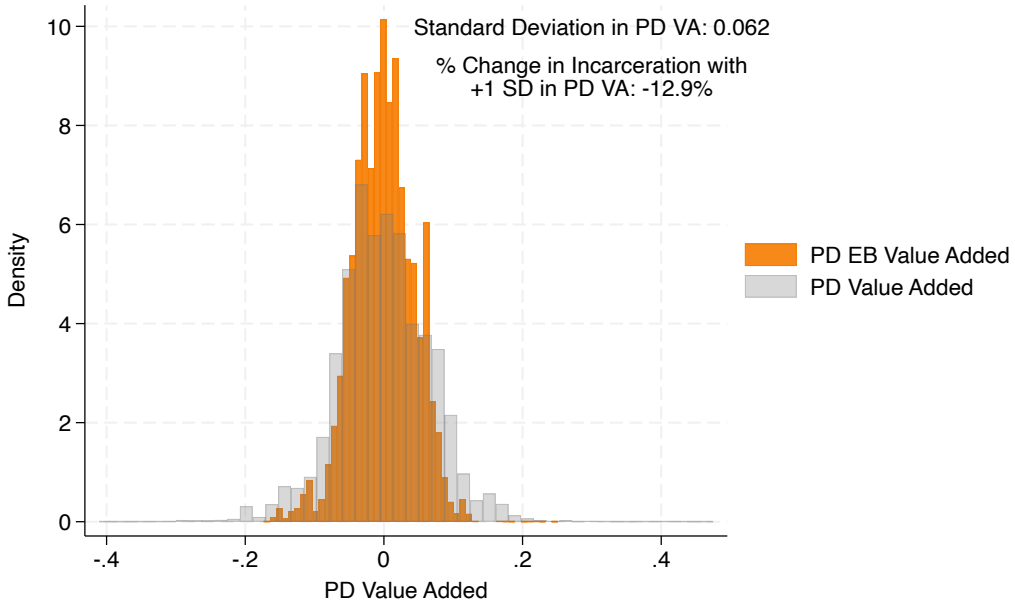
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FIGURES

Figure 1: Attorney Value-Added



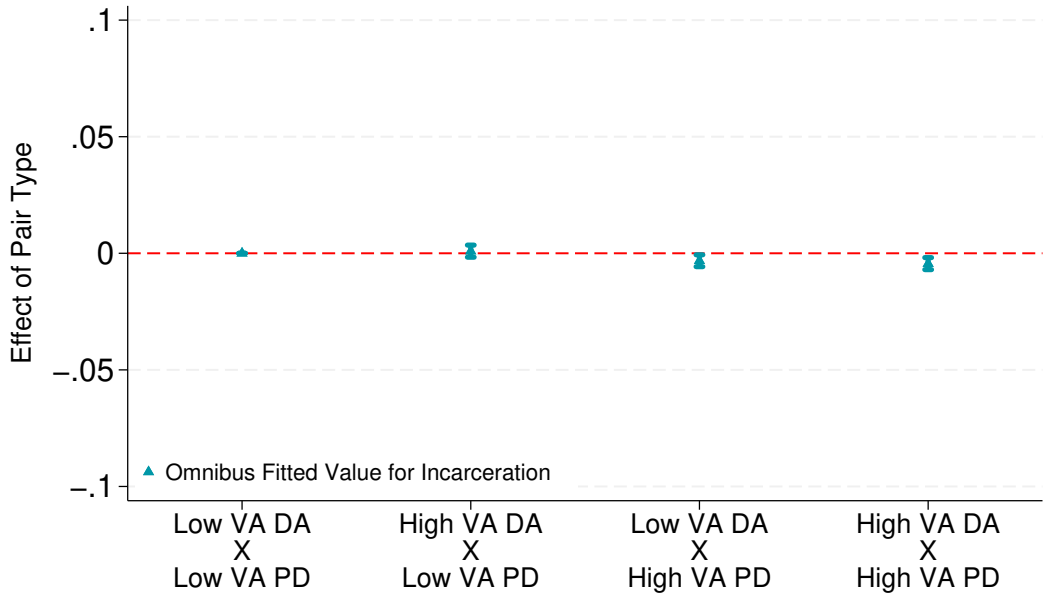
(a) DA Value-Added Histogram



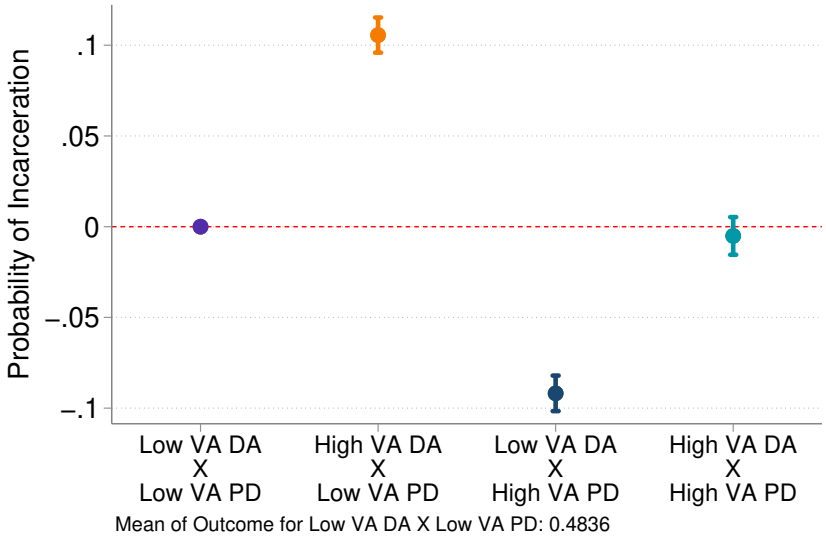
(b) PD Value-Added Histogram

This figure displays PD and DA fixed effects estimated in Equation 1. Figure 1a reports DA value-added for the OLS and Empirical Bayes (EB) shrunk estimates, $\hat{\gamma}_{d(i)}$ and $\hat{\gamma}^{EB}_{d(i)}$. Figure 1b reports PD value-added for the OLS and Empirical Bayes (EB) shrunk estimates, $\hat{\lambda}_{p(i)}$ and $\hat{\lambda}^{EB}_{p(i)}$. Standard deviations of attorney value-added and the percentage change in the probability of incarceration with a one standard deviation increase attorney value-added are presented in each figure. The specification includes design controls (year, offense type, and offense level fixed effects) and demographic controls (age, race, and sex). PD EB value-added and PD value-added have a correlation of 0.96. DA EB value-added and DA value-added ahve a correlation of 0.98.

