# Representation Matters: Legal Representation and Outcomes in Hamilton County Eviction Court.

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## Summary

Everyone who's watched a police procedural knows the spiel: "... *You have the right to speak to an attorney... If you cannot afford a lawyer, one will be provided for you at government expense.*" The Sixth Amendment ensures that defendants in criminal proceedings are represented by an attorney. If criminal defendants were forced to defend themselves against a properly trained and funded lawyer from the prosecutor's office on their own it is unlikely they could mount a successful case, regardless of the facts at hand.

The same guarantee does not extend, however, for defendants in eviction hearings. Thousands of eviction cases are heard every month in Hamilton County, but only 7% of tenants have a lawyer, compared to 93% of the landlords. There thus appears to be an inherent power imbalance in the courts favoring landlords. "Equal Justice Under Law" is a core tenet of the American legal system, but when eviction court has such lopsided representation, is that principle being upheld?

To address this power imbalance (among other reasons), a number of cities and states have passed Right/Access to Counsel laws to ensure legal representation in eviction hearings for tenants. Proponents assert that this makes the trials more equitable, improving tenant outcomes. There is an intuitive appeal to this claim - properly trained lawyers with experience in eviction court are more likely to be successful in presenting a defense or challenging an eviction suit than a pro se defendant. To investigate, this paper examines eviction cases heard in Hamilton County from March 2021 to January 2023 and finds that tenants who have lawyers have an 84% lower risk of receiving an eviction order than tenants without lawyers. Further analysis to isolate the effect of legal representation reveals a slight increase in the impact a defense attorney has on whether a client is evicted, demonstrating the reliability of the original conclusion. This paper concludes with a discussion of the policy implications of these findings.

## Previous Research

Prior investigations into the impact of legal representation on evictions demonstrate a reliable relationship between legal representation for tenants in eviction court and a reduction in the likelihood of receiving an eviction order.

A [2022 study out of Princeton ](#)looked into the rollout of New York City's Universal Access to Counsel program from 2016 to 2019, in which tenants at or below 200% FPL were offered free legal representation in housing court. The study found that "tenants who gain access to lawyers are less likely to be subject to possessory judgments, face smaller monetary judgments, and are less likely to have eviction warrants issued against them. [Universal Access to Counsel] also reduces executed evictions in these locations." This effect was most pronounced in poorer areas and areas with larger shares of non-citizens. Another study of the program found it was able to keep 84% of represented tenants in their homes after the proceedings had concluded in its first year of operation, July 2017 to June 2018.

A study of eviction cases filed in Hennepin County between January 1 and June 30, 2018 showed marked benefits for tenants with legal representation. Represented tenants won or settled their cases 96% of the time, compared to 62% of the time for unrepresented tenants. Represented tenants were almost twice as likely to stay in their homes; when they did agree to move, represented tenants had nearly twice as long to do so than unrepresented tenants. Represented tenants were also over 60 times more likely to leave court without an eviction record and four times less likely to use homeless shelters.

An analysis by Stout Risius Ross of Baltimore's housing court found that tenants who did not have legal representation likely experienced "disruptive displacement" in approximately 93% of eviction cases. Tenants who did have legal representation, on the other hand, avoided disruptive displacement in approximately 92% of cases.

An analysis of Tulsa's eviction docket found that landlords won evictions against unrepresented tenants in 79% of cases, while they won evictions against represented tenants at roughly half that rate, 43%. Moreover, money judgments were issued against unrepresented tenants in 78% of cases, while represented tenants received money judgments just 34% of the time. Represented tenants' money judgements were on average $800 less than money judgements rendered against unrepresented tenants.

In 2021, Cleveland's Right to Counsel Program was able to prevent an eviction or involuntary move in 93% of cases, secured monetary relief in 97% of cases, mitigated damages in 94% of cases, and secured 30 days or more to move in 92% of cases.

There have also been Random Control Trials (RCTs) of the effects of legal representation on eviction in housing court. RCTs are considered the "gold standard" of social science experiments because of their ability to eliminate covariates and other outside factors that could have an effect on the experiment's results. If the lawyers can choose the cases they represent, there is a likelihood they will pick the cases they believe they are most likely to win, leading to an inflated effect size. Even if tenants simply have to opt-in to receive lawyers, this could skew results, as it may signify that these tenants have more resources than tenants who don't opt in, they may believe their case is more winnable, they may be more comfortable in bureaucratic settings & better able to defend themselves in court. By randomly assigning lawyers to some tenants and not others, these effects as well as other possible biases and confounds are minimized, allowing us to better observe the true impact a lawyer has on a tenant's eviction case.

One such study, conducted in Manhattan from September 1993 to June 1994, randomly assigned lawyers to tenants who met the income eligibility of legal aid. It found that judgements against tenants occurred 22% of the time for represented tenants and 51% of the time for unrepresented tenants. Tenants with lawyers received warrants of eviction in 10% of cases, while tenants without lawyers received warrants of eviction in 44% of cases. Not only were tenants with lawyers more likely to avoid negative consequences, they were also more likely to receive positive outcomes; tenants with lawyers received stipulations requiring rent abatements in 31% of cases and stipulations requiring repairs in 64% of cases, compared to 2% and 25% of cases for tenants without lawyers, respectively.

Another study in which tenants were randomly assigned legal representation occurred in Boston. All tenants recruited to the study received "unbundled" assistance from lawyers, which included "how-to" sessions such as instruction on the summary eviction process as well as help in filling out answer and discovery request forms. A select group of these tenants was then provided full legal representation for their eviction cases. The results were substantial: two-thirds of tenants with lawyers, as opposed to one-third of tenants without lawyers, were able to maintain possession of their rental units after their court cases were concluded. The difference in rates of writs of eviction issuance was even more substantial, with 60% of tenants without lawyers receiving such writs, compared to 12% of tenants with lawyers. Greater still was the gulf between tenants for whom judgements of possession for the landlord were issued; 75% of the tenants without lawyers received these, while only 17% of tenants with lawyers received these.

# Eviction Court Process in Ohio

Most eviction cases in Hamilton County consist of two parts, known as "causes" or "claims." They are technically part of the same lawsuit, but the court treats them as though they are separate trials.

The First Cause is what most people think of as the eviction: the landlord has brought an action against their tenant to force the tenant to leave their apartment. Typically it takes about a month from when the landlord files the eviction to the eviction being heard by the court, and tenants are to receive notice roughly a week before the hearing. The only issue decided at the First Cause trail is whether the tenant will be evicted. Common defenses to an eviction filing are that the tenant did pay the rent the landlord claims was owed, the rent had been escrowed, the landlord attempted to evict the tenant illegally, or that the claim the tenant broke the lease is somehow not true. If the tenant wins this case, they may remain in their apartment; if they lose, the court issues an order known as a "writ of eviction," which starts the process of a tenant being put out of their apartment. The Second Cause of Actions occurs when the landlord claims the tenant owes them money and is suing them for the amount they believe they are owed.

