# THE IMPACT OF AUTOMATION ON THE LEGAL FIELD: AN ANALYSIS OF ENTRY LEVEL LEGAL COMPENSATION AND EMPLOYMENT

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# THE IMPACT OF AUTOMATION ON THE LEGAL FIELD: AN ANALYSIS OF ENTRY LEVEL LEGAL COMPENSATION AND EMPLOYMENT

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**Abstract**

This paper considers the impact of the current generation of automation technologies on determining compensation and hiring trends of entry level legal professionals over the past decade. Analysis is conducted through qualitative interviews of legal professionals as well as regression analysis of occupational and wage data from the Bureau of Labor Statistics. Amidst academic speculation as to what role the future of AI technologies will have on the job market, this paper hypothesizes that in the face of more and more capable automation technologies, compensation and hiring of entry level legal workers has decreased relative to the rest of the legal field. The empirical results fail to produce statistically significant evidence of this relationship, but along with the results of the interview process, point towards an emerging trend of decreased need for legal support.

KEYWORDS: (Legal Support, Automation, Paralegal, AI, Skills, Industry 4.0)
JEL CODES: (L84, O33, J30)

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Ryan Evans

Signature

TABLE OF CONTENTS

## Introduction

Automation innovation has been a driving force behind economic growth in the United States and worldwide for centuries. Different waves of automation have revolutionized manufacturing across the world, increasing outputs and decreasing human labor costs, bolstering efficiency and competition in industries. First seen at a large scale during the industrial revolution, waves of automation have the power to augment and replace jobs. While automation has the power to replace tasks and activities previously assigned to labor, it also contains the power to decrease output costs and increase real wages (Drozd, Dumouchel & Tavares, 2022). The potential for automation to replace labor completely in certain roles spells a harrowing tale for young professionals and students, though economists have overestimated this effect before. Notably, John Keynes predicted in 1930 that technology would cause widespread unemployment as machines replaced human jobs in 100 years (Keynes 1930). With the emergence of AI technologies, it remains to be seen whether he was right. Recent research has supported Keynes' hypothesis, and suggested that the newest wave of automation, coined "industry 4.0", will substantially reduce the amount of labor needed (Szabo-Szentgroti, Vegvari & Varga, 2021). A decrease in required labor in the face of Artificial Intelligence leaves lower skilled laborers at risk of replacement.

The 1980s experienced automation in the form of increased computerization. Research by economist James Bessen found that computerization effectively grew the industries and firms that utilized it the most. Additionally, industries that used computers the most saw a 1.7% increase in employment per year, implying a shift of laborers towards jobs related to the newest wave of technological automation (Bessen, 2016).

Furthermore, computer use is associated with greater within-occupation wage inequality, as skills are expensive to learn (Bessen, 2016). These trends indicate that automation technologies contribute both to increase growth of adopting firms and decrease the value of laborers who fail to adjust to new technologies.

Historical waves of automation have sometimes replaced jobs, and other times augmented them. Augmentation refers to the increased efficiency or output capability of a laborer whose ability to complete their job increases alongside a new technology. An example of this augmentation of labor might exist in an office worker who has one of their normal tasks automated by a computer technology and can now focus more of their effort on more meaningful projects, increasing their overall effectiveness. The research in this paper holds the opinion that augmentation of high skilled occupations by the current generation of automation technologies may decrease the need for supportive entry level positions. Pasquale and Cashwell support this general notion in "Four Futures of Legal Automation" (Pasquale & Cashwell, 2015).

The legal industry exists as an example of a highly skilled industry exposed to industry 4.0 automation and heavily reliant on human capital. The legal industry is also projected to be one of the industries most impacted by future automation (Pasquale & Cashwell). Already, some lawyers utilize AI technologies when reviewing documents for litigation, analyzing contracts, conducting research, and predicting case outcomes. Although AI use across the whole field has so far been slow to develop, early adopting lawyers experience decreased time spent on menial tasks, a higher quality of work, and a higher probability of preferable case outcomes. This is not the first time that the practice of law has felt threatened by an automation technology. A 1966 article published by the

American Bar Association notes that some lawyers in the time of developing computerization felt that the human factor in the practice of law was threatened by the emergence of electronic legal research, a notably similar tonality to what is sometimes expressed by lawyers considering the future impact of AI on the field today (Landes, 1966). This research holds the opinion that increasing automation technology adoption into the legal field has resulted in a decreased demand for the services of entry level positions. As such, this paper hypothesizes that over the last 10 years, employment of legal support workers has decreased relative to the greater legal field, and persons occupying legal support jobs have seen their annual compensations shrink. The remainder of this paper will consider the previous research related to this topic in the Setting and Context section, before outlining research methods in the methodology section, and conclude with results and analysis of interaction regressions that seek to determine the change in compensations relative to the legal field experienced by legal support workers, as well as the hiring demand relative to the field of legal support workers.

