

# **From Causal Inferences to Predictive Analytics: Using AI to Settle on Damages**

**Frank S. Giaoui  
Columbia Law School**

*From the perspective of both plaintiffs and defendants, the measurement of damages quantum is of the utmost importance. It is surprising to see this process left entirely to the court's discretion, as quantum is traditionally considered a question of fact. Quantifying damages presents significant challenges due to the subjective nature of court discretion, leading to uncertainty for both plaintiffs and defendants. This research addresses this issue by examining difficult-to-quantify contract damages through empirical and comparative methodologies. Based on prior studies on French civil law and American common law, this empirical study involved quantitative analysis of various contract cases. Methodological advancements, including Machine Learning (ML), and Natural Language Processing (NLP) techniques, facilitated automated extraction and analysis of key variables. With a focus on overcoming sample size limitations and enhancing accuracy, this study achieved a classification accuracy of over 85% for identified essential variables. The more recent integration of generative AI and Large Language Modeling marked significant progress in quantifying damages. I conclude with recommendations for sustainable management practices in this field.*

*Keywords: comparative empirical analysis, damages, predictive analytics, risk management, artificial intelligence*

## **INTRODUCTION**

### **Contractual Dispute That Motivated This Research**

The catalyst for this research stemmed from a contractual dispute, where I provided advisory services to a clean-tech start-up during a private placement endeavor. Despite securing an exclusive negotiation agreement with a corporate venture fund, the promising investment fell through, leading to the start-up's eventual bankruptcy and a loss of professional fees. The subsequent lawsuit for breach of contract resulted in only partial compensation, highlighting the challenges associated with quantifying damages without objective market pricing. This experience prompted a shift in my career trajectory, inspiring a pursuit of legal studies and a comprehensive examination of contract law, revealing striking similarities in the challenges of damages quantification between the French and American legal systems. Recognizing the need for improved benchmarks and guidelines for assessing economic losses, this research addresses the complexities and uncertainties surrounding contract damages in both jurisdictions.

## General Issues With Damages Calculation

From the perspective of both plaintiffs and defendants, the measurement of damages *quantum* is obviously of the utmost importance. Nevertheless, throughout Western jurisprudence, the measurement of economic loss and contractual damages has traditionally navigated between two difficulties: legal uncertainty and technical complexity (Atiyah, 1995). Legal uncertainty is permanent, as damages are supposed to be a question of facts, calling for case-by-case *sui generis* solutions and leaving their appreciation entirely to the court's discretion (Barnes, 1998).

Technical complexity arises when objective data is lacking or when such data exists, but current quantitative methods are too sophisticated and costly to be worth the implementation in most cases. But even assuming that an aggrieved party's resources permit full and unbound pursuit of the quantification of damages, such endeavors are moot *ab initio* when courts might not fully recognize the underlying cause of action. This is the case for non-pecuniary injuries to reputation, which until the last two decades, were not fully recognized at either the individual or corporate level. Once courts slowly became less hesitant to grant relief to these types of wrongs, they — perhaps unsurprisingly — only began to do so with the same skepticism toward the quantification of damages.

For all the above reasons, the parties, their counsel, and sometimes even the courts essentially rely on (mostly inefficient) bargaining. This increases the risk of unnecessary litigations and uncertain judicial decisions, potentially lacking legitimacy. To reduce this risk at both the intra- and international level, there is a need for alternative methods that are factual, simpler, and more widely applicable than current quantitative damages calculation methods. Once shared and accepted, those methods may serve as a decision support to judicial decisions and eventually help damages become a question of facts and law.

My earlier works have shown ample legal literature on the theory of contractual liability in both the United States and France (Giaoui, 2020). However, this same literature is much sparser concerning recovery and contractual damages, in both jurisdictions, it is practically nonexistent on the *quantum* of damages. The only academic literature on damages *quantum* was found from either tort law (personal injury) (Koch, 2002), or economic scholars, probably because damages and their calculation are considered a question of fact and not a question of law (Posner, 1998). This is unsurprising in French civil law, where the default recovery rule is specific performance.<sup>1</sup> However, the same occurs in international commercial law, and even in the United States, where the default rule is the award of expectation damages as a remedy for contract breach (Collins, 1995). However, the doctrine and jurisprudence have been less hesitant to deal with this in other areas of civil liability, particularly in Tort. If initially, the idea of organizing different types of bodily injury into rubrics and damages schedules seemed offensive (Voorheis, 1903), it is today fully accepted (Laycock & Hasen, 2018; Scarso Alessandro Pietro, 2005).

The following comparative research develops the groundwork for a data-driven contract damages methodology applicable to different global jurisdictions. Building upon major findings of earlier works, this paper takes from personal injury doctrine to posit the viability of alternative assessment methods involving the development of damages guidelines or schedules for different economic and non-economic losses that are difficult to quantify.

## PRIOR RESEARCH

The development of my research can be delineated through a series of four publications, each representing significant milestones in advancing my work. These publications collectively form a robust foundation for developing a comprehensive and standardized approach to damages assessment and awards.

Beginning with “Towards Legally Reviewable Damage Awards” (Giaoui, 2020), my initial exploration emphasized the critical nature of damages quantification in legal proceedings. Drawing attention to the discrepancy between legal uncertainty and technical complexity, the study highlighted the necessity for a model that upholds the principle of full recovery. It identified three specific business situations where simple quantitative methods were most applicable for assessing damages, ultimately advocating for a comprehensive framework that ensures reviewable and standardized damage awards.