# Methodology

For the purposes of this study, an "eviction" is defined as the court issuing a writ of eviction after the First Cause of Action is heard. This was chosen, rather than the physical execution of the eviction, because the issuance of the writ is the step in the process where an attorney has the most impact on the proceedings. Writs of eviction can expire or be reissued, the tenant may move before the physical eviction occurs, or the tenant and landlord may come to an agreement that ultimately avoids the final eviction action, all of which may happen without any input from the attorney.

To examine the impact of legal representation on tenant evictions, I gathered information on all the eviction cases heard from March 16, 2021 to January 31, 2023 from the Hamilton County Clerk of Courts Electronic Docket. Counting the number of cases where a writ of eviction was issued and grouping by whether the tenant had an attorney yields the following results (Table 1, Figure 1):

| | **No Writ Issued** | **Writ of Eviction Issued** | **Eviction Rate** |
|---|---|---|---|
| **No Tenant Attorney (n=18,555)** | 9,351 | 9,204 | 49.60% |
| **Has Tenant Attorney (n=1,321)** | 1,215 | 106 | 8.02% |

Table 1.

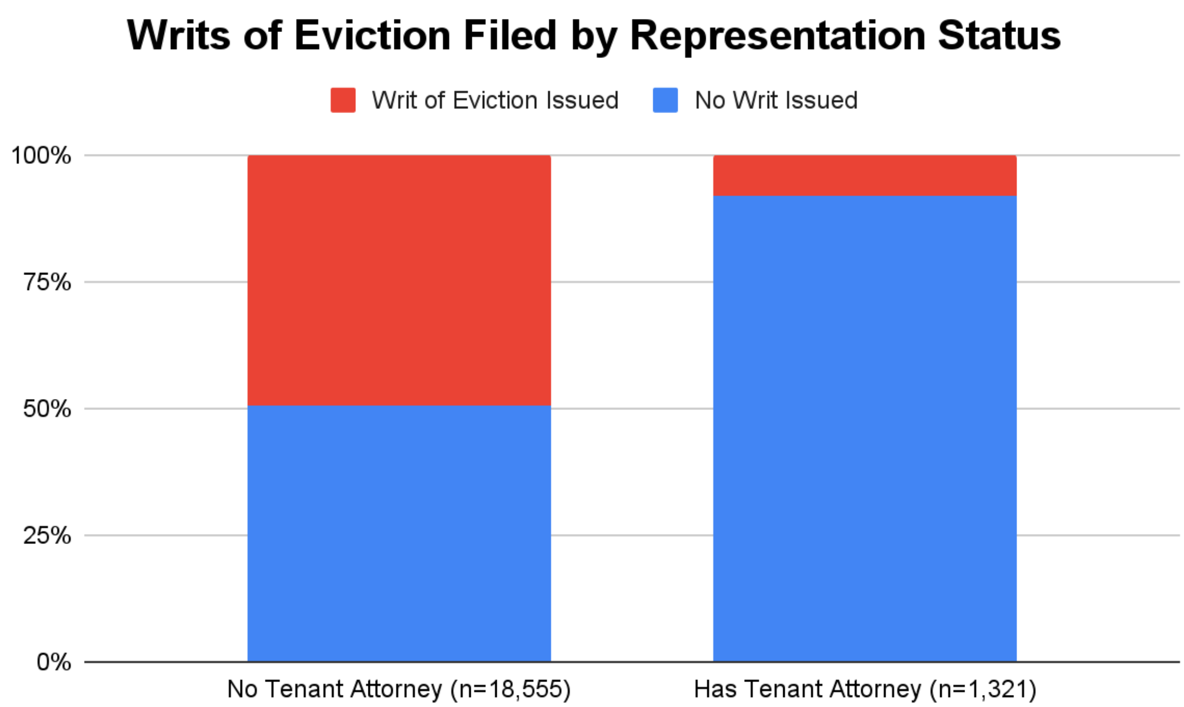


Figure 1

From the data provided, we see that tenants without attorneys received eviction orders in 49.6% of cases, while tenants with attorneys received eviction orders 8.0% of the time. This means tenants with lawyers are (8%/49.6%) = 0.16 times as likely to be evicted as tenants without lawyers.  Said another way, tenants with lawyers are at an 1- 0.16 = 84% [lower risk] of an eviction order than tenants without lawyers. This conclusion has a very high level of statistical significance, with a p-value of $4.8 \times 10^{-188}$.[1]

Because the lawyers are not randomly assigned to cases, the choice of which cases to represent could be distorting the true impact legal representation has in eviction court. To investigate this, several logistic regression models were employed, detailed in Table 2. The analysis, described more thoroughly in Appendix B, found the original risk reduction within the 95% confidence interval of all four models' coefficients, with the benefit slightly increasing, rather than decreasing, when the controls were implemented.

| **Impact of Defense Attorneys for Tenants Facing Eviction** | | | |
|---|---|---|---|
| **Model Description** | **Reduced Risk of Eviction** | **Risk Reduction: 95% Confidence Interval (Lower)** | **Risk Reduction: 95% Confidence Interval (Upper)** |
| **1. No control variables** | 84.25% | 80.26% | 87.44% |
| **2. Control for Tenant's Landlord** | 85.57% | 81.79% | 88.56% |
| **3. Control for tenant's neighborhood** | 85.08% | 81.24% | 88.14% |
| **4. Control for landlord and neighborhood** | 86.44% | 82.80% | 89.30% |

Table 2.

# The Consequences of Evictions & Policy Implications

It bears repeating the trauma evictions inflict on the people who experience them. A study performed by [Case Western Reserve University researchers]() found that households who received eviction orders experienced significantly higher rates of residential mobility and homeless shelter use than households that did not receive eviction orders. When families are evicted, their belongings can be lost or destroyed during a forced move. An eviction on someone's record can negatively impact their ability to find new housing.  Children may need to switch schools midyear, and families are likely to relocate to neighborhoods with [higher crime and poverty rates]().

Furthermore, although the above analysis focused on disparate rates of eviction orders, tenants with legal representation were less likely to experience physical eviction as well.  During the period of the study 2,403 physical evictions were executed, 98.5% of which happened to tenants without lawyers (Table 3).

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[1] The p-value was calculated using a Chi Square test of Independence. Refer to Appendix A for more information.

| Physical Evictions by Representation Status | | | |
|---|---|---|---|
| | **No Physical Evictions** | **Physical Eviction** | **Physical Eviction Rate** |
| **No Defense Attorney** | 16,188 | 2,367 | 12.76% |
| **Has Defense Attorney** | 1,286 | 36 | 2.72% |

Table 3

This is likely an undercount of the forced moves occurring after an eviction order, as a tenant who leaves before being physically evicted wouldn't be included in these statistics. Still, we can see that tenants with lawyers have a 79% reduced risk of physical eviction compared to tenants who did not have lawyers. With the p-value of the Chi Square Test being $4.86*10^{\wedge -27}$, we can conclude that the relationship is statistically significant.

A paper from the National Bureau of Economic Research found that evictions increase residential mobility by 28%, the use of homelessness services by 200%, and hospital visits by 29%. At the same time, they reduced household earnings by thousands of dollars for years following evictions as well as financial health overall. The effects of forced moves can be especially traumatizing for children, resulting in diminished educational outcomes, which can lead to higher incarceration rates and lower incomes as adults.