## Setting and Context

As previously outlined, waves of automation have continuously changed the most in-demand jobs in labor markets. The second wave of automation saw jobs shift alongside new technologies, introduction of the railroad and steam engine, for example, saw new jobs created for engineers, back-office workers, and managers (Acemoglu & Restrepo, 2018). Regardless of the jobs created or lost in the process, AI automation will impact the legal field by rendering certain skills more valuable, and others less valuable. At most concern for being rendered less valuable are support jobs that can be routinized by automation technologies (Pasquale & Cashwell, 2015).

The convergence of human capital with machines is the key characteristic of automation that drives improvements in efficiency, and AI technologies in human-capital occupations will exhibit this effect. The research paper "Skills, Tasks, and Technologies: Implications for Employment and Earnings" introduces a framework for estimating the impact of new technologies on the labor market. The research suggests that implication of new automation technologies may augment the tasks of workers, leading to increased output, increasing aggregate demand, and thus labor demand (Acemoglu & Autor, 2011). Acemoglu and Autor primarily focus their efforts on building a framework for analyzing the impact of new technologies on the labor market as a result of the skills and tasks a technology can replace, rather than identifying occupational or earnings consequences. Of course, the particular skills needed to adapt to AI technologies may differ across different legal occupations. Additionally, different firms will adapt to AI technology at different rates. As such, firms should experience hiring trends and benefits of AI technology at different rates.

Building on Acemoglu and Autor's research, Dawid and Neugart find that their model indicates that higher automation technology productivity results in decreases in the wage ratio between high and low skilled workers, while increasing the employment rate. These results stem from the idea that the reallocation of tasks to automation technologies mainly affects low tasks (Dawid & Neugart, 2022). The research conducted by Dawid, Neugart, Acemoglu, and Autor is largely theoretical, and substantiates little with data-driven empirical analysis. These analyses span industries, and do not examine in particular the legal industry. Additionally, these analyses primarily focus on the production of goods, whereas the legal industry is largely a service industry.

Fareri et al. use a text mining approach to estimate the impact of industry 4.0 on job profiles and skills. The key finding of interest However, Fareri et al.'s research is that managerial roles may be more impacted by the future automation technologies of industry 4.0, a contrast to the previous research outlined (Fareri, Fantoni, Chiarello, Coli & Binda, 2020). However, Fareri et. al.'s research was applied to a specific case study of job profiles at manufacturer Whirlpool, irrelevant to the legal field.

Ryan Whalen considers the implications of forthcoming legal technologies in their paper "Defining Legal Technology and its Implications" but stops short at considering the efficiency impacts that these technologies will have, offering that these new technologies will both increase the understanding of those who adopt them, but also potentially lead to increasing inequality. The analysis of the topic does not consider the implications on the occupational makeup of the field (Whalen, 2022).

Employment of entry level legal positions declined more than 20% between 2007 and 2018. As a result, fear that the legal industry may be undergoing transformative change has manifested itself in the minds of some legal professionals. However, much of this trend can be attributed to decreased enrollment in law school and hiring of law firms after the 2007 financial crisis (Carpenter, 2020). The analysis contained in this paper attempts to examine the employment and compensations of entry level legal positions relative to the rest of the legal industry, to gather a more adjusted perspective of the health of entry level legal occupations and identify any predictive trends of what is to come from the highly anticipated continuation of legal technological automation.

## Methodology

Analysis of the research question was two-fold. First, a series of qualitative interviews gathered knowledge and experience from legal industry professionals. These interviews informed the second stage, an empirical analysis of the progression of entry level legal compensations and employment.