Figure 2: Effect of PD-DA Combinations



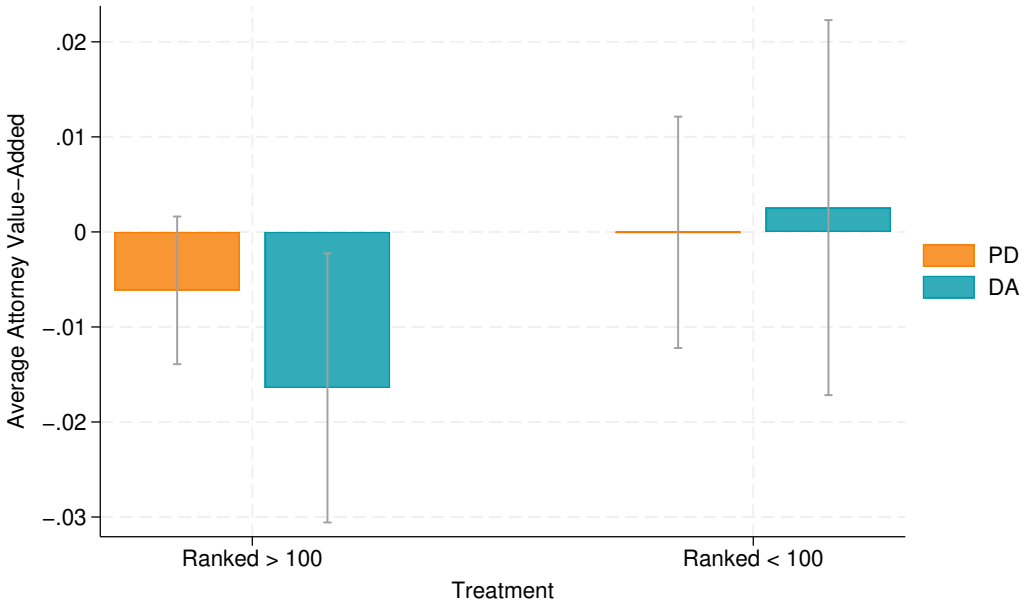
(a) Effect of PD-DA Combination on Incarceration



(b) Effect of PD-DA Combination on the Probability of Incarceration

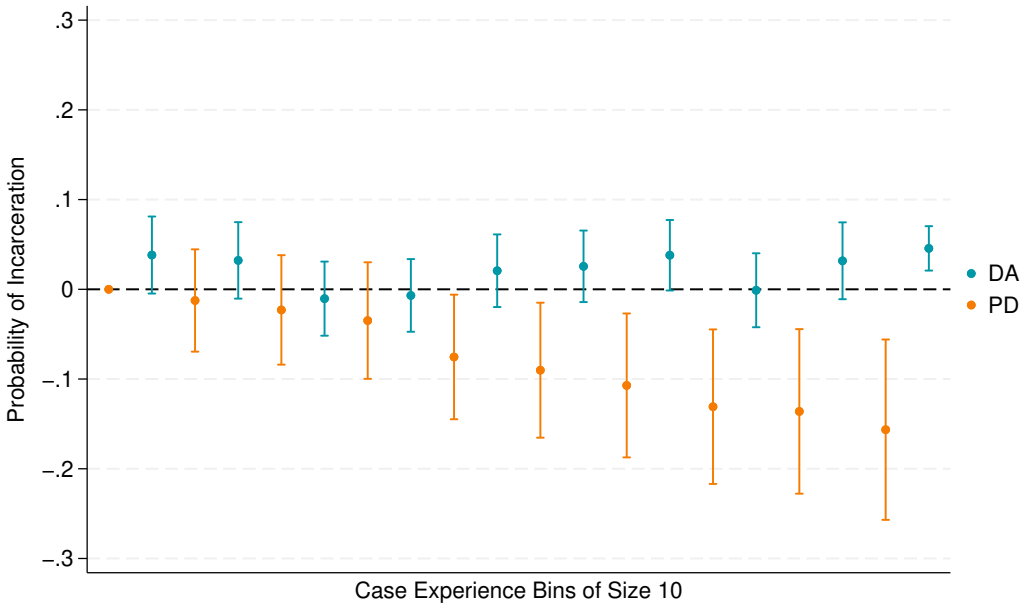
Panel A plots omnibus fitted incarceration probabilities by PD–DA combination type. Omnibus fitted values are constructed by regressing incarceration status on defendant demographics (age, race, gender, felony and misdemeanor conviction history) and case characteristics (offense type, year, and crime type), and then applying the estimated coefficients to observed characteristics. High value-added PDs (DAs) are those above the median and are associated with lower (higher) incarceration probabilities. The specification tests for balance across PD–DA combination types by regressing omnibus fitted values on indicators for each combination type and including design controls (year, offense type, and offense level fixed effects). *Panel B* presents the effect of PD-DA combination types on the probability of incarceration and sentence length. PD-DA combination type indicators are regressed on incarceration status. High value-added DAs increase the probability of incarceration, while high value-added PDs decrease the probability of incarceration. The specification includes design controls (year, offense type, and offense level fixed effects) and demographic controls (age, race, and sex).

Figure 3: Law School and Attorney Value-Added



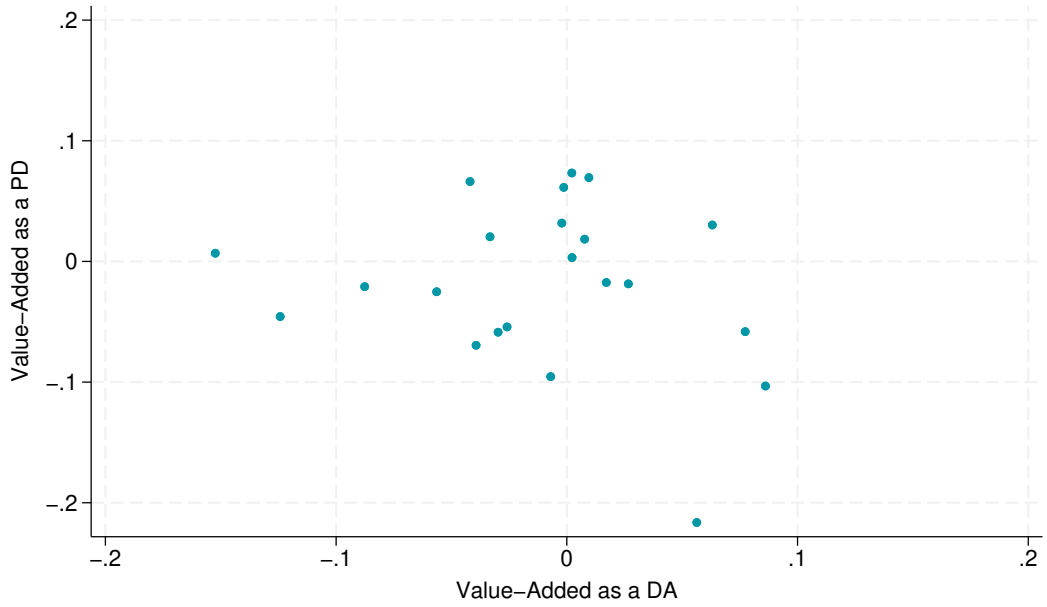
This figure shows the relationship between attorney value-added and law school rank. Ranked schools are those with U.S. News & World Report rankings 1–99; unranked schools are those ranked 100 or higher. The figure reports average value-added by law school rank, with standard errors shown for each mean.