Building upon this foundational framework, the subsequent publication, “Predicting Damages Award: Comparative Analysis on Contract Breach Litigations” (Giaoui, 2023), delved deeper into empirical analysis, examining factors influencing judicial outcomes in contractual disputes. By developing a comprehensive database and identifying predictive trends, the study revealed the convergence of case laws in the United States and France, while proposing best practices for litigated disputes.

In “Breaches of Agreements to Negotiate: Comparative Analysis of Damages” (Giaoui, 2022), my research focused on breaches of agreements to negotiate and agree, further solidifying the need for standardized damages methodologies. Exploring global convergences and the impact of various factors on litigation outcomes, the study highlighted the implications of the globalization of legal practices and the potential for developing damages guidelines and schedules.

The latest publication, “Damage to Reputation: Comparative Analysis of Compensation for Non-Pecuniary Harm” (Giaoui, 2023), shifted the focus to compensatory damages for non-pecuniary harm, particularly emphasizing the challenges associated with objectively evaluating harm to reputation. Through a comprehensive review of legal scholarship and case law, the study provided insights into the increasing quantification of damages and their extension from tort law to contract law, culminating in practical suggestions for enhancing the recovery of damages and facilitating equitable assessments in legal decisions.

## **METHODOLOGY**

### **Underlying Methodology**

As with empirical research in the social sciences, my methodology used inductive reasoning, extracting relevant data to test working hypotheses based on legal thought<sup>X</sup>. A deductive approach, consisting of gathering all kinds of data without any initial working hypotheses, would run the risk of being too vast. Certain analyses are common to all situations and all jurisdictions, while others are specific to particular ones.

For the United States, I concentrated primarily on three states: New York, California, and Delaware.<sup>2</sup> For France, most cases were decided in Paris or Versailles. These choices are consistent with the geographic concentration of U.S. and French disputes. That concentration is even more pronounced because the cases that interest us must be well documented to prove the damages, which requires parties with sufficient financial resources to pay for expert opinions. However, I also collected decisions from other French cities and U.S. states.

For each situation and jurisdiction, I used keywords<sup>3</sup> to identify relevant cases and to extract them from the principal online databases: Court Listener, Westlaw, and Lexis Nexis in the United States, Dalloz and Lamyline in France, and Pace, Uncitral, and Unilex for international commercial law. The relevant decisions were then systematically mapped into databases. More specifically, I analyzed the quantitative and coded qualitative data likely to explain the decision of a court or an arbitral tribunal regarding the *quantum* of damages. The purpose of this analysis was to first track the evolution over time of the average probability of recovery (the Win Rate) and the average ratio of recovery to the plaintiff’s claim (the Recovery Rate); to then identify the variables that explain the deviation of the actual ratios from the average and measure the relative weight of those variables; compare these measurements between the various jurisdictions, and where a theory emerges, develop the associated model.

When values are high (thousands or millions of dollars), the functional forms Log Grant/Log Claim generally makes sense to analyze the relation between Grant and Claim on one particular jurisdiction and one particular legal situation. However, my sample covers three jurisdictions or bodies of law and even three legal situations with different scales. The average grant of Expectation General Damages is five to six times larger in the U.S. than in France and two to three times larger in situation 1 than in situation 3.<sup>4</sup> Finally, I needed a simple way to combine Win Rate, which measures the merit of a case – the odds for a claimant to get a non-zero award, and the Recovery Rate, which measures the economic stake of the case – the portion of the claim quantum that is awarded to the claimant. So, the best way to keep one single dependent metric and compare it easily across all the sample cases was to opt for a functional form in ratios:

Win Rate/Log Claim and Recovery Rate/Log Claim. As it happens, this functional form demonstrated a good fit. The same applies when analyzing the relation between Grant and any particular independent variable or combination.

Throughout this process and many iterations, two main challenges appeared: i) finding enough relevant cases documenting both the *quantum* of the claim and the *quantum* of the award; and ii) the consequent selection biases created by this limited sample. In the coming section I explain how I overcame, and even embraced these challenges.

### **Dataset Limitations and Selection Bias Are Considerable but Not Insurmountable**

The issue of obtaining data for all the empirical analyses I wanted to conduct for this research was rightfully brought up early on by consulted scholars and practitioners. As very detailed rulings were needed to extract useful data and trends (especially the quantum of both claims and grants), finding relevant and representative cases in both American and French jurisdictions was a great challenge.<sup>5</sup> This subset then developed the unfortunate tendency of becoming smaller whenever cases were culled to focus on specific situations.<sup>6</sup>

Moreover, the limited size of the dataset also resulted in greater risk of several selection biases. The first possible bias was a product of deciding to do a comparative analysis on jurisdictions where the proportion of litigated cases is likely different: The United States and France are characterized by different proportions of litigated commercial disputes and those settled out of court. The common knowledge is that most commercial disputes are settled out of court in the United States. At the same time, given the lower cost of litigation, the proportion of settlements is (probably) lower in France. Likewise, including a liquidated damages clause in a contract — a common practice in international transactions as highlighted in the earlier literature review — reduces the number of cases that continue to the verdict stage. However, the potential difference in the share of litigated cases between the jurisdictions should not affect the validity of the conclusions drawn from the observations on the sample. After all, I focused primarily on litigated cases and their outcomes (as opposed to non-litigated cases and their outcomes). Throughout my literature review, I learned that selection effects, while unavoidable, still allow for valid inferences (Klerman & Lee, 2014; Lee & Klerman, 2016; Schweizer, 2016). So even if there is a selection bias, the best course of action was embracing it to predict not all cases but litigated cases primarily as they are used as reference (or potential threat) by all parties, even those who would rather not litigate (Priest & Klein, 1984).