### Qualitative Interviewing Methods

The first form of research undertaken by this project was a series of qualitative interviews. Participants included a Judge, a Paralegal, a former Assistant Dean of a law school, and practicing lawyers of various specialties. The interviews lasted anywhere from 30 minutes to one hour and most were conducted remotely. Interviewees responded to a series of prepared questions as well as engaged in self-originating discussions. Often, the discussion in interviews would be determined by the knowledge and interest of a person on particular topics. The main focus of the interviews was the impact of the adoption of automatic technologies into the legal field on the skills necessary to achieve a successful legal career, and how future Artificial Intelligence will make similar or different impacts. Discussions often engaged in discussion of the future occupational makeup of the legal field, and the driving factors behind potential changes in the concentration of legal support occupations. The questionnaire used to guide these interviews is included in the addendum.

### Empirical Analysis Methods

The data used for empirical analysis of this topic was collected from the U.S. Bureau of Labor Statistics' public data resources. 10 BLS Occupational and Wage Statistics datasets, each representing a year, were appended to create a master dataset containing industry-spanning occupational and compensation data from 2012 through 2022. These data identify individual occupations by occupation codes, allowing a researcher to analyze trends by individual occupations. Example occupation codes, denoted as OCC_CODE, as well as their associated job titles are included in the table below.

**Table 1: Occupational Codes and Titles**

| OCC_CODE | OCC_TITLE |
|---|---|
| 23-1020 | Judges, Magistrates, and other Judicial Workers |
| 23-2010 | Paralegals and Legal Assistants |
| 41-9020 | Real Estate Brokers and Sale Agents |

Source: Bureau of Labor Statistics, 2012-2022

To analyze trends across the legal field, occupations that did not correspond with the legal industry were dropped from the dataset, leaving only occupations that began with the OCC code "23", indicating a legal profession.

Table 2 displays the dependent variables of interest that were analyzed in this research. These include the total number of people employed in each occupation, represented by the variable TOT EMP, as well as the annual mean and median compensations for an observed occupation, designated by A MEAN and A MEDIAN, respectively. Table 2 displays values for these variables from the year 2014.

**Table 2: Data Summary 2014**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| TOT EMP | 1394 | 484678.06 | 3796485.8 | 400 | 1.351e+08 |
| A MEAN | 1388 | 55095.058 | 29617.153 | 19030 | 246320 |
| A MEDIAN | 1380 | 49920.746 | 25089.54 | 18410 | 181880 |
| year | 1394 | 2014 | 0 | 2014 | 2014 |

Source: Bureau of Labor Statistics, 2014

**Interaction Regression Models**

To produce results in terms of 2022 dollars, annual mean and median compensation numbers were adjusted for inflation. Consumer Price Index data from the Bureau of Labor was collected to calculate inflation-adjusted compensation values, this data was gathered from the Federal Reserve Bank of St. Louis' website. These dependent variables are titled "a_mean_adj" and "a_median_adj", for mean and median annual compensation, respectively.

OLS Regressions were used to examine the change over time of compensations for different entry level legal positions. Dummy variables were created to identify different entry level legal positions. These include the variables "paralegal", "legal_support", and "court_reporter". These variables assume value 1 should the OCC code associated with a particular observation identify that observation as being the intended occupation. The dummy variable assumes the value "0" for any other legal occupation. For paralegals, for example, the dummy variable "paralegal" returned value "1" if the OCC code matched the designation of a paralegal, and value "0" for all other legal occupations. The "court_reporter" variable denotes a court reporter, and "legal_support" represents all legal support positions recognized by the BLS dataset (including court reporters and paralegals).

Interaction terms were used in each of the annual wage regressions to estimate the difference in compensation change year over year when a model includes the occupations represented by a dummy variable or doesn't. This allows for analysis of the impact a given occupation has on a dependent variable.

Model 1:

a_mean_adj = $B_0$+ $B_1$(paralegal) + $B_2$(year) + $B_3$(paralegal x year)

In models 1, 2, and 3, the dependent variable is annual mean compensation, adjusted for inflation. Here in model 1, the coefficient $B_1$ represents the effect on mean annual income should the observation be a paralegal, and the year equal to 0. $B_2$ represents the effect on mean compensation from each year increase for non-paralegal legal industry occupations. The interaction term captured by coefficient $B_3$ indicates the difference in the effect on annual compensation from a one year increase should the observation be a paralegal. $B_0$ estimates the mean compensation when the independent variables equal 0.