Figure 4: Effect of Case Experience on Incarceration



This figure presents the relationship between attorney experience and the probability of incarceration. Panel A presents the relationship between DA experience and the probability of incarceration. Panel B presents the relationship between PD experience and the probability of incarceration. Incarceration indicators are regressed on indicators for the number of cases the attorney has handled. The number of cases handled by attorneys are binned by ten such the first non-omitted coefficient summarizes performance for cases ten through 20. All coefficients are relative to cases one through ten. The specification includes design controls (year, offense type, and offense level fixed effects), demographic controls (age, race, and sex), and attorney fixed effects to control for time invariant attorney characteristics. To avoid mismeasuring attorney experience, the sample is restricted to attorneys who first appear in 2006 despite the data beginning in 2005.

Figure 5: Value-Added as an PD and DA for Attorneys who Serve in Both Roles



This figure compares attorney value-added across roles for attorneys who have served as both PDs and DAs. PD value-added is defined as effectiveness at avoiding incarceration, and DA value-added as effectiveness at securing incarceration. I control the effect of attorney experience by residualizing the effect of experience in the value-added estimate.

TABLES

Table 1: Defendant Summary Statistics

Panel A: Demographics	
Male	.781
White	.293
Latino	.521
Black	.180
Age	32.640
Case per Defendant	1.522
Panel B: Offense Level	
First Degree	.091
Second Degree	.157
Third Degree	.258
State Degree	.492
Panel C: Case Outcomes	
Plea Guilty	.825
Incarceration	.479
Probation	.127
Deferred Adj.	.265
Plea and Incarcerate	.478
Number of Cases	70438

This table summarizes the characteristics of defendants and their cases. Panel A presents demographics of defendants. Panel B presents the offense level of a case. Panel C presents case outcomes. Observations are at the case level.

Table 2: Attorney Summary Statistics

Panel A: PD Characteristics	
Number of PDs	694
Average Number of Cases per PD	183.6
Average Yearly Caseload per PD	18.0
Panel B: DA Characteristics	
Number of DAs	286
Average Number of Cases per DA	593.3
Average Yearly Caseload per DA	115.1

This table summarizes information about attorneys and their caseloads. Panel A presents information about public defenders (PD). Panel B presents information about district attorneys (DA).

Table 3: Linearity of PD and DA Skill on Incarceration

	Incarceration								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PD VA	-.86***		-.85***	-.85***	-.85***	-.85***	-.85***	-.85***	-.85***
	(.041)		(.041)	(.041)	(.041)	(.041)	(.041)	(.041)	(.041)
DA VA		.92***	.92***	.92***	.91***	.92***	.92***	.91***	.92***
		(.032)	(.032)	(.032)	(.032)	(.032)	(.032)	(.032)	(.032)
PD VA				-1			-.89		
× DA VA				(.71)			(.79)		
(PD VA					-82		-93		
× DA VA)^2					(69)		(71)		
(PD VA						-2246	-1588		
× DA VA)^3						(2662)	(3007)		
PD VA^2								-82	
× DA VA^2								(69)	
PD VA^3									-2246
× DA VA^3									(2662)
R-Squared	.113	.117	.123	.123	.123	.123	.123	.123	.123
Dep. Var. Mean	.48	.48	.48	.48	.48	.48	.48	.48	.48
N	70270	70270	70270	70270	70270	70270	70270	70270	70270

The table reports the relationship between attorney value added and incarceration and tests for linearity of attorney effects. PD VA is $\hat{\lambda}^{EB}$. DA VA is $\hat{\gamma}^{EB}$. PD VA × DA VA is $\hat{\lambda}^{EB}$ multiplied by $\hat{\gamma}^{EB}$. Subsequent depedent variables are squares and cubes of the interaction. Each specification includes design controls (year, offense type, and offense level fixed effects) and demographic controls (age, race, and sex). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Relative Value-Added versus Absolute Value-Added on Incarceration

	Incarcerated	
	(1)	(2)
Relative Value-Added:		
DA Value-Added - PD Value-Added	.86***	.86***
	(.041)	(.041)
Absolute Value-Added:		
DA Value-Added	.049	.043
	(.052)	(.052)
Relative Value-Added × Absolute Value-Added		-.2
		(.23)
N	70436	70436

This table shows the relationship between relative value-added and absolute value-added. Attorney value-added is an empirical bayes shrunk leave-one-out measure of attorney value-added. Relative value-added is the difference between DA and PD value-added. Absolute value-added is DA value-added. Specifications (2) and (4) include the interaction of relative and absolute value-added. The specification includes design controls (year, offense type, and offense level fixed effects) and demographic controls (age, race, and sex). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effect of Relative Value-Added versus Absolute Value-Added on Characteristics and Recidivism of the Released

	Characteristics of the Released								Recidivism within of the Released
	(1) Black	(2) Felony History	(3) Misdemeanor History	(4) Predicted Recidivism	(5) Age	(6) First Degree	(7) Second Degree	(8) Third Degree	(9) Recidivism within 5 Years
Absolute Value-Added: DA Value-Added	-.062***	-.35***	-.024	-.0031	-.048***	-.032**	-.076***	.059	.21***
	(.023)	(.08)	(.043)	(.012)	(.018)	(.016)	(.026)	(.049)	(.039)
Control for Relative Value-Added	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	70436	70436	70436	70431	70436	70436	70436	70436	40525

This table shows the relationship between relative value-added and absolute value-added. Attorney value-added is an empirical bayes shrunk leave-one-out measure of attorney value-added. Relative value-added is the difference between DA and PD value-added. Absolute value-added is DA value-added. Specifications (2) and (4) include the interaction of relative and absolute value-added. The specification includes design controls (year, offense type, and offense level fixed effects) and demographic controls (age, race, and sex). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

APPENDIX

Appendix A: Two-Side Value Added Simulation

Consider a case i with a PD and a DA who each affect a case's outcome. In a finite sample, the estimate of a PD's skill may be biased by the skill of the DAs she faces. For example, if the PD stochastically faces only highly skilled DAs, the skill of a PD is downward biased relative to her true skill due to her unlucky assignment. By accounting for the DA's skill, bias in measuring the PD's skill can alleviated.

To exemplify this problem and how it relates to the size of finite samples, I simulate PD and DA skill and interactions. First, I generate 500 PDs and 500 DAs each with skill, $\lambda_p \sim \mathcal{N}(0,1)$ and $\gamma_d \sim \mathcal{N}(0,1)$, respectively. Each PD is randomly paired with a DA X times where X is the number of times each attorney is observed in a pair. Case outcome, Y_i, is estimated to be the addition of each attorney's skill, $Y_i = \lambda_{p(i)} + \gamma_{d(i)}$.