The second selection bias is that as my selected disputes are litigated, they are arguably the ones in which the involved parties face the highest degree of uncertainty. In other words, because those parties have very different expectations about the potential outcome of the litigation, they are less likely to settle in the first place. This said, this subset of cases is ideal for a study aiming to reduce judicial uncertainty.

The third is inherent to most legal research, and it is the risk that cases that get carried to court and then published online do not necessarily constitute a representative sample of all disputes that take place. This is especially true regarding first instance cases and is why my sample mainly comprises appeal/last resort cases. While this bias seems to have decreased over time as a greater proportion of cases are collected and then published in major databases, the only way to definitively address this issue would be to manually access all the dockets of the jurisdictions under investigation — an endeavor beyond my current scope and means. However, this trend set up the foundations for the next step of my research, discussed in the coming sections.

The fourth and last (but not least) bias turns around the potential impacts of different trends affecting the different jurisdictions. Let's say for the sake of the argument that, during the observed period, the proportion of cases going to settlement increases in the U.S. and decreases in France. How would this distort the sample and, hence, the conclusions of the empirical analysis? In theory, we can make three assumptions over the 25-30 years: 1) the change is continuous and permanent, 2) there are isolated events of changes, or 3) there is no change at all. The two extreme assumptions do not seem realistic. However, if — as it is more likely — there are a couple of isolated changes, then the long-term general trends observable would not be significantly affected.

Despite these challenges, the research design accounted for potential biases and adopted a rigorous approach to ensure the integrity of the findings. I found that valid inferences could still be drawn despite selection effects. The apparent issues of uneven samples of litigated and highly uncertain cases for each jurisdiction became negligible upon realizing that focusing on attempting to predict litigated cases was in line with my research goal of reducing judicial uncertainty. Throughout each subsequent phase of my work, the methodology's limitations were carefully reconsidered, providing valuable insights for later research extensions now composing this article. Reassured at the soundness of the methodology and intimately understanding its limitations, I was able to extend it to addressing biases through more data collection, adopting new automation technologies — such as natural legal language processing, machine learning and generative AI— and obtaining access to expanded data sources, both public and private.

## DISCUSSION OF MAJOR FINDINGS

### Divergences and Convergences of Jurisdictions Over Time

Some important divergences remain in the case laws and — even more so — in the statutory laws between the three jurisdictions or bodies of law. As mentioned, the most fundamental statutory difference stays in the default remedy for contract breach: in France it remains specific performance, whereas it has always been expected damages in the U.S. However, two other divergences have more concrete consequences on the case law: the role of good faith and the scope of damages.

In France, good faith is a fundamental notion of contract law, a guiding principle enshrined in the reform of February 10, 2016 to article 1104 of the Civil Code: “*Contracts must be negotiated, formed and performed in good faith. This provision is of public order.*” In the U.S., there is an equivalent provision neither in the UCC nor in the Restatement (Second) of Contracts. Case law had anticipated the move for more than a decade in France, making bad faith a popular cause of action, although challenging to evidence for the plaintiff.

When damages are enforced in France, they are supposed to compensate all harms (Bussani, 2003); in the U.S, only pure economic loss is compensated. This results in a long list of damages in France, including emotional distress, moral prejudice and harm to reputation, often nominally compensated. It also results in more frequent use and wider acceptance of economic valuation techniques in the U.S. than in France.

As I already observed, International Commercial Law harmonization bodies fall somewhere between the two major laws. Arguably, CISG (Vienna Convention) falls closer to the U.S. Common Law — particularly for the default remedy of damages, and Unidroit (the PICC) closer to French Civil Law — including for compensating emotional harm (Briggs, 2013).

However, empirically studying the outcomes of comparable cases in both jurisdictions show a similar marked trend toward uniformity of Win Rates and Recovery Rates (Priest & Klein, 1984).<sup>7</sup> These results were proven to be likely caused by ever-increasing globalization of the economy, corporations, law firms, accounting firms, etc.<sup>8</sup> Further, in the US and France, models — initially developed on a limited dataset — showed a negative correlation between the absolute value of the plaintiff's claim and the percentage of that claim actually granted. Since then have been confirmed more robustly on studies with larger sample sizes as described in the forthcoming sections.<sup>9</sup>

Early on and throughout each research iteration, a striking convergent pattern formed in American and French jurisprudences and judicial outcomes. At the theoretical level, and despite their fundamental differences, I observed a shift in both jurisdictions toward the recognition and availability of the same (or at least very similar) monetary remedies like break-up fees for each of the situations studied (Giaoui, 2020; Giaoui, 2022) — though ironically, this convergence has also signified that both jurisdictions face the same uncertainty in determining the *quantum* of such monetary remedies.