To allow for a broader depiction of the progression of wages and employment among supportive roles in the legal field, model 2 considers all legal support workers, including paralegals and court reporters.

Model 2:

a_mean_adj = $B_0$+ $B_1$(legal_support) + $B_2$(year) + $B_3$(legal_support x year)

As before, $B_2$ indicates the effect on a mean compensation from a one year increase for occupations not included in the dummy variable, now legal_support. $B_1$ identifies he effect on annual mean compensation of being a legal support worker when the year is 0, and $B_3$ the difference in the effect on compensation from a one year increase when the observation is a legal support worker. Again, the constant $B_0$ provides the estimated mean compensation when the independent variables are set to 0.

Inspired by anecdotal evidence from the interview process that suggested the court system adjusts more slowly to technological innovations than other areas of the legal industry, the third model examines the same relationships for court reporters.

Model 3:

$a\_mean\_adj = B_0 + B_1(court\_reporter) + B_2(year) + B_3(court\_reporter \times year)$

Model 3's dummy variable denotes court reporters. $B_0$ is the mean wage with independent variables set to 0. $B_1$ is the effect on mean compensation from being a court reporter, versus any other legal occupation when the year is 0, $B_2$ the effect on mean compensation from a one year increase for legal occupations other than court reporters, and $B_3$ the difference in the effect on mean compensation from a one year increase when the observation is a court reporter.

These models were run again, with everything the same except the dependent variable, which changed to a_median_adj, representing the inflation-adjusted median annual wage for occupations. The models for the median compensation regressions are included below.

Model 4:

$a\_median\_adj = B_0 + B_1(paralegal) + B_2(year) + B_3(paralegal \times year)$

Model 5:

$a\_median\_adj = B_0 + B_1(legal\_support) + B_2(year) + B_3(legal\_support \times year)$

Model 6:

$a\_median\_adj = B_0 + B_1(court\_reporter) + B_2(year) + B_3(court\_reporter \times year)$

Finally, another interaction term regression was run to examine the estimated difference in total employment in the legal industry year over year when legal support workers are omitted or included in the regression. The results of this regression are included in Table 3. In this regression $B_0$ is the constant term when the independent variables are set to zero, and $B_1$ is the effect of being a legal support worker when the year variable equals 0. $B_2$ presents the change in total employment across the legal industry excluding support workers for a year increase. $B_3$ represents the change in total employment across the legal field from a one year increase when support workers are considered.

Model 7:

$$TOT\_EMP = B_0 + B_1(legal\_support) + B_2(year) + B_3(legal\_support \times year)$$

## Results and Analysis

### Interview Results

The interviewing process revealed a widespread interest among legal professionals of the future implications of Artificial Intelligence technologies on the field. Most of the participants anticipated a decline in the number of entry level legal positions that will be required to complete normal legal processes in the future, while some felt that automation technologies have not and will not have a significant impact on the number of legal support workers employed relative to the field. Participants with more exposure to automation technologies at work tended to be more pessimistic about the future of entry level legal positions. Most notably, one participant- who themself uses AI tools to automate time-consuming tasks- felt that they were already able to rely on AI to complete basic drafting responsibilities- which previously would have been completed by a paralegal. The participant mentioned that while generative AI tools require careful oversight, so has the work of supporting legal researchers and paralegals in the past. Another participant, with a background working in a small law firm, noted that they have yet to use or even seen used any AI technologies at their firm. A theme reflecting this contrast in experience emerged over the course of the interviews; larger law practices would adopt the next wave of automatic technologies quicker than their smaller counterparts. A judge interviewed during the process mentioned that the courts are often the last area of the legal field to adopt new technologies, citing comparatively small budgets and the unchanging nature of required research in the courts- with the mostly consistent nature of laws- as the main reasons.

Another trend emerged throughout the interviews. The younger the legal professional, the more likely they were to have used an AI tool at work. This supported the notion that AI tools will augment or replace first the tasks of legal support workers. It is difficult to gather, from the conflicting opinions of the interviewees, whether this will have an impact on the number of paralegals and other legal support workers employed in the field. The interviewees with experience at large law firms felt that the roles and responsibilities of legal support workers would likely change, but not be replaced. Perhaps, one interviewee offered, slightly fewer support workers would be required to create the same output, but the output required to remain competitive in the legal field may also change with the increased capacity of AI-augmented support workers.