Without loss of generality, I focus on the estimation of PD skill using case outcomes. I regress case outcome, Y_i, on PD FEs, $\Lambda_{p(i)}$ to estimate the contribution of each PD. $\Lambda_{p(i)}$ is an indicator that PD p is assigned to be the PD on case i.

$$Y_i = \Lambda_{p(i)} + \epsilon_i \tag{4}$$

Next, I investigate the extent to which estimated PD skill, $\hat{\Lambda}_p$, is biased by the true skill, γ_d, of the set of DAs she faces. I regress estimated PD skill, $\hat{\Lambda}_{p(i)}$, on the true skill of the DAs she faces, $\gamma_d(i)$. This specification returns the relationship, β, between a PD's estimated skill and the true skill of the DAs she faces. If $\beta \neq 0$, estimated PD skill is biased by true DA skill.

$$\gamma_{d(i)} = \beta \hat{\Lambda}_{p(i)} + \epsilon_i \tag{5}$$

Figure D5 shows that the bias arising from DA skill in the presence of finite pairings can be an important source of bias when estimating PD skill. When only 5 pairings are observed, a PD's estimated skill is highly correlated with true DA skill. As the number of pairings increases, this effect dissipates since we observe the PD across an increasing number of simulated pairings.

This finding suggests that accounting for each attorney's effect is important when estimating attorney skill. This is especially true when we observe a small and finite number of pairings. In my setting, each PD handles approximately 59 cases over her career. Using Figure D5, we see that the bias arising from DA skill is still present in this number of pairings.

Appendix B: Empirical Bayes Procedure

To adjust my estimates of the fixed effects based on the scale of their prior variance, I use a two step empirical Bayes procedure. I will consider a linear model of the form

$$y_i = \lambda_{p(i)} + \gamma_{d(i)} + X_i'\beta + \epsilon_i \tag{6}$$

where ϵ_i is a mean zero normal random variable with variance σ_ϵ^2 given $\lambda_{p(i)}$ and $\gamma_{d(i)}$. I also assume that the fixed effects follow a prior distribution that is mean zero normal with variances $\sigma_{\lambda_p}^2$ and $\sigma_{\gamma_d}^2$. If the variances $\sigma_\epsilon^2, \sigma_{\lambda_p}^2, \sigma_{\gamma_d}^2$ were known, then the Bayesian posterior estimate of the fixed effects would be a shrunken version of the MLE estimate $\hat{\lambda}_p$ given by

$$\hat{\lambda}_p^{EB} = \hat{\lambda}_p \left(\frac{\sigma_{\lambda_p}^2}{\sigma_{\lambda_p}^2 + \frac{\sigma_\epsilon^2}{n_p}} \right) \tag{7}$$

where the coefficient $\alpha = \frac{\sigma_{\lambda_p}^2}{\sigma_{\lambda_p}^2 + \frac{\sigma_\epsilon^2}{n_p}} \in [0, 1]$ and n_p counts the number of observed cases involving PD p. As the number of observations n_p approaches infinity, this shrinkage effect disappears.

In practice, the likelihood variance σ_ϵ^2 and prior variances $\sigma_{\lambda_p}^2$ are not known prior to measuring the data, so they must be empirically estimated.

1. First, I estimate σ_ϵ^2 from the residuals obtained from a MLE regression $\{\hat{\epsilon}_i\}_{i=1}^n$

$$\hat{\sigma}_\epsilon^2 = \frac{1}{n} \sum_{i=1}^{n} \hat{\epsilon_i}^2 \tag{8}$$

2. Next, I empirically estimate the variance of the MLE coefficients using the MLE estimates of each PD fixed effect which we call $\hat{\lambda}_p$

$$\hat{\lambda}_p = \lambda_p + \epsilon_p \tag{9}$$

$$\sigma_{\lambda_p}^2 = \sigma_{\hat{\lambda}_p}^2 - \frac{\sigma_{\epsilon_p}^2}{n_p} \tag{10}$$

3. Lastly, I use the above formula to obtain an empirical Bayes estimate of the PD fixed effect

$$\hat{\lambda}_p^{EB} = \hat{\lambda}_p \left(\frac{\sigma_{\lambda_p}^2}{\sigma_{\lambda_p}^2 + \frac{\sigma_\epsilon^2}{N_p}} \right) \tag{11}$$

4. These steps are then repeated for the DA fixed effects.

Appendix C: Describing Characteristics of the Released

Consider the regression

$$C_i(1 - D_i) = \alpha + \beta R_i + \gamma A_i + \epsilon_i \tag{12}$$

where C_i denotes a defendant characteristics, $D_i \in \{0, 1\}$ indicates incarceration, R_i is relative value-added of i's PD-DA combination, and A_i is absolute value-added of i's DA. Let $D_i(r, a) \in \{0, 1\}$ denote potential incarceration outcome when $(R_i, A_i) = (r, a)$.

We assume PDs and DAs are independently and randomly assigned, so R_i and A_i are statistically independent of C_i and $D_i(r, a)$.[9] Motivated by the empirical finding that PD and DA value-added combine linearly, we impose that when $D_i(r, a) = 1$ variation in relative value-added r, holding absolute value-added a fixed, does not affect the probability of incarceration:

$$\frac{\partial}{\partial r} Pr(D_i(r, a) = 1) = 0. \tag{13}$$

This assumption rules out effects of relative value-added on the rate of incarceration while allowing relative value-added to shift the composition of who is incarcerated.

Relative value-added is linear in absolute value-added because $R_i = \gamma_{d(i)} - \lambda_{p(i)}$ and $A_i = \lambda_{p(i)}$ where $\gamma_{d(i)}$ and $\lambda_{p(i)}$ are independently assigned DA and PD value-added. Thus,

$$\begin{aligned} E[R_i|A_i, C_i, D_i(r, a)] &= E[R_i|A_i] && (14)\\ &= E[\gamma_{d(i)} - \lambda_{p(i)}|\lambda_{p(i)}] && (15)\\ &= E[\gamma_{d(i)}|\lambda_{p(i)}] - \lambda_{p(i)} && (16)\\ &= E[\gamma_{d(i)}] - A_i && (17) \end{aligned}$$

We can therefore apply the well-known results (Yitzhaki, 1996; Angrist and Krueger, 1999; Borusyak and Hull, 2024) to write the OLS coefficient β as a weighted average derivative of the conditional expectation $E[C_i(1 - D_i))|R_i = r, A_i = a] = E[C_i(1 - D_i(r, a))]$:

$$\beta = \iint \frac{\partial}{\partial r} E[C_i(1 - D_i(r, a))]\omega(r, a)drda, \tag{18}$$

where $\omega(r, a) \geq 0$ and $\iint \omega(r, a)drda = 1$ are convex weights.

[9] It is straightforward to extend the analysis to incorporate additional design controls. I omit these controls here to keep the notation compact.