Eviction correlates with many negative health indicators in adults. Adults who have been evicted experience a higher mortality rate than matched control study participants, HIV-positive people's viral load is more likely to be detectable after an eviction, and drug use rates increase. One study of low-income urban mothers found that evicted mothers were more likely to experience worse health for themselves and their children, parenting stress, depression, and material hardship, in comparison to mothers who were not evicted. Children who were subject to eviction were twice as likely to experience food insecurity as non-evicted children in their cohort. Children who are food insecure are more likely to develop chronic conditions such as anemia and asthma, repeat a grade in elementary school, and have more social and behavioral problems.

Financial and medical hardships of eviction have been seen to compound: in New York, evictions lead to a 63% increase in the odds of a tenant losing their Medicaid coverage, fewer pharmaceutical prescription fills, and decreased odds of generating any healthcare spending. Among tenants who did incur healthcare spending, the average spending amount was 20% higher among evictees. People who have been evicted not only see higher average healthcare spending but are also more likely to have lost their insurance, compounding the harm of illness with an increased financial burden.

A number of studies show that evictions are a leading cause of homelessness, with 98 percent of homeless shelter requestors having once been primary tenants. Experiencing homelessness is associated with marked declines in physical and mental health, resulting in greater emergency room use, greater inpatient admissions, and longer hospital stays than the housed population. Additionally, as life-sustaining activities people take while being unhoused have become increasingly criminalized in recent years, greatly increasing the odds of unhoused people experiencing police contacts or spending time in jail, feeding into a homelessness-jail cycle that can be very difficult to break.

Furthermore, the harm of eviction tends to fall disproportionately on historically marginalized and oppressed people. After examining more than 4 million eviction cases filed from 2012 to 2016, researchers from Rutgers and Princeton found Black and Latinx renters were the subject of a disproportionately high percentage of eviction filings. The eviction filing rate against Black tenants was 6.2%, an 80% increase from the eviction rate of white tenants. The Latinx eviction rate was 6% higher than the white tenant rate, which was a smaller difference, but still statistically significant. Black renters also experienced a 70% higher eviction rate than white renters. The compounding mental health effects associated with eviction, along with the racial disparity in eviction filings, has been cited as a major contributor to racial health inequities in Memphis, according to researchers at the University of Memphis. There is also a gender disparity in evictions, with Black and Latinx female renters receiving eviction filings and eviction orders at higher rates than Black and Latinx male renters.

In addition to the harm evictions cause families, their effects are felt by the communities where they occur as well. A study of homicide, robbery, and burglary rates in Philadelphia neighborhoods from 2006 through 2016 showed an association between eviction rates and rates of all three types of crime in fully controlled models. A study of Ohio evictions from 2000 to 2014 found that each 10 percent increase in evictions leads to 5.5 percent higher burglary into structures and 8.5 percent higher vehicle theft.

Evictions have also been shown to adversely affect the budgets of the cities where they occur. An analysis by the Urban Institute showed that, in addition to the emergency services and shelter costs associated with families subject to forced displacements, evictions also result in decreased collections of property taxes and utility bills and their associated taxes. This results in hundreds of millions of dollars in lost revenue for large cities like New York and Los Angeles and tens of millions of dollars of lost revenue for cities like Columbus.

# Conclusion

Being evicted can be incredibly stressful and traumatizing for families. Tenants who are unfamiliar with the legal process are matched up against landlords and their lawyers with years of experience in eviction court. In Hamilton County, only 7.2% of residential tenants are represented by counsel, while landlords in those cases have legal representation 92.6% of the time. If a tenant does lose their case and get evicted, the results can be dire and long-lived. Eviction increases rates of homelessness and hospitalization, increases childrens' food insecurity, and can diminish total income by thousands of dollars annually. In addition to the strife caused to city residents, addressing these negative outcomes can precipitate tens of millions of dollars of lost income for municipalities where evictions occur.

Fortunately, by leveling the playing field in eviction court, a Tenant's Right to Counsel can help tenants avoid these negative outcomes. Cleveland's Right To Counsel program was 92-99% effective in securing tenants' goals of avoiding involuntary moves, securing monetary relief, or securing 30+ days to move. These positive outcomes for tenants resulted in cost reductions to the city, yielding an estimated ROI of 159% - 174%.

The positive impacts of legal representation for tenants in eviction court are already apparent in Hamilton County. Tenants with lawyers are at a substantially reduced risk both of receiving an eviction order and being physically evicted, allowing them to avoid the associated costs and trauma caused by eviction. Extending the benefits of legal representation to all tenants facing eviction not only makes the process fairer but avoids massive harm to families, neighborhoods, and municipalities.

# APPENDIX A: CHI SQUARE TEST OF INDEPENDENCE

In reference to the conclusion that the decreased risk of eviction for tenants with lawyers is statistically significant: when performing an observational study such as this, there is a possibility that the results are the product of coincidence or random chance. To investigate this, a Chi-square test of independence was used. This analysis allows us to calculate a p-value of the test, which represents the likelihood of the results being a product of random chance. Conventionally, a p-value less than 0.05 indicates the results are not the product of chance, while a value greater than 0.05 suggests otherwise. In this instance, the p-value is $4.8 \times 10^{-188}$, which is nearly indistinguishable from zero and much much smaller than the threshold value of 0.05. From this we can conclude that there is a statistically significant relationship between a tenant having a defense attorney and whether the First Cause trial results in an eviction order for the tenant.

# Appendix B: Explanation of Logistic Regression Methodology

Logistic regression operates similarly to linear regression, in that it can help to explain phenomena influenced by multiple variables by calculating the influence each variable has on the outcome. The influence is represented by the coefficients calculated when fitting the model to the dataset. While linear regression is used for continuous outputs, logistic regression is used when the dependent variable can be one of a set of discrete values. In this case, the dependent variable is binary - either the defendant received a writ of eviction (output = 1), or they didn't (output = 0). The resulting model coefficients indicate how much a given variable affects the outcome. A negative number means the presence of the variable decreases the odds of the dependent variable being 1, while a positive number increases it. Also, a coefficient with a larger magnitude will have a greater effect than a coefficient with a smaller magnitude.