A final commonality between interviews worth noting pertains to the industry professionals' recollections of the impact past automatic technologies have had on the field. Commonly mentioned when asked to recall past automatic technologies and their impacts were the now essential legal databases Lexis and Westlaw. Some interviewees either attended law school or were already employed in the legal industry and remember how access to legal databases dramatically shortened the amount of time needed to conduct research for any assignment or case. One participant mentioned that they felt large scale access to legal databases generally resulted in legal professionals becoming less knowledgeable of case law pertaining to their specialty, as the necessity for memorization and deep familiarity with case law became lesser. No participant had a strong remembrance of if the adoption of legal databases resulted in changes to the amount of legal support workers employed in the field. The paralegal interviewed also mentioned more recent automation technologies, such as automated voice messaging systems and other online automatic scheduling technologies as having reduced the responsibilities typically required of their position. They also felt that this was not a foreboding sign of a decreasing need for legal support workers. Overall, it became clear that in large, the interviewees did not connect automatic technologies with a decrease in demand for legal support work, although a couple outliers did feel differently about the next wave of automation.

**Empirical Analysis Results**

Table 3 displays the regression results from model 7, where the interaction term legal_support x year attempts to estimate the difference in the change in total employment across the legal industry over a year when legal support jobs are considered by the model. The coefficient on "year" represents the estimated change in total employment in the legal industry each year when all legal support jobs are excluded from the model. The coefficient on the interaction term suggests that when legal support workers are accounted for in the model, the change in total employment across the industry decreases by the coefficient: -293. This suggests that legal support occupations are growing at a slower rate than other legal occupations. However, though the coefficients suggest that legal support jobs are shrinking relative to the industry, the results are significantly insignificant, and as such of these regression results cannot be used to support the hypothesis that legal support jobs have been shrinking relative to the legal field.

**Table 3: Total Employment of Legal Support**

| TOT_EMP | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| legal_support | 419164.67 | 33744807 | 0.01 | .99 | -66304562 | 67142891 | |
| year | 6232.525 | 10805.624 | 0.58 | .565 | -15133.475 | 27598.524 | |
| | . | . | . | . | . | . | |
| legal_support x year | -293.27 | 16735.587 | -0.02 | .986 | -33384.606 | 32798.067 | |
| Constant | -12215007 | 21788969 | -0.56 | .576 | -55298413 | 30868400 | |

| | | | |
|---|---|---|---|
| Mean dependent var | 278138.662 | SD dependent var | 323564.109 |
| R-squared | 0.074 | Number of obs | 142 |
| F-test | 3.696 | Prob > F | 0.013 |
| Akaike crit. (AIC) | 4002.152 | Bayesian crit. (BIC) | 4013.975 |

**** p<.01, ** p<.05, * p<.1*

Tables 4, 5, and 6 project the results of models 1, 2, and 3, respectively. The coefficient included on the interaction term of Table 4 shows that the mean income increase of paralegals is estimated to be roughly 462 dollars less year over year than other occupations in the legal field.

**Table 4: Paralegal Regression Results Mean Annual Wage**

| a_mean_adj | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| paralegal | 888225 | 5453557.1 | 0.16 | .871 | -9878106.7 | 11654557 | |
| year | 178.795 | 971.324 | 0.18 | .854 | -1738.779 | 2096.369 | |
| | . | . | . | . | . | . | |
| paralegal x year | -462.613 | 2703.809 | -0.17 | .864 | -5800.433 | 4875.207 | |
| Constant | -251271.7 | 1959072.8 | -0.13 | .898 | -4118844.1 | 3616300.7 | |

| | | | |
|---|---|---|---|
| Mean dependent var | 103604.420 | SD dependent var | 40028.024 |
| R-squared | 0.141 | Number of obs | 172 |
| F-test | 9.199 | Prob > F | 0.000 |
| Akaike crit. (AIC) | 4114.436 | Bayesian crit. (BIC) | 4127.026 |

**** p<.01, ** p<.05, * p<.1*

The interaction coefficient in Table 5 indicates that legal support workers in general experience a slightly lower increase in mean annual wage compared to other legal occupations. Table 6's interaction term "court_reporter x year" interestingly suggests that the mean annual wage for court reporters has increased each year over the analyzed time period by an estimated amount of roughly 996 dollars more than other legal occupations.