We can decompose the inner derivative as

$$\frac{\partial}{\partial r}E[C_i(1-D_i(r,a))] = \frac{\partial}{\partial r}(E[C_i \mid D_i(r,a)=0]\ \Pr(D_i(r,a)=0)) \tag{19}$$

$$= \left(\frac{\partial}{\partial r}E[C_i \mid D_i(r,a)=0]\right)\Pr(D_i(r,a)=0) \tag{20}$$

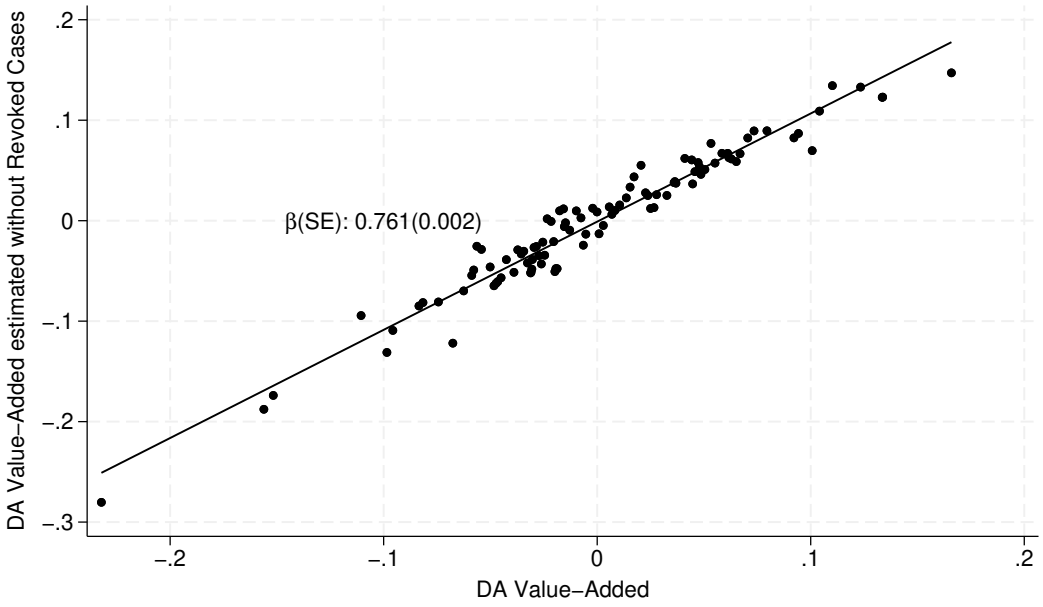
$$+ \underbrace{\left(\frac{\partial}{\partial r}\Pr(D_i(r,a)=0)\right)}_{=0} E[C_i \mid D_i(r,a)=0] \tag{21}$$

$$= \left(\frac{\partial}{\partial r}E[C_i \mid D_i(r,a)=0]\right)\Pr(D_i(r,a)=0). \tag{22}$$

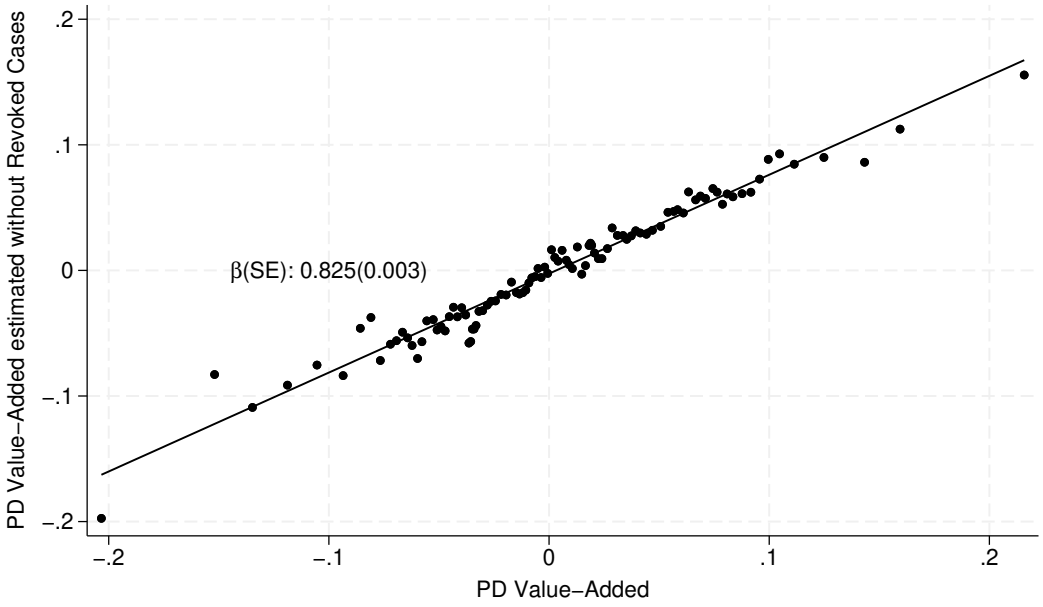
Thus, β gives a weighted average of marginal effects on the characteristics of released individuals as we move across relative value-added, $\frac{\partial}{\partial r}E[C_i|D_i(r,a)=0]$, weighted by the probability of release, $Pr(D_i(r,a)=0) = Pr(D_i(a)=0)$. The scaling makes the quantity of β hard to interpret, in general, but the sign is interpretable since $Pr(D_i(a)=0) \geq 0$.

Appendix D: Figures

Figure D1: Attorney Value-Added and Attorney Value-Added without Revoked Cases



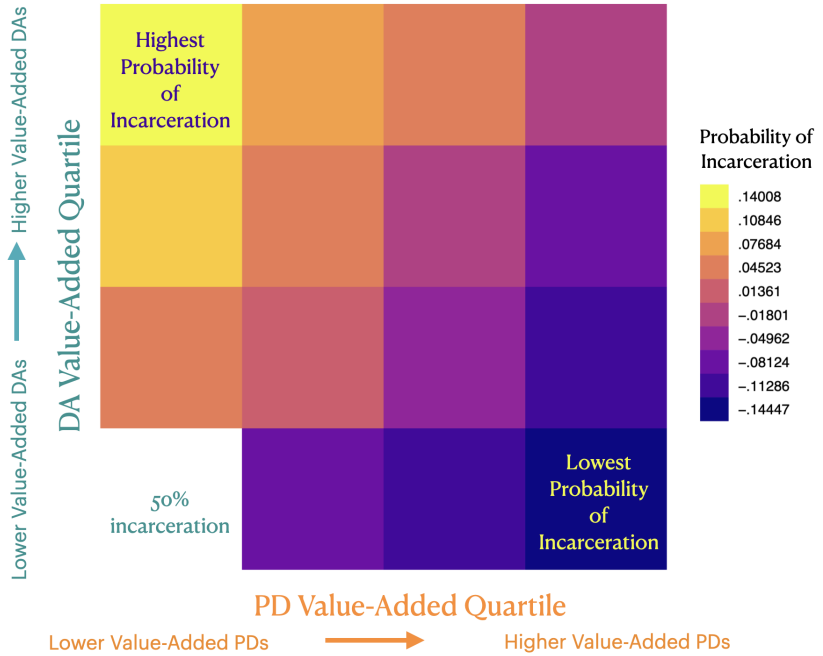
(a) DA Value-Added versus Non-Revoke DA Value-Added



(b) PD Value-Added versus Non-Revoke PD Value-Added

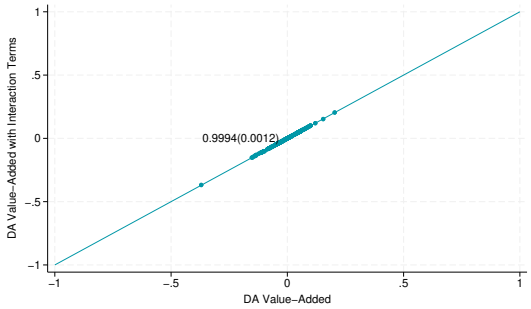
This figure presents the relationship between value-added estimated in the full sample and value-added estimated without revoked cases. The correlation between value-added measures is presented.