In an attempt to isolate the effect of legal representation from other possible factors, a control group of unrepresented tenants was selected to match the treatment group as closely as possible. The attributes used to pair the cases were geographic proximity (all cases were within a mile of each other, save for one pair of cases that was 1.2 miles apart) and by landlord when possible (1112 of the 1321 treatment records were paired with cases from the same landlord, while 209 were not). The tenant's landlord and neighborhood were also added as control variables in subsequent models to further isolate the impact of legal representation in eviction court.[2]

The crosstabulation values of the constructed control dataset along with the treatment dataset are:

| | **writ not issued** | **writ issued** | **eviction order rate** |
|---|---|---|---|
| **No Defense Attorney** | 648 | 673 | 50.95% |
| **Defendant Has Attorney** | 1215 | 106 | 8.02% |

The four models investigated are listed in Table 4:

| **Logistic Regression Model Formulas** | |
|---|---|
| Description | Formula |
| 1. No control variables | $logit(y) = \alpha + X_{ATTY} * \beta_{ATTY}$ |
| 2. Control for Tenant's Landlord | $logit(y) = \alpha + X_{ATTY} * \beta_{ATTY} + X_{LL} * \beta_{LL}$ |

[2] To explain why landlord and neighborhood were chosen as controls: Cincinnati is well-known to have distinct neighborhoods with regards to income, race, education, etc. As tenants' income, education, and demographic data were not available for this study, this was chosen as a proxy. Landlords were included in the matching process due to the assumption that a given landlord is likely to use a consistent approach when evicting their tenants, leading to similar experience for tenants with and without representation.

| | |
|---|---|
| 3. Control for tenant's location (neighborhood in Cincinnati, municipality outside of Cincinnati). | $logit(y) = \alpha + X_{ATTY} * \beta_{ATTY} + X_{NHBD} * \beta_{NBHD}$ |
| 4. Control for tenant's landlord and location | $logit(y) = \alpha + X_{ATTY} * \beta_{ATTY} + X_{NHBD} * \beta_{NBHD} + X_{LL} * \beta_{LL}$ |

Table 4

For each model, $y$ indicates whether a writ of eviction was issued in the tenant's case. The y-intercept is represented by $\alpha$, the $X$ variables represent data gathered from the tenants' eviction cases (binary values for $X_{ATTY}$ and one-hot encodings for $X_{NHBD}$ and $X_{LL}$, where the value is 1 when the tenant lives in that neighborhood or rents from that landlord and 0 otherwise. The $\beta$ values are the coefficients calculated by the model that represent how a given variable affects the outcome i.e. whether a tenant is evicted.

# Model 1

The first model did not include any control variables:

$$logit(y) = \alpha + \beta_{ATTY} * X_{ATTY} \qquad \text{(Equation 1)}$$

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In Equation 1, $y$ is the binary variable indicating whether an eviction case had a writ of eviction filed (1 if a writ was filed, 0 if a writ was not filed), $X_{ATTY}$ is a binary variable indicating whether the tenant had an attorney (1 if the tenant had an attorney, 0 if the tenant did not), $\beta_{ATTY}$ is the regression coefficient, and $\alpha$ is the y-intercept.

This gave the following results:

## Logistic Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | writ_issued | **No. Observations:** | 2642 |
| **Model:** | Logit | **Df Residuals:** | 2640 |
| **Method:** | MLE | **Df Model:** | 1 |
| **Date:** | Thu, 23 Mar 2023 | **Pseudo R-squ.:** | 0.1983 |
| **Time:** | 16:20:51 | **Log-Likelihood:** | -1284.4 |
| **converged:** | TRUE | **LL-Null:** | -1602.2 |
| **Covariance Type:** | nonrobust | **LLR p-value:** | 3.13E-140 |

| | coef | std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **defendant_has_atty** | -2.4769 | 0.115 | -21.489 | 0 | -2.703 | -2.251 |
| **y-intercept** | 0.0379 | 0.055 | 0.688 | 0.492 | -0.07 | 0.146 |

We see that the coefficient has a p value of 0, suggesting that it is statistically significant. A $\beta1$ value of -2.4769 indicates that a tenant having a lawyer is associated with a decrease in the likelihood of receiving an order of eviction. This translates to an odds ratio of exp( $\beta1$) = exp(-2.4769) = 0.084 of a tenant with a lawyer receiving an eviction order versus a tenant without a lawyer receiving such an order; the relative risk associated with this is calculated with Formula 1:

$$RR = \frac{OR * (1 - P_T)}{(1 - P_C)} \qquad \text{(Formula 1)}$$

where $P_T$ is the probability of the event occurring in the treatment population and $P_C$ being the probability of the event occurring in the control population, with the event in this case being the receipt of an eviction order. Thus, tenants with attorneys are 0.1575 times as likely to receive an eviction order than unrepresented tenants, or 1- 0.1575 = 84.25% less likely to receive an eviction order. The 95% confidence interval of $\beta1$ being between -2.703 and -2.251 corresponds to reduced risk of eviction orders of 80.26% and 87.44%, which is consistent with the original analysis of the data in Table 1, where the risk was reduced by 83.82%.

**Model 2**

To further tease out the defense attorney effect, the next model introduced variables to control for the tenant's landlord. Different properties owned by the same landlord were matched using the mailing address listed for the plaintiff in the eviction filing. Due to inconsistent listings, a fuzzy matching algorithm (Levenshtein distance) was used to calculate the similarity of landlords' addresses. Addresses with a similarity score of 90% or higher were grouped together and manually inspected to remove any false matches.

This model's formula is:

$$logit(y) = \alpha + X_{ATTY} * \beta_{ATTY} + X_{LL} * \beta_{LL} \qquad \text{(Equation 2)}$$

In Equation 2, $\beta_{LL}$ is a coefficient vector for $X_{LL}$, a one-hot encoded matrix of dummy variables. In that matrix, each column represents an individual landlord, with the value being 1 when that landlord owns the tenant's building 0 for all other values in that row.

Not all landlords filed with equal frequencies. In the 2,642 paired cases, some landlords filed hundreds of evictions while others only filed one. The lower the variance in a given column, the harder it is for the algorithm to converge on a solution, to the point that many landlord columns had to be dropped. The resulting threshold variance, found iteratively, was at the 87th percentile of the columns' variances, 0.00302.

This analysis gave the following results:

## Logistic Regression Results- Control for Landlord

| | | | |
|---|---|---|---|
| **Dep. Variable:** | writ_issued | **No. Observations:** | 2642 |
| **Model:** | Logit | **Df Residuals:** | 2585 |
| **Method:** | MLE | **Df Model:** | 56 |
| **Date:** | Thu, 23 Mar 2023 | **Pseudo R-squ.:** | 0.2232 |
| **Time:** | 19:40:06 | **Log-Likelihood:** | -1244.5 |
| **converged:** | TRUE | **LL-Null:** | -1.60E+03 |
| **Covariance Type:** | nonrobust | **LLR p-value:** | 4.06E-115 |