This result interestingly corresponds with the anecdote from the interview process that the court system is the last to adjust to new technologies. As automation innovation has increased over the last decade, court reporters have experienced wage growth relative to the legal industry, according to the model. This reflects an increased demand for the services of court reporters, rather than a decline. That said, again, these results are far from statistically significant. The effect sizes cannot be determined as significantly different from zero, and as a result, cannot be used to support the hypothesis that entry level legal positions have seen declining compensation relative to the legal field.

**Table 5: Legal Support Regression Results Mean Annual Wage**

| a_mean_adj | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| legal_support | -42114.272 | 2551307 | -0.02 | .987 | -5078866.8 | 4994638.2 | |
| year | -217.943 | 818.603 | -0.27 | .79 | -1834.018 | 1398.131 | |
| | . | . | . | . | . | . | |
| legal_support x year | -9.969 | 1264.97 | -0.01 | .994 | -2507.255 | 2487.316 | |
| Constant | 569585.3 | 1651124.9 | 0.34 | .731 | -2690041.1 | 3829211.7 | |

| | | | |
|---|---|---|---|
| Mean dependent var | 103604.420 | SD dependent var | 40028.024 |
| R-squared | 0.593 | Number of obs | 172 |
| F-test | 81.664 | Prob > F | 0.000 |
| Akaike crit. (AIC) | 3985.887 | Bayesian crit. (BIC) | 3998.477 |

*** *p*<.01, ** *p*<.05, * *p*<.1

**Table 6: Court Reporter Regression Results Mean Annual Wage**

| a_mean_adj | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| court_reporter | -2042736.3 | 15276262 | -0.13 | .894 | -32200906 | 28115433 | |
| year | -220.468 | 979.304 | -0.23 | .822 | -2153.796 | 1712.86 | |
| | . | . | . | . | . | . | |
| court_reporter x year | 996.372 | 7581.142 | 0.13 | .896 | -13970.206 | 15962.95 | |
| Constant | 549697.42 | 1975259.2 | 0.28 | .781 | -3349830.1 | 4449224.9 | |

| | | | |
|---|---|---|---|
| Mean dependent var | 103604.420 | SD dependent var | 40028.024 |
| R-squared | 0.030 | Number of obs | 172 |
| F-test | 1.714 | Prob > F | 0.166 |
| Akaike crit. (AIC) | 4135.409 | Bayesian crit. (BIC) | 4147.999 |

*** *p*<.01, ** *p*<.05, * *p*<.1

Tables 7, 8, and 9 display the results of models 4, 5, and 6, respectively. These results display the same interaction terms, but with the dependent variable set to an inflation adjusted annual median wage. The median compensation interaction coefficients indicate that legal support roles, barring paralegals, have seen their annual wages increase relative to the field over the past decade. The coefficients on "year" imply that median compensation for the legal field outside of legal support workers has been decreasing over the analyzed period. Meanwhile, these models predict that legal support workers, particularly court reporters, have seen their annual median wages increase relative to the field. Again, however, statistical insignificance renders the research incapable of drawing conclusions based on these results.

**Table 7: Paralegal Regression Results Median Annual Wage**

| a_median_adj | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| paralegal | 8135.547 | 5061889.3 | 0.00 | .999 | -9984971.4 | 10001243 | |
| year | -130.446 | 901.565 | -0.14 | .885 | -1910.302 | 1649.41 | |
| | . | . | . | . | . | . | |
| paralegal x year | -22.238 | 2509.625 | -0.01 | .993 | -4976.702 | 4932.226 | |
| Constant | 360275.74 | 1818374.6 | 0.20 | .843 | -3229532.4 | 3950083.9 | |

| | | | |
|---|---|---|---|
| Mean dependent var | 92479.788 | SD dependent var | 36567.322 |
| R-squared | 0.113 | Number of obs | 172 |
| F-test | 7.158 | Prob > F | 0.000 |
| Akaike crit. (AIC) | 4088.799 | Bayesian crit. (BIC) | 4101.389 |