The observation of clear converging trends concerning the probability of grant and even more concerning grant-to-claim ratios between the United States and France and, to a certain extent, with international commercial law<sup>10</sup> has led us to the hypothesis that globalization is at work. In order to validate the hypothesis, I documented the globalization among corporations, among accounting firms, among law firms and also among lawyers. The result of the analysis clearly confirms my initial hypothesis.

It is no surprise that with the advance of logistics, transportation, telecommunications and other digital technologies, the world is becoming smaller, and the borders of international business transactions are becoming more and more invisible. It is also a fact that companies and big conglomerates have enhanced their global presence. This forces professional services providers to become global as well to continue to be competitive and serve their clients as they chase business opportunities abroad. As a result, in recent decades, law firms, investment banks and accounting firms, among other services providers, have had to adapt themselves to this new reality. Again, since the 1990s this powerful globalization trend has shown no signs of weakening despite recent political postures.

In light of the preceding, I can now confidently assert that law firms—similarly to other professional services providers such as investment banks and accounting firms—are becoming more global and tend to provide somewhat standardized services. Hence, it is also reasonable to infer that judicial decisions and arbitration awards are likely to adopt similar patterns. In common law countries, courts are required to follow precedent or distinguish the cases before them from precedent. In civil law countries, although precedents are not binding, they serve as a good indication of the direction the court should take. As such, if the types of claims and their defenses become standardized, one might infer that their outcomes would follow the same path. Is it possible that judicial decisions and arbitration awards will become more automated and simplified when each case can be assigned to a particular category among other pre-established categories? If so, decision-making would become a more efficient “check-in-the-box” process rather than a lengthy, costly, and often complex one.

### **Heavy Drivers Are Identified to Predict the Outcome**

I identified criteria that could influence the outcomes and determined their relative weight in explaining the recoverable damages. My intuition as to the relevant factors was first of all grounded in the idea that judges might be sensitive to some business factors, most likely in the form of what has been called in behavioral literature “attribute substitution” (Kahneman & Frederick, 2002) — in other words, faced with the uncertainty and difficulty of the calculation of the real damages, judges might unconsciously proceed by answering different, simpler questions as decision proxies. Working with the data, I took note of various parameters that commonly described contract breach cases across the jurisdictions and concentrated on six of these factors after identifying which seemed most relevant to court decision-making on the outcome of a particular lawsuit:

#### *Selected Factors*

**Quantum Value of Claim.** The *quantum* value of the claim is defined as the amount of money the plaintiff declares as their damages. It is measured in thousands of U.S. dollars or euros and is not scaled. The outcome was defined as two different metrics: the win rate (the probability of a claim being granted) and the recovery rate (the proportion of *the* claim being granted). Win rate and recovery rate were calculated over time and compared by jurisdiction to evaluate possible convergence towards a common value. Time was measured in years and divided into three relatively equal years ranges for each jurisdiction. Also, I define the win rate as either 0% (no grant) or more than 0% (grant). In the same way, the recovery rate studies the grant as the amount awarded to the claimant (including legal fees) as a percentage of the amount claimed.

**Sophistication of Claimant’s Methodology.** As the disputing parties have to prove or argue among themselves the exact *quantum* of the real damages, one would expect that the greater the sophistication of the methodology used for this calculation the better the results. Despite not having full access to expert reports in collected court opinions, I devised a sophistication index to especially test, the link between this index and the recovery rate based upon the assumption that a report not mentioned by the court was likely not deemed persuasive. The index thus scales sophistication from 1 (the lowest) to 4 (the highest). This index also allowed me to see whether the sensibility of judges to greater sophistication evolved.

**Claimant’s Business Risk.** The law & economics tradition would seem to suggest that the risk linked with the particular business endeavor at hand might play a role: in fact, the riskier the business (e.g. a novel tech venture) the less certain the exact *quantum* of the real damage for the plaintiff, for she might have

failed to achieve the awaited results even if the contract had been concluded. I then devised a business risk index which will allow us to test this intuition.

The business risk is the degree to which the claimant's business performance is volatile. This index ranges from 1 (very low risk) to 4 (very high risk). To classify the cases on a risk scale, I extracted data based on qualitative elements. For instance, I classified each case depending on the claimant's industry type (Distribution, Service, High Tech, Manufacturing, and Construction). I attributed a claimant's business risk index to each case about multiple factors (industry type, market price volatility, tenure of operations, business size).

**Law Firm Size.** I also became interested in uncovering any link between the final result, especially in terms of the recovery rate, and the size of the law firms representing the claimant in court. If such a link exists and is positive, it is plausible to infer that judges are more prone to award more damages to clients defended by large firms, or that those firms are more sophisticated and can therefore use their larger resources to better substantiate their clients' claims. Law firm size is measured by the number of attorneys working at the law firm. It is scaled from 1 (Very Small) to 4 (Very Large). Unfortunately, this analysis was not conducted in France for breach of agreements to negotiate cases due to the extreme variation of the *quantum* value of claim across my different categories that could have biased my results.