| | coef | std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **defendant_has_atty** | -2.5647 | 0.119 | -21.613 | 0 | -2.797 | -2.332 |
| **LL_69** | 0.3413 | 0.606 | 0.563 | 0.573 | -0.847 | 1.529 |
| **LL_83** | -0.5145 | 0.574 | -0.896 | 0.37 | -1.64 | 0.611 |
| **LL_88** | -1.6571 | 1.101 | -1.506 | 0.132 | -3.814 | 0.5 |
| **LL_89** | -0.4385 | 0.902 | -0.486 | 0.627 | -2.206 | 1.329 |
| **LL_109** | -0.2076 | 0.413 | -0.503 | 0.615 | -1.017 | 0.601 |
| **LL_111** | 0.6766 | 0.661 | 1.024 | 0.306 | -0.619 | 1.972 |
| **LL_147** | -0.3787 | 0.497 | -0.761 | 0.446 | -1.353 | 0.596 |
| **LL_159** | -0.1238 | 0.519 | -0.239 | 0.811 | -1.141 | 0.893 |
| **LL_282** | -0.5853 | 0.481 | -1.216 | 0.224 | -1.529 | 0.358 |
| **LL_294** | -0.6382 | 0.72 | -0.886 | 0.375 | -2.049 | 0.773 |
| **LL_297** | -0.4809 | 0.458 | -1.05 | 0.294 | -1.379 | 0.417 |
| **LL_322** | 0.6166 | 0.803 | 0.768 | 0.442 | -0.957 | 2.19 |
| **LL_323** | -0.8366 | 0.699 | -1.196 | 0.232 | -2.207 | 0.534 |
| **LL_327** | -0.3101 | 0.468 | -0.662 | 0.508 | -1.228 | 0.608 |
| **LL_372** | 0.0057 | 0.627 | 0.009 | 0.993 | -1.222 | 1.234 |
| **LL_420** | -0.3598 | 0.758 | -0.475 | 0.635 | -1.845 | 1.126 |
| **LL_482** | 2.1969 | 0.695 | 3.161 | 0.002 | 0.835 | 3.559 |
| **LL_484** | 0.2106 | 0.351 | 0.599 | 0.549 | -0.478 | 0.899 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **LL_495** | 0.0875 | 0.704 | 0.124 | 0.901 | -1.292 | 1.467 |
| **LL_501** | -0.3764 | 0.536 | -0.702 | 0.483 | -1.428 | 0.675 |
| **LL_567** | 0.0689 | 0.398 | 0.173 | 0.863 | -0.712 | 0.849 |
| **LL_613** | -0.6801 | 0.474 | -1.434 | 0.152 | -1.61 | 0.25 |
| **LL_697** | -0.4749 | 0.253 | -1.878 | 0.06 | -0.971 | 0.021 |
| **LL_740** | -0.7721 | 0.61 | -1.265 | 0.206 | -1.968 | 0.424 |
| **LL_774** | -0.7753 | 0.467 | -1.66 | 0.097 | -1.691 | 0.14 |
| **LL_791** | 0.5318 | 0.774 | 0.687 | 0.492 | -0.986 | 2.05 |
| **LL_810** | -0.7267 | 0.618 | -1.176 | 0.24 | -1.938 | 0.485 |
| **LL_830** | -0.093 | 0.696 | -0.134 | 0.894 | -1.457 | 1.271 |
| **LL_865** | -0.077 | 0.354 | -0.218 | 0.828 | -0.77 | 0.616 |
| **LL_881** | 0.3117 | 0.451 | 0.691 | 0.489 | -0.572 | 1.195 |
| **LL_931** | 0.4522 | 0.341 | 1.326 | 0.185 | -0.216 | 1.121 |
| **LL_937** | 1.2376 | 0.739 | 1.674 | 0.094 | -0.211 | 2.686 |
| **LL_939** | 1.1211 | 0.706 | 1.588 | 0.112 | -0.263 | 2.505 |
| **LL_942** | -1.1243 | 1.146 | -0.981 | 0.326 | -3.37 | 1.121 |
| **LL_948** | -0.3925 | 0.65 | -0.603 | 0.546 | -1.667 | 0.882 |
| **LL_950** | 0.4577 | 0.752 | 0.609 | 0.543 | -1.016 | 1.931 |
| **LL_1005** | -0.4054 | 0.855 | -0.474 | 0.636 | -2.082 | 1.271 |
| **LL_1009** | 0.0353 | 0.177 | 0.2 | 0.842 | -0.311 | 0.382 |
| **LL_1011** | -0.3369 | 0.447 | -0.754 | 0.451 | -1.213 | 0.539 |
| **LL_1012** | -0.2062 | 0.407 | -0.507 | 0.612 | -1.003 | 0.591 |
| **LL_1013** | -0.9066 | 0.495 | -1.832 | 0.067 | -1.876 | 0.063 |
| **LL_1014** | -0.5256 | 0.36 | -1.461 | 0.144 | -1.231 | 0.179 |
| **LL_1015** | 1.0173 | 0.437 | 2.326 | 0.02 | 0.16 | 1.874 |
| **LL_1018** | -1.1926 | 0.818 | -1.458 | 0.145 | -2.796 | 0.411 |
| **LL_1019** | -0.0837 | 0.282 | -0.297 | 0.767 | -0.637 | 0.469 |
| **LL_1020** | -0.1671 | 0.219 | -0.762 | 0.446 | -0.597 | 0.263 |
| **LL_1028** | -0.7721 | 0.858 | -0.899 | 0.368 | -2.455 | 0.91 |
| **LL_1030** | -2.719 | 1.04 | -2.616 | 0.009 | -4.756 | -0.682 |
| **LL_1040** | 0.6166 | 0.803 | 0.768 | 0.442 | -0.957 | 2.19 |
| **LL_1041** | -0.0395 | 0.359 | -0.11 | 0.912 | -0.742 | 0.663 |
| **LL_1050** | 0.4287 | 0.628 | 0.682 | 0.495 | -0.802 | 1.66 |
| **LL_1057** | -0.3764 | 0.536 | -0.702 | 0.483 | -1.428 | 0.675 |
| **LL_1064** | -0.8271 | 0.613 | -1.35 | 0.177 | -2.028 | 0.374 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **LL_1456** | -0.7108 | 0.874 | -0.813 | 0.416 | -2.424 | 1.002 |
| **LL_1671** | 0.3117 | 0.451 | 0.691 | 0.489 | -0.572 | 1.195 |
| **y-intercept** | 0.1613 | 0.092 | 1.749 | 0.08 | -0.019 | 0.342 |

Again the coefficient defendant_has_atty has a p-value of 0, suggesting that it is statistically significant. A $\beta 1$ of -2.5647 gives an 85.57% reduction in the risk of eviction for tenants with lawyers. The 95% confidence interval values of -2.797 and -2.332 correspond to reduced eviction risks of 81.79% and 88.56% for tenants with lawyers.

# Model 3

As there are significant variations in income, demographics, and economic activity across neighborhoods in Cincinnati and the other municipalities in Hamilton County, it is plausible that the neighborhood a tenant lives in has some explanatory power when it comes to the likelihood of a tenant being evicted. To isolate this potential covariate from the defense attorney effect, another logistic regression was performed, this time controlling for the tenant's neighborhood.

$$logit(y) = \alpha + X_{ATTY} * \beta_{ATTY} + X_{NHBD} * \beta_{NBHD} \qquad \text{(Equation 3)}$$

For Equation 3, $X_{NHBD}$ is a matrix of dummy variables for the neighborhood a tenant lives in, where each column represents a different neighborhood in Cincinnati or municipality outside Cincinnati in Hamilton County, and $\beta_{NBHD}$ is a vector of the coefficients showing the relative increase or decrease in the odds of an eviction for a tenant in a given neighborhood.

Like with the landlord matrix, a number or columns with low variances had to be dropped so that the algorithm was able to converge to a solution. Iterative testing revealed the lowest threshold that still allowed for the algorithm to converge was at the 40th percentile of column variance at 0.00302.