**** $p<.01$, ** $p<.05$, * $p<.1$*

**Table 8: Legal Support Regression Results Median Annual Wage**

| a_median_adj | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| legal_support | -666290.39 | 2426750.2 | -0.27 | .784 | -5457144.7 | 4124563.9 | |
| year | -559.498 | 778.638 | -0.72 | .473 | -2096.675 | 977.679 | |
| | . | . | . | . | . | . | |
| legal_support x year | 303.006 | 1203.213 | 0.25 | .801 | -2072.36 | 2678.372 | |
| Constant | 1244363.3 | 1570515.7 | 0.79 | .429 | -1856125.6 | 4344852.2 | |

| | | | |
|---|---|---|---|
| Mean dependent var | 92479.788 | SD dependent var | 36567.322 |
| R-squared | 0.559 | Number of obs | 172 |
| F-test | 70.986 | Prob > F | 0.000 |
| Akaike crit. (AIC) | 3968.669 | Bayesian crit. (BIC) | 3981.259 |

**** $p<.01$, ** $p<.05$, * $p<.1$*

**Table 9: Court Reporter Regression Results Median Annual Wage**

| a_median_adj | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| court_reporter | -2548137.2 | 13972342 | -0.18 | .856 | -30132127 | 25035853 | |
| year | -433.297 | 895.715 | -0.48 | .629 | -2201.604 | 1335.01 | |
| | . | . | . | . | . | . | |
| court_reporter x year | 1249.408 | 6934.046 | 0.18 | .857 | -12439.683 | 14938.5 | |
| Constant | 967649.76 | 1806659 | 0.54 | .593 | -2599029.8 | 4534329.3 | |

| | | | |
|---|---|---|---|
| Mean dependent var | 92479.788 | SD dependent var | 36567.322 |
| R-squared | 0.027 | Number of obs | 172 |
| F-test | 1.575 | Prob > F | 0.197 |
| Akaike crit. (AIC) | 4104.717 | Bayesian crit. (BIC) | 4117.307 |

**** p<.01, ** p<.05, * p<.1*

## Conclusion

The empirical analysis contained in this paper returned results that suggest there may be an effect where compensations of legal support workers have been adjusting differently over time compared to the legal field. This analysis fails to determine whether this effect is positive or negative and concludes that the results are insignificant. While the positive effect observed in the median annual wage regressions suggests that the average support worker is experiencing a wage increase each year greater than the average wage increase experienced across the field, the negative effect seen in the mean annual wage regressions may indicate that the total amount of money earned by support workers each year has been decreasing, given that analysis of the population of support workers could not statistically prove that the share of support workers in the field has been decreasing.

These results coincide with the sentiment expressed by participants of the interview series, that suggested there has not been a meaningful change in the concentration of legal support workers alongside growing automation innovation. The Bureau of Labor Statistics dataset was limited in its power to examine the field by its small number of identifying legal occupation codes, which provided for difficulty in analyzing individual legal roles, and how their compensations and employments might be changing. Most of the occupation codes pertaining to the legal industry combined two or three legal roles under one observation. As a result, it was difficult to examine more occupations individually within the legal industry.

One area for deeper analysis may be present in the notion that the court systems are largely unaffected by technological advances, as court reporters seem to potentially experience increasing wages relative to the field. Further research should seek to identify if these trends are representable statistically. Additional research should consider which particular skills and tasks are most at risk within the legal industry of being automated by new technologies, this would provide a better understanding of the factors that may contribute to future demand for certain occupations, and lack thereof for others.

Due to a lack of data representing the past couple years, it is difficult to examine whether the emergence of AI technologies has contributed to a larger trend in entry level compensation and employment in the past two years. With some industry professionals expressing concern for the future of legal support jobs in the face of growing AI technology, and the literature's insistence that industry 4.0 will cause sweeping changes to the way legal services are conducted, it will be important for prospective legal professionals to be mindful of the malleable landscape surrounding them.

## References


Acemoglu, D., & Autor, D. (2023, October 3). Skills, tasks and technologies: Implications for employment and earnings. https://shapingwork.mit.edu/research/skills-tasks-and-technologies-implications-for-employment-and-earnings/

Acemoglu, Daron, and Pascual Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review*, 108 (6): 1488-1542.

Bessen, James, *How Computer Automation Affects Occupations: Technology, Jobs, and Skills*, *in* No. 15-49 Boston University School of Law, Law and Economics Research Paper (2016).