Figure D2: Effect of DA and PD Value-Added on Incarceration

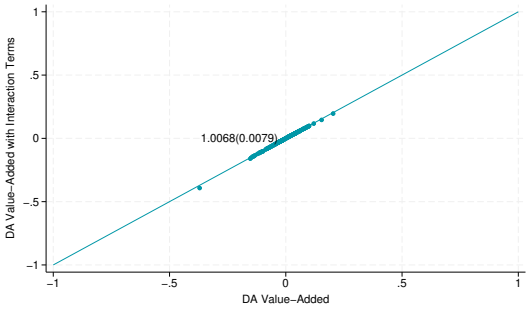


This figure presents the relationship between PD and DA value-added quartile and the probability of incarceration. DA value-added quartile is presented on the y-axis. Higher DA value-added represents DAs who are better at incarcerating defendants. PD value-added is presented on the x-axis. Higher PD value-added represents PDs who are better avoiding incarceration. PD-DA combination type is defined by the value-added level of the DA and the PD paired on a case. Cells in the grid are colored by the PD-DA combination types incarceration rate which is obtained from a specification that regresses incarceration on PD-DA combination type fixed effects in addition to fixed effects for offense level, year, and crime type. The cell for the combinations of the lowest value-added PDs and lowest value-added DAs is omitted and all coefficients are relative to this value-added cell.

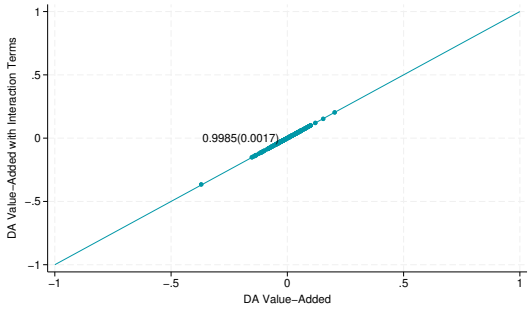
Figure D3: Relationship between DA Value-Added and DA Value-Added with Non-Linear Terms



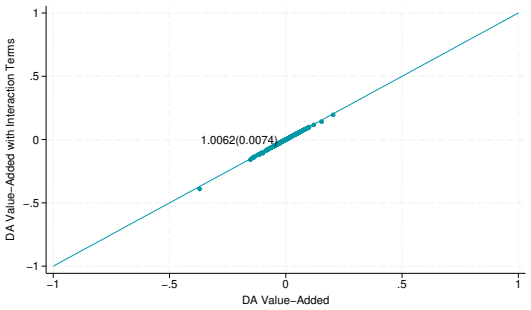
(a) Including PD VA × DA VA Term



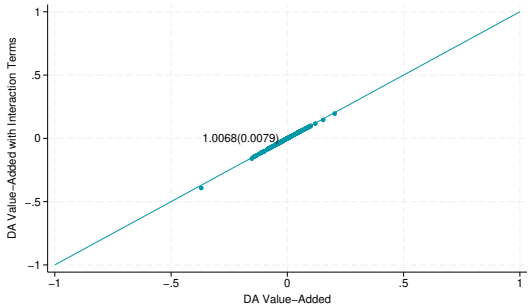
(b) Including (PD VA × DA VA)^2 Term



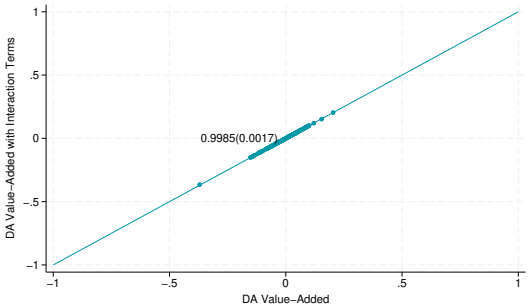
(c) Including (PD VA × DA VA)^3 Term



(d) Including (PD VA × DA VA)^2 + (PD VA × DA VA)^3 Term



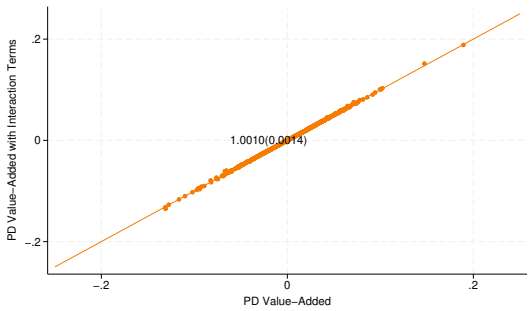
(e) Including (PD VA)^2 + (DA VA)^2 Term



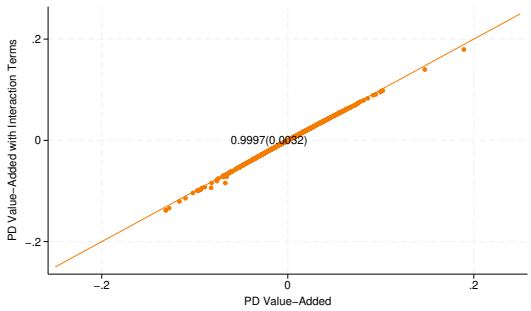
(f) Including (PD VA)^3 + (DA VA)^3 Term

This figure compares DA value-added with DA value-added with an interaction term. To construct the latter, I use the coefficients from Table 3 together with DA value-added estimates to compute the contribution of the non-linear interaction, which I then add to the DA's value-added. The figure reports the relationship between the baseline measure and the augmented measure.