**Length of Negotiations or Relationship.** Another seemingly relevant factor seems to be the duration of the claimant and the defendant's contractual relationship or – alternatively—the length of negotiations to reach a contract, which intuitively is directly linked to the *quantum* of restitution damages but may also be correlated with the *quantum* of the expectation damages granted. It is measured in years and is not scaled. Beyond reliance damages, it is likely that as time invested into the negotiation or the relationship goes up, courts will be more receptive to allowing claimants to recover wider damages.

**Claimant's Reputation.** Lastly, I also used an indicator measuring the importance of the plaintiff's reputation in each case. I designed the indicator to measure the degree to which the plaintiff's reputation was a key factor for success in its business sector. The indicator enabled me to assign a rank to each case (ranging from 1, for low importance, to 4, for high importance). I built this composite index encompassing among others: average advertising expenditures, brand awareness and word of mouth, referrals as sources of business, search engine results, news coverage, publicized actions of the company, etc. In both jurisdictions, I noted a striking correlation between the importance of the plaintiff's reputation and the court's decision, particularly the recovery rate.

### *Correlation to Outcomes*

Out of the six factors, Claim *Quantum* and Sophistication were proved to have the strongest predictive effect on outcomes. Overall, the six variables impacted the ability of a plaintiff to obtain the desired outcome of a litigation both in terms of Win Rate and Recovery Rate in the following ways.

- *Quantum* Value of Claim (negative impact);
- Sophistication of Claimant's Methodology (positive impact);
- Claimant's Business Risk (negative impact);
- Law Firm Size (generally positive impact);
- Length of Relationship (positive impact); and,
- Claimant's Reputation (positive impact).

Claim *Quantum* and Business Risk were negatively correlated with Win Rate and Recovery Rate. Everything else being equal, court skepticism may increase as Claim *Quantum* increases. It is also possible that very high claims are more likely to be regarded as unreasonable and hence strongly disputed by the defendant or may be the result of overestimation by the plaintiff. For Business Risk, the data generally showed that the negative correlation to Win Rate is similar for all industries (damages are granted in approximately one-third of all cases), except for Construction (where the dataset didn't contain any winning case). However, when damages were granted, Services and Manufacturing industries got higher Recovery Rates than High Tech industries. This seems to corroborate my hypothesis: high-tech industries are riskier, and it is more difficult to determine what the real damages are, especially for expectancy damages, as a myriad of factors could upset expected gains even if a contract were to be finalized and performed.

Level of Sophistication, Law Firm Size, Length of Relationship, and Reputation, all four positively affected the Recovery Rate and Win Rate. Concerning the Level of Sophistication and the underlying reasoning of claimants — and of courts and judges — I often found quite inconsistent and simplistic methodologies for calculating the *quantum* of damages. However, when claimants used more sophisticated methods, their success rates significantly increased.<sup>11</sup> Likewise, when the Law Firm Size increased, so did the Recovery Rate and Win Rate, with the largest change occurring when moving from smaller law firms (categories 1 and 2) to larger law firms. The effects of Length of Relationship, however, were more divided across jurisdictions. My initial hypothesis predicted that as more time is invested in negotiation (or relationship), and parties invest more resources to eventually reach a final agreement (or a larger outcome), courts would be more willing to allow for higher damages. In the US, I failed to uncover a clear positive link between the Length of Relationship and the Win Rate or the Recovery Rate. At the same time, in France I observed that the length of the relationship between the parties had a considerable influence on the Win Rate or the Recovery Rate, especially when the relationship between the parties lasted more than twelve months. This trend was reversed when looking at the importance of Reputation in both jurisdictions. In the US, I noted a striking correlation between the importance of the plaintiff's reputation and the court's decision, particularly the Recovery Rate. This evolution in the decisions shows the courts' increased understanding of harms to reputation, image, and goodwill depending on the industry.

## **IMPROVING FINDINGS THROUGH AN EXTENDED METHODOLOGY**

When combined, the four following methodological extensions have, and hopefully will continue to, allow me to further reduce biases in the data and increase accuracy in findings. Because most of the underlying research remains unpublished, these sections will focus on shedding some light on technical aspects.

### **Extension 1: Aiming to Optimize the Limited Sample Size**

Throughout my earlier research, emerging AI technologies and predictive algorithms like natural language processing (NLP) and machine learning (ML) caught my eye as likely solutions for all my data woes (Giaoui, et al., 2023).

NLP technology allows a user to train a computer to “read and comprehend” text. Accessible to the public and fairly cheaply, NLP can be used to automate the extraction and curation of a massive corpus of data, so long as the right text is used in the training. This presented one of the first issues with its early use in my research. The majority of NLP models available are trained on common language lexicons, so my use of NLP would have necessitated diverting limited resources to training models on specific legal language (entailing considerable tagging of hundreds of cases and checking their extraction). Though it was clear that improvements in the methodology would have been exponential, it was decided to defer the application of NLP until my early hypotheses were confirmed.

ML technologies are what most people understand as artificial intelligence. They greatly go beyond linear regression models and allow for training any kind of model architecture.<sup>12</sup> Their main benefit is that, when many variables are present, it can sort them in an almost infinite number of architectures with multiple layers of variables that are not necessarily linearly correlated (it can find any type of relation). However, there is a cost to this: interpretation. When going further into different layers of variables, it becomes more and more complex to interpret the results.