Running this algorithm gave the following coefficients:

**Logistic Regression Results - Control for Neighborhood**

| | | | |
|---|---|---|---|
| **Dep. Variable:** | writ_issued | **No. Observations:** | 2642 |
| **Model:** | Logit | **Df Residuals:** | 2590 |
| **Method:** | MLE | **Df Model:** | 51 |
| **Date:** | Thu, 23 Mar 2023 | **Pseudo R-squ.:** | 0.2148 |
| **Time:** | 19:48:13 | **Log-Likelihood:** | -1258 |
| **converged:** | TRUE | **LL-Null:** | -1602.2 |
| **Covariance Type:** | nonrobust | **LLR p-value:** | 1.65E-112 |

| | coef | std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **defendant_has_atty** | -2.5313 | 0.117 | -21.63 | 0 | -2.761 | -2.302 |
| **ANDERSON TOWNSHIP** | 0.5898 | 0.677 | 0.872 | 0.383 | -0.736 | 1.916 |
| **AVONDALE** | 0.2278 | 0.286 | 0.796 | 0.426 | -0.333 | 0.788 |
| **BOND HILL** | -0.1639 | 0.386 | -0.424 | 0.671 | -0.921 | 0.594 |
| **CARTHAGE** | 0.27 | 0.709 | 0.381 | 0.704 | -1.121 | 1.661 |
| **CHEVIOT** | -0.3231 | 0.448 | -0.721 | 0.471 | -1.201 | 0.555 |
| **CLIFTON** | -0.5558 | 0.419 | -1.327 | 0.185 | -1.377 | 0.265 |
| **COLERAIN TOWNSHIP** | -0.6766 | 0.306 | -2.21 | 0.027 | -1.277 | -0.077 |
| **COLLEGE HILL** | 0.1635 | 0.339 | 0.482 | 0.63 | -0.501 | 0.828 |
| **COLUMBIA TOWNSHIP** | -0.1257 | 0.828 | -0.152 | 0.879 | -1.748 | 1.496 |
| **CORRYVILLE** | -1.4691 | 0.822 | -1.788 | 0.074 | -3.08 | 0.142 |
| **CUF** | -0.4085 | 0.442 | -0.924 | 0.356 | -1.275 | 0.458 |
| **DELHI TOWNSHIP** | -0.9392 | 0.721 | -1.302 | 0.193 | -2.352 | 0.474 |
| **DOWNTOWN** | -0.4855 | 0.475 | -1.023 | 0.306 | -1.416 | 0.445 |
| **EAST PRICE HILL** | 0.0922 | 0.298 | 0.309 | 0.757 | -0.492 | 0.677 |
| **EAST WESTWOOD** | -0.5772 | 0.431 | -1.339 | 0.181 | -1.422 | 0.268 |
| **EVANSTON** | 0.5243 | 0.509 | 1.03 | 0.303 | -0.473 | 1.522 |
| **FOREST PARK** | -0.2142 | 0.378 | -0.567 | 0.571 | -0.954 | 0.526 |
| **GOLF MANOR** | 0.1781 | 0.551 | 0.323 | 0.746 | -0.901 | 1.258 |
| **GREEN TOWNSHIP** | -0.4251 | 0.426 | -0.999 | 0.318 | -1.26 | 0.409 |
| **HARTWELL** | -0.1001 | 0.481 | -0.208 | 0.835 | -1.043 | 0.842 |
| **KENNEDY HEIGHTS** | -0.0648 | 0.504 | -0.129 | 0.898 | -1.052 | 0.923 |
| **LINCOLN HEIGHTS** | -0.3286 | 0.579 | -0.568 | 0.57 | -1.463 | 0.806 |
| **LOCKLAND** | -0.3487 | 0.575 | -0.606 | 0.544 | -1.476 | 0.778 |
| **LOVELAND** | 0.5201 | 0.727 | 0.716 | 0.474 | -0.904 | 1.944 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **MADISONVILLE** | 0.1587 | 0.589 | 0.27 | 0.787 | -0.995 | 1.313 |
| **MOUNT HEALTHY** | -0.152 | 0.596 | -0.255 | 0.799 | -1.321 | 1.017 |
| **MT. AIRY** | -0.2767 | 0.297 | -0.932 | 0.351 | -0.859 | 0.305 |
| **MT. AUBURN** | -0.9392 | 0.529 | -1.775 | 0.076 | -1.976 | 0.098 |
| **MT. WASHINGTON** | -0.2663 | 0.514 | -0.518 | 0.605 | -1.274 | 0.742 |
| **NORTH AVONDALE** | -0.2013 | 0.587 | -0.343 | 0.732 | -1.351 | 0.948 |
| **NORTH COLLEGE HILL** | -0.2825 | 0.388 | -0.727 | 0.467 | -1.044 | 0.479 |
| **NORTH FAIRMOUNT** | -0.9563 | 0.633 | -1.51 | 0.131 | -2.197 | 0.285 |
| **NORTHSIDE** | -0.1001 | 0.481 | -0.208 | 0.835 | -1.043 | 0.842 |
| **NORWOOD** | 0.0518 | 0.382 | 0.136 | 0.892 | -0.698 | 0.801 |
| **OAKLEY** | 0.0961 | 0.576 | 0.167 | 0.867 | -1.032 | 1.224 |
| **PLEASANT RIDGE** | 0.1514 | 0.405 | 0.374 | 0.709 | -0.642 | 0.945 |
| **READING** | 0.4339 | 0.469 | 0.926 | 0.354 | -0.484 | 1.352 |
| **ROSELAWN** | -0.4965 | 0.345 | -1.441 | 0.15 | -1.172 | 0.179 |
| **SHARONVILLE** | -0.7413 | 0.741 | -1.001 | 0.317 | -2.193 | 0.711 |
| **SILVERTON** | -0.0308 | 0.667 | -0.046 | 0.963 | -1.338 | 1.276 |
| **SOUTH FAIRMOUNT** | 0.1079 | 0.459 | 0.235 | 0.814 | -0.791 | 1.007 |
| **SPRING GROVE VILLAGE** | -0.4965 | 0.609 | -0.815 | 0.415 | -1.69 | 0.697 |
| **SPRINGDALE** | -0.9646 | 0.494 | -1.952 | 0.051 | -1.933 | 0.004 |
| **SPRINGFIELD TOWNSHIP** | -0.599 | 0.358 | -1.672 | 0.094 | -1.301 | 0.103 |
| **WALNUT HILLS** | 0.2751 | 0.381 | 0.721 | 0.471 | -0.472 | 1.023 |
| **WEST END** | -0.9538 | 0.36 | -2.65 | 0.008 | -1.659 | -0.248 |
| **WEST PRICE HILL** | -0.1088 | 0.305 | -0.357 | 0.721 | -0.706 | 0.489 |
| **WESTWOOD** | -0.1789 | 0.249 | -0.719 | 0.472 | -0.667 | 0.309 |
| **WHITEWATER TOWNSHIP** | -0.3024 | 0.408 | -0.741 | 0.459 | -1.102 | 0.497 |
| **WINTON HILLS** | -0.4965 | 0.609 | -0.815 | 0.415 | -1.69 | 0.697 |
| **y-intercept** | 0.2592 | 0.202 | 1.285 | 0.199 | -0.136 | 0.655 |

In this scenario, the $\beta_{ATTY}$ value of -2.53 corresponds to an 85.08% reduction in the risk of eviction for tenants with a lawyer. The 95% confidence interval, -2.761 to -2.302, gives us a range of risk reductions between 81.24% and 88.14% of eviction for tenants with lawyers.