Carpenter, M. (2020, October). *Legal education: A call to action*. American Bar Association. https://www.americanbar.org/groups/intellectual_property_law/publications/landslide/2020-21/september-october/legal-education-call-action/

Dawid, H., Neugart, M. Effects of technological change and automation on industry structure and (wage-)inequality: insights from a dynamic task-based model. *J Evol Econ* **33**, 35–63 (2023). https://doi.org/10.1007/s00191-022-00803-5

Drozd, Lukasz A., et al. “Understanding Growth through Automation: The Neoclassical PE.” *Working Papers*, Federal Reserve Bank of Philadelphia, 26 Aug. 2022, ideas.repec.org/p/fip/fedpwp/94680.html.

Fareri, S., Fantoni, G., Chiarello, F., Coli, E., & Binda, A. (2020b, March 13). *Estimating industry 4.0 impact on job profiles and Skills Using Text Mining*. Computers in Industry. https://www.sciencedirect.com/science/article/abs/pii/S0166361519309327?casa_token=kXo4Ie1NSBUAAAAA%3AmR7zhFEGcH1WGwzbSu-oK92mwKI6MGuUd894xaRSokHgsPYjQyEIrdlY4g_hwxbRKn8leobwwg

Floridi, L. Technological Unemployment, Leisure Occupation, and the Human Project.*Philos. Technol.* **27**, 143–150 (2014). https://doi.org/10.1007/s13347-014 0166-7

Keynes, John Maynard, “Economic Possibilities for our Grandchildren (1930),” in*Essays in Persuasion* (New York: Harcourt Brace, 1932), 358-373, April 18 2024.

Landes, M. S. (1966). Project: Automated Legal Research. *American Bar Association Journal*, *52*(8), 730–733. http://www.jstor.org/stable/25723710

Pasquale, F., & Cashwell, G. (2021b, March 8). *Four Futures of Legal Automation*. HeinOnline. https://heinonline.org/HOL/LandingPage?handle=hein.journals%2Fucladis63&div=4&id=&page=

Szabó-Szentgróti G, Végvári B, Varga J. Impact of Industry 4.0 and Digitization on Labor Market for 2030-Verification of Keynes' Prediction. *Sustainability*. 2021; 13(14):7703. https://doi.org/10.3390/su13147703

U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL], retrieved from FRED, Federal Reserve. Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL, April 16, 2024.

U.S. Bureau of Labor Statistics. *Occupational and Wage Statistics*. U.S. Bureau of Labor Statistics. https://www.bls.gov/oes/. April 03, 2024

Vucic, Franjo. "Changes in Legal Education in the Digital Society of Artificial Intelligence." *SpringerLink*, Springer Nature Switzerland, 1 Jan. 1970, link.springer.com/chapter/10.1007/978-3-031-36833-2_12.

Whalen, Ryan, Defining legal technology and its implications, *International Journal of Law and Information Technology*, Volume 30, Issue 1, Spring 2022, Pages 47–67, https://doi.org/10.1093/ijlit/eaac005

## Addendum

### Interview Questionnaire

1. Have you noticed a shift in the skill profiles that persons ascribe to themselves since you entered your field? Can you explain the development of these skill trends?

a. What technologies have influenced these trends?

2. In what ways have you had to adapt your own skill set alongside automation?

a. How has computerization of your occupation led you to adapt or adjust your skills?

b. Can you name other forms of automation that have led you to adjust your skill set? What skills do you associate with these technologies?

3. What elements of your job/firm's operations have been automated in the past?

a. Can you associate particular skills requirements that have emerged alongside this technology?

4. Have you experienced, in your field, a shift in the skill profiles that persons ascribe to themselves? Would you explain the development of these skill trends?

a. What technologies have influenced these trends? How have people in your field adjusted?

5. When making hiring decisions, how important do you consider an applicant's proficiency in the latest technology?

6. What is your understanding of AI technologies and how they will impact the legal industry?

7. What is your interpretation of how application of AI technologies will differ from past technological automation in your field?

a. In your opinion what skills will be rendered unnecessary by AI, and which skills will become more valuable?

b. In what ways might your answer to the previous question be relevant to your occupation, but irrelevant to other legal practitioners?

8. What advice would you give to a person seeking employment in the legal industry? How might they curate their own skillset to be most competitive in a hiring process?

a. How does advice you would give today differ from advice you would have given 20 years ago?

b. Does your advice consider the implications of future generations of AI technologies?

9. Is there anything that I didn't ask you that you wish I had?