But as promising as these two technologies were, the irony was that the limited size of the initial sample of about 200 cases was more than unsuitable for NLP and Machine Learning models. My first extension had to respond to limited sample size while keeping the same methodology and iterating on different scripts. Challenges were quick to appear at each iteration, but workarounds and solutions were found with some creativity and resourcefulness.

Pattern matching and careful use of heuristics were used to develop a script capable of scanning the contents of each case and then identifying named entities of interest. The script successfully downloaded about 8,000 cases, but accidentally gave way for the next issue: confirming whether a case was relevant or



not. Determining relevance involved carefully using search queries to filter out irrelevant cases from the onset and then encoding heuristics to filter out irrelevant cases that still managed to slip through. The final query resulted in a much more robust set of 6,500 relevant cases (out of 8,000) where important entities like case id, date of filing, claimant, defendant, the court, and the court's jurisdiction were identified.

More recently generative AI and LLMs (Large Language Modeling) were used to structure documents into individual variables that would geometrically increase the sample size. For example, on the sophistication of the methodology, we used generative AI to identify and count the number of unique claims and unique methodologies.

## **Extension 2: Implementation of Classifiers and Regressors to Capture and Predict**

This new sample was more than enough to use as a foundation for NLP and ML. Still, its size made it clear that tagging and extracting key variables identified earlier, chiefly *Quantum* or Level of Sophistication, was no longer viable manually.

### *Automated Capturing*

**Quantum.** With considerably more raw data available, the next iterations focused on improving textual analysis to automate the extraction from an even larger number of case sentences likely to contain *quantum*, and then extracting *quantum* itself. Consistently identifying and classifying *quantum* with at least 85% and up to 99% accuracy (a fairly good metric by most standards) presented another roadblock I tried solving with sentence extraction.

After building an annotated corpus with a total of 48 classes of sentences identified across various lawsuits, 96 cases from US law were annotated manually to extract and build a corpus of 8,500 sentences with a high probability of containing grant and claim *quantum* values.

Several engineered variables — such as location of claim *quantum*, grant *quantum* values, surrounding words — were extracted from each file and prepared for contextual analysis through NLP. There were two main parts of this analysis: 1) identifying the sentences which had a high probability of containing grant and claim *quantum* values; 2) from the sentences identified, extract the likely grant and claim *quantum* values.

A classification model was developed to differentiate between the four categories of sentences within the 48 classes: Claim, Grant, FID (First Instance Decision), and Others (to refer to any sentence that belongs to neither of the above mentioned three categories). For each case, the corresponding textual file was pre-processed in Python's NLTK library to tokenize each collection to individual sentences. This expanded the data set to 12,000 sentences. Next, the Gensim library was used to pre-process each sentence into a group of words, removing any punctuation or numerical values inside a sentence. Lastly, an LSTM (purely neural network-based) model was trained on the labeled sentences from a case, after splitting into training and test sets.<sup>13</sup>

A major drawback of the above model was losing information like numerical values and symbols about the sentence while preprocessing the data set. This extra information was deemed to provide some knowledge to potentially improve the distinction between categories in contention. As an alternative approach to identify relevant sentences, a "hybrid" model<sup>14</sup> was developed by engineering 26 variables that combined the results of the LSTM model and also incorporated other heuristics or contextual information such as the presence of certain distinguishing words, the location of sentences and the reference to any numbers. An XGboost model<sup>15</sup> was used to train on the generated set of 26 features. The best F1 scores were observed on this hybrid model out of several other ML models tested.

**Sophistication.** This above process was repeated in analyzing the Level of Sophistication of the claimant's evidentiary methodology (alternatively referred to as Sophistication Index), albeit with some modifications. The first step of the analysis was to again build a Machine Learning model that could correctly identify the sentences strongly indicative of methodology sophistication in a case over the set of 8500 sentences. To do this, a model was trained on the set of 96 annotated cases having tags for the sophistication sentences. The model was trained to classify between three different categories of legal

sentences: SOPHISTICATION, LAC (Legal Argument Claimant) and OTHERS. These 3 categories of sentences were also part of the 48 categories of sentences mentioned earlier.

Similar to the *quantum* model, an LSTM based network using word embeddings was first trained for the sophistication model. Again, it was observed that the results obtained from training a purely contextual model were not that promising, primarily because enough importance is not given to certain legal or economics words and terminologies which are very specifically indicative of Sophistication.

In order to incorporate these words, a second hybrid model was developed using a variable set combining the contextual confidence scores with the manually selected list of words by legal researchers. Taking from the previous iteration, an XGBoost classifier was promptly trained on these sets of variables created to classify between the 3 categories of sentences. Eventually, it was observed that the new model performed extremely well on the classification task achieving an F1 score > 0.85 for the classification of ‘SOPHISTICATION’ sentences. This model was then used for further analysis in index classification which is explained next.

The next step was to extract information from the sophistication sentences identified in the previous step and then use that information to categorize the cases into different indices.<sup>16</sup> In the previous step, in order to define the index of a case we need to count the number of unique methodologies and the number of claim values present in the case. To do this, legal researchers defined each group of methodologies with keywords representative of that group.<sup>17</sup> The ensuing index classification model was again tested on 96 cases.