**Model 4**

The final model incorporated the control variables for both the tenant's landlord and the tenant's neighborhood:

$$logit(y) = \alpha + X_{ATTY} * \beta_{ATTY} + X_{NHBD} * \beta_{NBHD} + X_{LL} * \beta_{LL} \quad \text{(Equation 4)}$$

Calculating the model in Equation 4 led to the following results:

## Logit Regression Results – Control for Landlord and Neighborhood

| | | | |
|---|---|---|---|
| **Dep. Variable:** | writ_issued | **No. Observations:** | 2642 |
| **Model:** | Logit | **Df Residuals:** | 2535 |
| **Method:** | MLE | **Df Model:** | 106 |
| **Date:** | Thu, 23 Mar 2023 | **Pseudo R-squ.:** | 0.2411 |
| **Time:** | 19:50:50 | **Log-Likelihood:** | -1216 |
| **converged:** | TRUE | **LL-Null:** | -1602.2 |
| **Covariance Type:** | nonrobust | **LLR p-value:** | 8.39E-102 |

| | coef | std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **defendant_has_atty** | -2.6266 | 0.121 | -21.691 | 0 | -2.864 | -2.389 |
| **ANDERSON TOWNSHIP** | 0.5154 | 0.693 | 0.744 | 0.457 | -0.843 | 1.874 |
| **AVONDALE** | -0.0305 | 0.306 | -0.1 | 0.921 | -0.63 | 0.569 |
| **BOND HILL** | -0.0424 | 0.412 | -0.103 | 0.918 | -0.85 | 0.765 |
| **CARTHAGE** | 0.0163 | 0.734 | 0.022 | 0.982 | -1.422 | 1.454 |
| **CHEVIOT** | -0.2016 | 0.471 | -0.428 | 0.669 | -1.125 | 0.722 |
| **CLIFTON** | -0.4461 | 0.468 | -0.953 | 0.341 | -1.364 | 0.472 |
| **COLERAIN TOWNSHIP** | -0.8096 | 0.334 | -2.426 | 0.015 | -1.464 | -0.155 |
| **COLLEGE HILL** | 0.0712 | 0.355 | 0.201 | 0.841 | -0.625 | 0.767 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **COLUMBIA TOWNSHIP** | -0.2491 | 0.836 | -0.298 | 0.766 | -1.888 | 1.39 |
| **CORRYVILLE** | -1.2654 | 0.852 | -1.485 | 0.138 | -2.936 | 0.405 |
| **CUF** | -0.4874 | 0.495 | -0.984 | 0.325 | -1.458 | 0.484 |
| **DELHI TOWNSHIP** | -1.4451 | 0.779 | -1.856 | 0.063 | -2.971 | 0.081 |
| **DOWNTOWN** | -0.4953 | 0.491 | -1.009 | 0.313 | -1.458 | 0.467 |
| **EAST PRICE HILL** | 0.1062 | 0.336 | 0.316 | 0.752 | -0.552 | 0.765 |
| **EAST WESTWOOD** | -0.5954 | 0.455 | -1.309 | 0.191 | -1.487 | 0.296 |
| **EVANSTON** | 0.6983 | 0.543 | 1.287 | 0.198 | -0.365 | 1.762 |
| **FOREST PARK** | -0.3013 | 0.393 | -0.767 | 0.443 | -1.071 | 0.468 |
| **GOLF MANOR** | 0.1421 | 0.568 | 0.25 | 0.802 | -0.97 | 1.254 |
| **GREEN TOWNSHIP** | -0.4643 | 0.435 | -1.068 | 0.285 | -1.316 | 0.388 |
| **HARTWELL** | 0.2576 | 0.882 | 0.292 | 0.77 | -1.471 | 1.986 |
| **KENNEDY HEIGHTS** | -0.2139 | 0.528 | -0.405 | 0.686 | -1.249 | 0.821 |
| **LINCOLN HEIGHTS** | 0.2472 | 0.777 | 0.318 | 0.75 | -1.276 | 1.77 |
| **LOCKLAND** | -0.1676 | 0.621 | -0.27 | 0.787 | -1.384 | 1.049 |
| **LOVELAND** | 0.4312 | 0.739 | 0.584 | 0.56 | -1.017 | 1.88 |
| **MADISONVILLE** | 0.095 | 0.599 | 0.159 | 0.874 | -1.08 | 1.27 |
| **MOUNT HEALTHY** | -0.1404 | 0.63 | -0.223 | 0.824 | -1.375 | 1.094 |
| **MT. AIRY** | -0.1422 | 0.362 | -0.393 | 0.694 | -0.852 | 0.567 |
| **MT. AUBURN** | -0.9642 | 0.551 | -1.751 | 0.08 | -2.043 | 0.115 |
| **MT. WASHINGTON** | -0.3152 | 0.529 | -0.596 | 0.551 | -1.351 | 0.721 |
| **NORTH AVONDALE** | -0.4525 | 0.619 | -0.731 | 0.465 | -1.665 | 0.76 |
| **NORTH COLLEGE HILL** | -0.4036 | 0.413 | -0.978 | 0.328 | -1.213 | 0.405 |
| **NORTH FAIRMOUNT** | -0.9145 | 0.663 | -1.378 | 0.168 | -2.215 | 0.386 |
| **NORTHSIDE** | -0.1522 | 0.517 | -0.294 | 0.769 | -1.166 | 0.862 |
| **NORWOOD** | 0.0246 | 0.403 | 0.061 | 0.951 | -0.764 | 0.814 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **OAKLEY** | 0.2431 | 0.614 | 0.396 | 0.692 | -0.961 | 1.447 |
| **PLEASANT RIDGE** | 0.1694 | 0.433 | 0.391 | 0.696 | -0.68 | 1.019 |
| **READING** | 1.0609 | 0.643 | 1.65 | 0.099 | -0.199 | 2.321 |
| **ROSELAWN** | -0.6681 | 0.373 | -1.789 | 0.074 | -1.4 | 0.064 |
| **SHARONVILLE** | -0.3707 | 0.798 | -0.465 | 0.642 | -1.934 | 1.193 |
| **SILVERTON** | 0.0603 | 0.688 | 0.088 | 0.93 | -1.288 | 1.409 |
| **SOUTH FAIRMOUNT** | -0.0122 | 0.485 | -0.025 | 0.98 | -0.962 | 0.938 |
| **SPRING GROVE VILLAGE** | 0.9707 | 1.235 | 0.786 | 0.432 | -1.45 | 3.391 |
| **SPRINGDALE** | -0.8226 | 0.659 | -1.248 | 0.212 | -2.115 | 0.469 |
| **SPRINGFIELD TOWNSHIP** | -0.7759 | 0.374 | -2.076 | 0.038 | -1.509 | -0.043 |
| **WALNUT HILLS** | 0.2009 | 0.405 | 0.496 | 0.62 | -0.594 | 0.995 |
| **WEST END** | -1.234 | 0.394 | -3.128 | 0.002 | -2.007 | -0.461 |