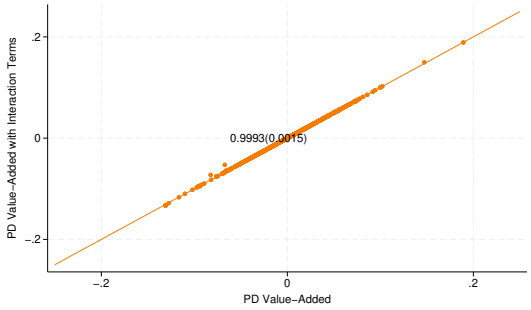
Figure D4: Relationship between PD Value-Added and PD Value-Added with Non-Linear Terms



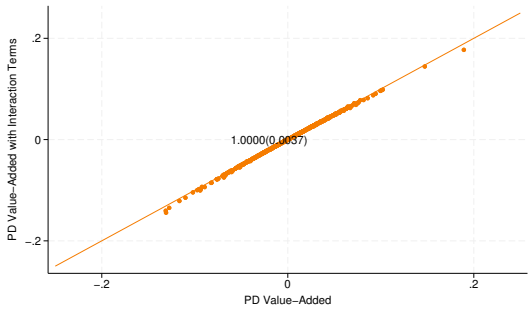
(a) Including PD VA × DA VA Term



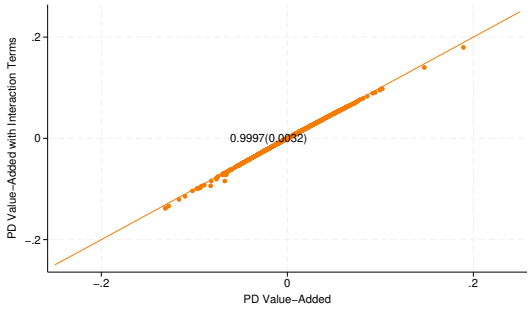
(b) Including (PD VA × DA VA)^2 Term



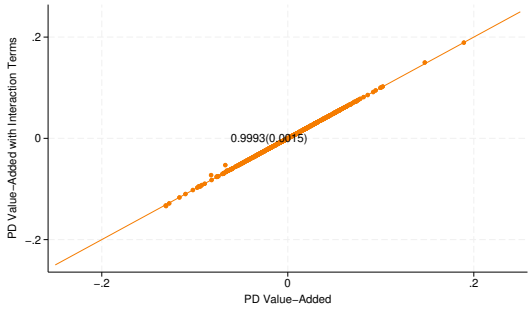
(c) Including (PD VA × DA VA)^3 Term



(d) Including (PD VA × DA VA)^2 + (PD VA × DA VA)^3 Term



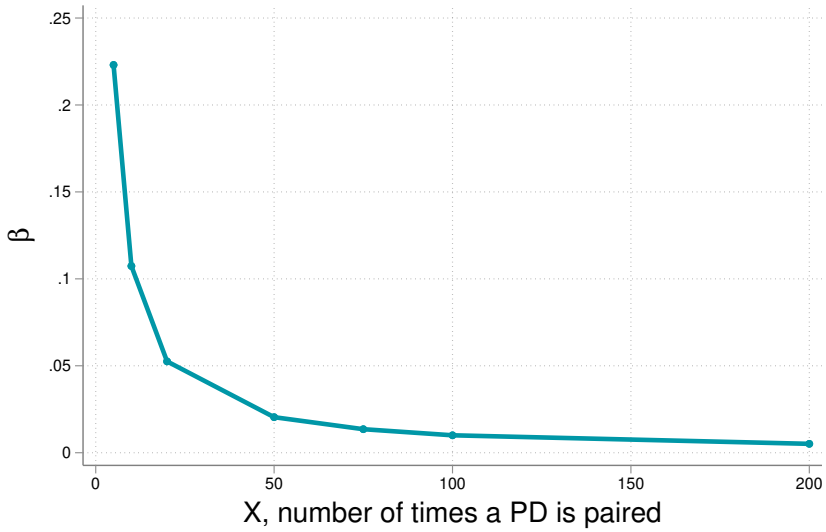
(e) Including (PD VA)^2 + (DA VA)^2 Term



(f) Including (PD VA)^3 + (DA VA)^3 Term

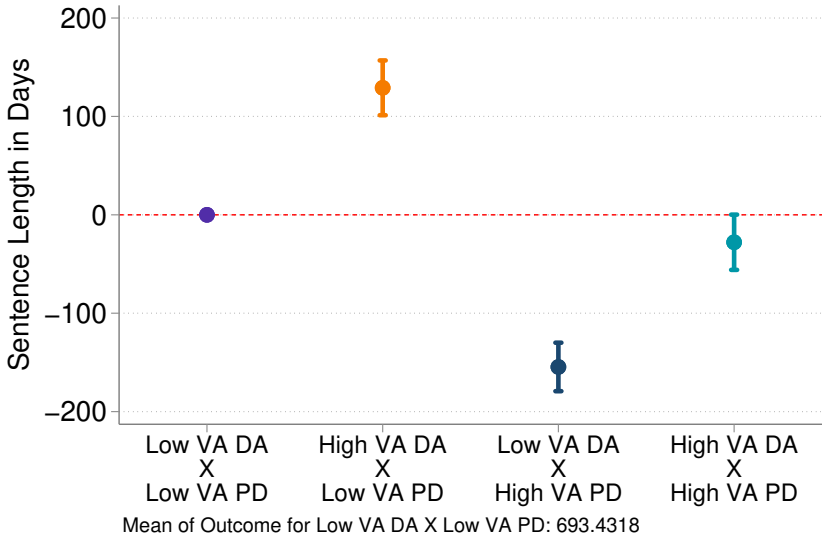
This figure compares PD value-added with PD value-added with an interaction term. To construct the latter, I use the coefficients from Table 3 together with PD value-added estimates to compute the contribution of the non-linear interaction, which I then add to the PD's value-added. The figure reports the relationship between the baseline measure and the augmented measure.

Figure D5: Relationship between true DA Skill and Estimated PD Skill



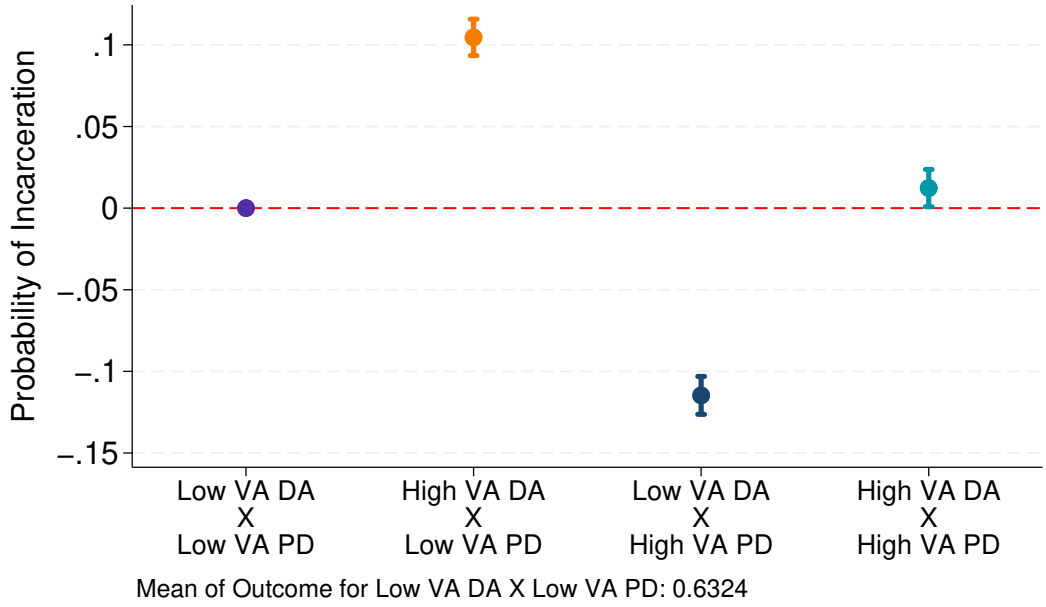
This figure presents the relationship between DA skill and estimated PD skill by sample size. The y-axis reports the coefficient β from Equation 5. The x-axis reports the number of pairs in which each PD and DA are observed.