Having identified the desired values and variables, we moved on extracting them using regular expression-based rules. Extraction began with grant and claim *quantum* values but was soon expanded to encompass the remaining variables that emerged from analyzing the small set of legal cases.<sup>18</sup>

#### *Machine Learning Prediction and Empirical Analysis*

The latter part of fourth iteration was concerned with using the expanded dataset in a new round of empirical analyses. Focus then shifted to extensive machine learning analysis to study the impact of Claim *Quantum* and the other engineered independent variables on the outcome of the case and the Grant *Quantum* (dependent variables). Though admittedly, additional emphasis was placed on the analysis of Claim *Quantum* and the Level of Sophistication, as these two variables consistently showed the strongest impact on the outcome of the case and the Grant *Quantum*. A series of regressions determined the relationship between each variable and the outcome, ultimately yielding significant findings that corroborated the initial hypothesis.<sup>19</sup>

Armed with the expanded dataset and the confirmed hypothesis, subsequent work focused on predicting the outcome of a case with a Grant *Quantum*. As an initial analysis, a linear model<sup>20</sup> was used to approximate the Recovery Rate and the Win Rate. Next, several permutations were performed by taking different subsets of cases based on the legal situations and different engineered variables. As a part of this first attempt, regression analyses were performed on the cases containing all six engineered variables.

To assess the quality of the formulated equations, the R<sup>2</sup> score<sup>21</sup> was computed for the different experiments performed. The coefficients of the variables and their P values<sup>21</sup> were computed for each of them to determine their importance and contribution in the final outcome.<sup>23</sup> More than satisfactory coefficients gave me the confidence to scale my research efforts to other legal situations and industries.

### **Extension 3: An Opportunity to Put Research into a Multidisciplinary Practice**

Throughout this research, my usual optimistic thinking allowed me to reframe the many hurdles I came across in my research as opportunities for improvement and growth. I eventually took the lack of legal research on the topic of contractual damages, and the consequent lack of structured datasets and opinions — while a major obstacle indeed — as a sign that there is an unmet social need for unbiased and accurate prediction of damages. Specially in a post-COVID court system that, to this date, is still trying to clear a massively backlogged docket, efficient and accurate damages prediction tools can bring immense value, both by reducing the number of disputes that enter the docket and speeding up the rate at which they reach a disposition.

As observed, damages are question of fact rather than a question of law, though earlier stages of my research tended to demonstrate that they should also be a question of law for the sake of reduction of uncertainty, fairness of judicial decisions, and economic efficiency. Hence, combining business facts with a good understanding and interpretation of the law is the recommended way to efficiently manage this field. However, reaching sustainable efficiency needs systematic documentation, and this can only be provided through modern data science techniques. Introducing such techniques will help identify and enhance best practices for preventing and curating business damages, particularly in fields where damages are important: anti-trust, intellectual property, insurance, healthcare, and personal injury.

#### **Extension 4: Transfer Learning Back to Personal Injury and More**

Torts inspired my research on contracts, so then it made sense that, having found some success with developing predictive contract damages models, I should transfer my learning back to attempting to predict one of the most uncertain personal injury damages: pain and suffering in bodily injury cases.

Just like in the prior stages, exploring the possibility of a unified damages calculator methodology in the shape of AI required me to dive deeply into the literature and assemble vast enough datasets. The new team of researchers, legal professionals, and data scientists helped me first focus on general liability of slip, trips, and falls as a test situation, largely because of the situation's availability and overall commonality in the circumstances. Thanks to the above models, test datasets ranging in the thousands of cases were quickly assembled from public sources.

As driving factors were being analyzed, it was decided that concurrently expanding the research to motor vehicles accidents would allow major progress at minimal expense. Through partnerships with legal and insurance companies, we later found ourselves analyzing the driving factors in medical malpractice cases and workers compensation cases.

#### **CLOSING REMARKS**

It has been years since starting this research. However, my ambition is still to contribute to fair compensation of damages, and hence less inefficient disputes and litigation through factual compensation damages schedules. As the reader will probably notice, sourcing and coding legal data issues have been a consistent bottleneck at each phase of this work. Though so far, scholarly research and mindful methodologies have allowed me to minimize the impact of limited datasets, early on I realized that the next major step in this research would entail re-visiting, and redoubling data collection efforts. This has driven me to use the second phase of my research to enlist the help of more quantitative and legal professionals and look toward emerging technologies like generative AI and large language modeling to expand the depth and scope of my research. Thus, the next phase has focused on mainly overcoming the data bottleneck by 1) identifying the key variables of each legal case and 2) automating large scale extraction of data. Once fully developed, I hope to take this work to other bodies of law (e.g., employment law, antitrust, or intellectual property) and other major comparative jurisdictions.

Though it has been successful, this application AI is not without its drawbacks. Ethical implications typical of the adoption of all AI technologies — chiefly the replacement of human processes — need to be considered. Beyond the possible loss of human jobs, there is also a risk that widely spread, automated systems with underlying errors or biases will have a negative ripple effect across industries, society, and social inflation. Oftentimes, the speed of the technological developments in this project — ironically, the very same speed that propelled expanding my research in the first place — had to be throttled to maintain accuracy. Testing models and datasets took on a new magnitude for this purpose. I also became aware of the risk of these technologies being used to undervalue claims for the sake of profits. A hard stance toward exclusively providing consistent, fair and unbiased results had to be taken early on — and it has become one of this work's main guiding principles. But all this said, and despite being constantly wary of the direction and path this work takes, I remain optimistic about its future.