| **WEST PRICE HILL** | -0.0867 | 0.332 | -0.261 | 0.794 | -0.738 | 0.565 |
| **WESTWOOD** | -0.1785 | 0.272 | -0.657 | 0.511 | -0.711 | 0.354 |
| **WHITEWATER TOWNSHIP** | -1.1246 | 0.746 | -1.507 | 0.132 | -2.587 | 0.338 |
| **WINTON HILLS** | 0.2903 | 0.899 | 0.323 | 0.747 | -1.471 | 2.052 |
| **LL_69** | 0.2987 | 0.65 | 0.459 | 0.646 | -0.976 | 1.574 |
| **LL_83** | -0.5497 | 0.597 | -0.92 | 0.357 | -1.72 | 0.621 |
| **LL_88** | -2.1591 | 1.409 | -1.533 | 0.125 | -4.92 | 0.602 |
| **LL_89** | -0.611 | 0.925 | -0.66 | 0.509 | -2.425 | 1.203 |
| **LL_109** | -0.1428 | 0.453 | -0.315 | 0.753 | -1.031 | 0.746 |
| **LL_111** | 0.6889 | 0.665 | 1.037 | 0.3 | -0.614 | 1.992 |
| **LL_147** | -0.5455 | 0.56 | -0.975 | 0.33 | -1.642 | 0.551 |
| **LL_159** | -0.586 | 1.003 | -0.584 | 0.559 | -2.552 | 1.38 |
| **LL_282** | -0.7199 | 0.516 | -1.395 | 0.163 | -1.731 | 0.291 |
| **LL_294** | -0.0239 | 0.953 | -0.025 | 0.98 | -1.891 | 1.844 |
| **LL_297** | -0.5466 | 0.543 | -1.006 | 0.314 | -1.611 | 0.518 |
| **LL_322** | 0.443 | 0.812 | 0.546 | 0.585 | -1.148 | 2.034 |
| **LL_323** | -2.0166 | 1.402 | -1.438 | 0.15 | -4.765 | 0.732 |
| **LL_327** | -0.3296 | 0.491 | -0.671 | 0.502 | -1.292 | 0.633 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **LL_372** | 0.2866 | 0.65 | 0.441 | 0.659 | -0.986 | 1.56 |
| **LL_420** | 0.2417 | 0.801 | 0.302 | 0.763 | -1.329 | 1.812 |
| **LL_482** | 2.2712 | 0.728 | 3.12 | 0.002 | 0.844 | 3.698 |
| **LL_484** | 0.0458 | 0.369 | 0.124 | 0.901 | -0.677 | 0.769 |
| **LL_495** | -0.0102 | 0.721 | -0.014 | 0.989 | -1.423 | 1.402 |
| **LL_501** | -0.47 | 0.56 | -0.84 | 0.401 | -1.567 | 0.627 |
| **LL_567** | 0.1218 | 0.473 | 0.258 | 0.797 | -0.804 | 1.048 |
| **LL_613** | -0.7735 | 0.486 | -1.591 | 0.112 | -1.726 | 0.179 |
| **LL_697** | -0.2906 | 0.288 | -1.008 | 0.314 | -0.856 | 0.275 |
| **LL_740** | -1.1227 | 0.82 | -1.37 | 0.171 | -2.729 | 0.484 |
| **LL_774** | -0.82 | 0.49 | -1.675 | 0.094 | -1.78 | 0.14 |
| **LL_791** | 0.5768 | 0.813 | 0.709 | 0.478 | -1.018 | 2.171 |
| **LL_810** | -0.7123 | 0.686 | -1.039 | 0.299 | -2.057 | 0.632 |
| **LL_830** | -0.1584 | 0.756 | -0.21 | 0.834 | -1.64 | 1.323 |
| **LL_865** | -0.0041 | 0.374 | -0.011 | 0.991 | -0.738 | 0.73 |
| **LL_881** | 0.3116 | 0.47 | 0.662 | 0.508 | -0.61 | 1.233 |
| **LL_931** | 0.4469 | 0.371 | 1.205 | 0.228 | -0.28 | 1.174 |
| **LL_937** | 1.1941 | 0.761 | 1.568 | 0.117 | -0.298 | 2.686 |
| **LL_939** | 1.01 | 0.731 | 1.382 | 0.167 | -0.422 | 2.442 |
| **LL_942** | -1.2798 | 1.157 | -1.106 | 0.269 | -3.548 | 0.989 |
| **LL_948** | -1.6602 | 0.895 | -1.855 | 0.064 | -3.414 | 0.094 |
| **LL_950** | 0.2416 | 0.781 | 0.309 | 0.757 | -1.289 | 1.772 |
| **LL_1005** | -0.4973 | 0.911 | -0.546 | 0.585 | -2.283 | 1.289 |
| **LL_1009** | 0.2312 | 0.201 | 1.149 | 0.251 | -0.163 | 0.626 |
| **LL_1011** | 0.0455 | 0.485 | 0.094 | 0.925 | -0.906 | 0.997 |
| **LL_1012** | -0.2911 | 0.424 | -0.687 | 0.492 | -1.122 | 0.54 |
| **LL_1013** | -0.4601 | 0.551 | -0.835 | 0.404 | -1.54 | 0.619 |
| **LL_1014** | -0.4926 | 0.377 | -1.306 | 0.191 | -1.232 | 0.246 |
| **LL_1015** | 0.9137 | 0.475 | 1.922 | 0.055 | -0.018 | 1.846 |
| **LL_1018** | -0.9879 | 0.86 | -1.149 | 0.251 | -2.673 | 0.697 |
| **LL_1019** | -0.1307 | 0.293 | -0.445 | 0.656 | -0.706 | 0.444 |
| **LL_1020** | 0.0236 | 0.238 | 0.099 | 0.921 | -0.443 | 0.49 |
| **LL_1028** | -0.9661 | 0.892 | -1.084 | 0.279 | -2.713 | 0.781 |
| **LL_1030** | -2.8798 | 1.062 | -2.711 | 0.007 | -4.962 | -0.798 |
| **LL_1040** | 0.5726 | 0.831 | 0.689 | 0.491 | -1.056 | 2.202 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **LL_1041** | -0.0551 | 0.396 | -0.139 | 0.889 | -0.831 | 0.721 |
| **LL_1050** | 0.5969 | 0.646 | 0.924 | 0.355 | -0.669 | 1.863 |
| **LL_1057** | -0.4805 | 0.553 | -0.869 | 0.385 | -1.564 | 0.603 |
| **LL_1064** | -1.1454 | 0.664 | -1.724 | 0.085 | -2.448 | 0.157 |
| **LL_1456** | -0.5996 | 0.936 | -0.641 | 0.522 | -2.434 | 1.234 |
| **LL_1671** | 1.2374 | 0.844 | 1.466 | 0.143 | -0.416 | 2.891 |
| **y-intercept** | 0.379 | 0.217 | 1.748 | 0.08 | -0.046 | 0.804 |

In the final model, the $\beta_{ATTY}$ value of -2.6266 corresponds to an 86.44% reduction in the risk of eviction for tenants with lawyers. The 95% confidence interval, -2.864 to -2.389, gives us a range of risk reductions between 82.80% and 89.30% for tenants with lawyers compared to tenants who do not have lawyers.