Figure D6: Effect of PD-DA Combination on Case Length

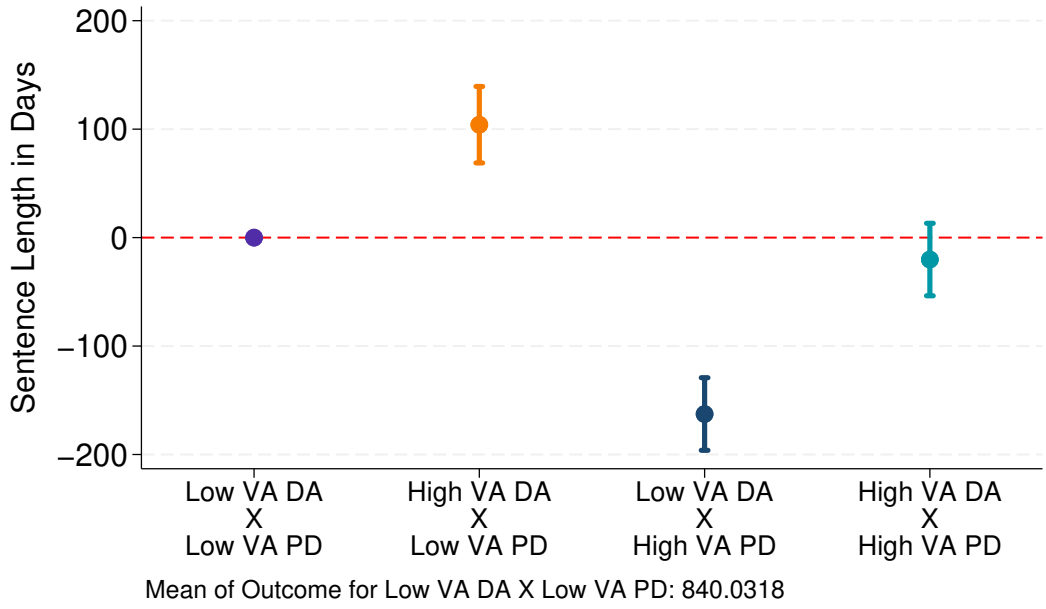


This figure presents the effect of PD-DA combination types on sentence length. PD-DA combination type indicators are regressed on sentence length. Sentence length is the number of days of incarceration imposed on a defendant in case sentencing and includes zeroes for cases where no incarceration is imposed. High value-added attorneys are those above the median, and low value-added attorneys are those below. High value-added DAs increase the probability of incarceration, while high value-added PDs decrease the probability of incarceration. PD-DA combination type indicators are regressed on sentence length which is the number of days an individual is incarcerated. The specification includes design controls (year, offense type, and offense level fixed effects) and demographic controls (age, race, and sex).

Figure D7: Effect of PD-DA Combinations, Non-Revoked Cases



(a) Effect of PD-DA Combination on Incarceration



(b) Effect of PD-DA Combination on Case Length

This figure presents the effect of PD-DA combination types on the probability of incarceration and sentence length. In figure D7a, PD-DA combination type indicators are regressed on incarceration status. In figure D7b, PD-DA combination type indicators are regressed on sentence length. Sentence length is the number of days of incarceration imposed on a defendant in case sentencing and includes zeroes for cases where no incarceration is imposed. High value-added attorneys are those above the median, and low value-added attorneys are those below. High value-added DAs increase the probability of incarceration, while high value-added PDs decrease the probability of incarceration. PD-DA combination type indicators are regressed on sentence length which is the number of days an individual is incarcerated. The specification includes design controls (year, offense type, and offense level fixed effects) and demographic controls (age, race, and sex).

Appendix E: Appendix Tables

Table E1: Measures of Value Added, Leave-One-Out

	Incarcerated			
	(1)	(2)	(3)	(4)
PD Leave-One-Out	.526***			
	(.0261)			
PD EB Leave-One-Out		.860***		
		(.0407)		
DA Leave-One-Out			.773***	
			(.0280)	
DA EB Leave-One-Out				.908***
				(.0324)

This table reports the relationship between incarceration status and leave-one-out value-added. Column 1 uses a leave-one-out PD value-added. Column 2 uses the empirical Bayes (EB) shrinkage of leave-one-out PD value-added. Columns 3-4 repeat these specifications for DAs. The specification includes design controls (year, offense type, and offense level fixed effects) and demographic controls (age, race, and sex).

Table E2: Linearity Simulation of PD and DA Skill on Incarceration

	Incarceration Outcome includes Non-Linear Terms					
	(1) PD VA × DA VA	(2) PD VA × DA VA	(3) PD VA^2 × DA VA^2	(4) PD VA^2 × DA VA^2	(5) (PD VA × DA VA)^2	(6) (PD VA × DA VA)^2
PD VA	.98***	.98***				
	(.0039)	(.0039)				
DA VA	1***	1***				
	(.0037)	(.0037)				
PD VA × DA VA		.036***				
		(.013)				
PD VA			.98***	.98***		
			(.0039)	(.0039)		
DA VA			1***	1***		
			(.0037)	(.0037)		
PD VA^2 × DA VA^2				-.027		
				(.1)		
PD VA					.98***	.98***
					(.0039)	(.0039)
DA VA					1***	1***
					(.0037)	(.0037)
(PD VA × DA VA)^2						-.027
						(.1)
R-Squared	.660	.660	.660	.660	.660	.660
N	70000	70000	70000	70000	70000	70000

The table reports the results of a simulation investigating the role of non-linear terms. I simulate 70,000 cases with a PD and a DA. PDs and DAs have a true observed value added terms simulated from a normal distribution with a mean 0 and standard deviation 0.06. This table presents three models of how PD and DA vale-added impacts incarceration status. First, incarceration is 1 when PD VA + DA VA + (PD × DA) is greater than the average of PD VA + DA VA + (PD × DA) and 0 otherwise. Second, incarceration is 1 when PD VA + DA VA + (PD^2 × DA^2) is greater than the average of PD VA + DA VA + (PD^2 × DA^2) and 0 otherwise. Third, incarceration is 1 when PD VA + DA VA + (PD × DA)^2 is greater than the average of PD VA + DA VA + (PD × DA)^2 and 0 otherwise. Call these incarceration statuses determined from non-linear specifications, $\tilde{y}$. For each $\tilde{y}$, I estimate PD VA ($\tilde{\lambda_p}$) and DA VA ($\tilde{\gamma_p}$) using my two-sided value added specification. In columns 1, 3, and 5, I regress the $\tilde{y}$ on $\tilde{\lambda_p}$ and $\tilde{\gamma_p}$. In columns 2, 4, and 6, I include the non-linear term to the specification. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.