Being considerably advanced in these new aspects of my research, I can confidently re-assert that the use of new natural language processing methods, machine learning techniques, and generative AI in

developing predictive analytics will prove useful for all participants and users of judicial systems. If broadly adopted, continuously updated damage schedules can trigger a virtuous cycle: corporate parties will use them in their contract drafting and settling their disputes, hence feeding into subsequent contracts and hopefully avoiding inefficient litigation. When litigation is unavoidable, judges will use the damages schedules to assist their discretionary decisions, providing data to improve the models, hence creating more incentive for all stakeholders to use them. Their responsible use would drastically reduce uncertainty and increase judicial fairness. With enough time and investment, predictive technologies will streamline unnecessary disputes, focus valuable resources on the most complex cases, and eventually generate value for society far beyond what can be imagined today.

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## ENDNOTES

1. Legal scholarship and, more recently, the law have evolved on this point. *See, e.g.*, Yves-Marie Laithier, *Étude comparative des sanctions de l'inexécution du contrat* [Comparative study of sanctions for breach of contract] (l.g.d.j. ed., 2004) (Fr.). *See also* CODE CIVIL [C. CIV.] [CIVIL CODE] art. 1221 (Fr.) (excluding specific performance where it “is impossible or where there is a manifest imbalance between its cost to the good-faith obligor and its value to the obligee”).
2. These three states comprise the majority of large commercial cases. *See* Jeffrey W. Bullock, Del. Div of Corps., Annual Report 1 (2012), <http://corp.delaware.gov/pdfs/2012CorpAR.pdf> (noting that 64% of Fortune 500 companies are incorporated in Delaware).
3. For instance, on Westlaw advanced, the exact search query took the form « (contract! breach! Agreement! negotiation!) & (dollars! million! billion! thousand! hundred!) & (claim! & grant! & damages!) ». The « ! » marks here serve as root expanders to pick up any stems or punctuation marks around the relevant word.
4. As an example, on my sample of cases in Situation 1 (Agreements to Agree and Agreements to Negotiate), the average grants of EGD (Expectation General Damages) are \$ 4,1 and 21 million respectively in France and in the U.S.A. Also, in Situation 3 (New Business), the average grant of EGD is \$ 8 million in the U.S.A.
5. Though I was able to fairly quickly collect 905 cases using different combinations of keywords and search parameters, I was only able to manually code data from 208 of them that were fully documented in the database.
6. Across all four publications, work datasets for each specific situation and jurisdiction tended to contain an average of about 30 to 40 fully documented cases.
7. Since the late 1980's, the trends in average Recovery Rate have been upward in French law –from 19%– and downward in American law –from 66% – converging towards similar percentages –to a 40-50% range– in recent years, see Priest & Klein (1984).
8. Several pieces of evidence are detailed in both Towards Legally Reviewable Damage Awards, *Arizona State*, 1 Corp. & Bus. L.J 173, 173–229 (2020) and Predictable Damages Award: Comparative Analysis on Contract Breach Litigations, *Journal of Complex Litigations*, Saint Thomas (2023).
9. *See also* Extensions 1 and 2.
10. As mentioned, this convergence is present throughout all the four publications listed.
11. E.g., in the US, in no cases across situations did the claimant receive damages where the methodology was not explained in detail (rankings 1-2); on the other hand, claimants received an award in about four out of eleven cases (35%) in which the methodology was detailed and/or sophisticated (rankings 3-4).
12. Including random forest, *XGboost*, and neural network.
13. The labeled sentences were divided into the train and test set using a 70:30 split for training and test respectively
14. Here meaning a mix of heuristics and NLP.
15. The *XGboost* model was selected for this analysis since it has proven to be the most effective and powerful Machine Learning approach for working with tabular/structured feature data.
16. The following was the definition of indices as developed by the legal experts:
  - Index 4: Multiple unique methodologies present
  - Index 3: Single unique methodology present
  - Index 2: No methodology and multiple claim values
  - Index 1: No methodology and single claim value
  - Index 0: No methodology and no claim value
17. The following were the steps to classify each case into one of the 5 indices:
  - Identify the sophistication sentences using the hybrid sentence classification model elaborated earlier.
  - Count the number of unique methodology groups using the definitions provided by the legal experts.
  - For those cases in which no methodology was present: count the number of claim values using the Grant-Claim model developed earlier by the research team.
  - Use both the number of unique methodologies and the number of claim values to classify the case into the appropriate index.

18. These six factors are: *Quantum* Value of Claim, Sophistication of Claimant's Methodology, Claimant's Business Risk, Law Firm Size, Reputation, and Length of Relationship.
19. For example, the correlations between Sophistication Indices and the outcomes of contract breach cases can be summarized as follows:
  - It can be seen that the average Recovery Rate shows a positive increasing trend as we move from Index 1 to Index 4, which is as expected since the amount granted against a given claim should increase with increased sophistication of the claimant's argument.
  - The average Recovery Rate (Non-Zero Grant) values corresponding to each index have now increased and are close to the expected values as per the legal experts' analysis. Further, an interesting trend can be observed. Here the average Recovery Rate increases from Sophistication Index 1 to Sophistication Index 3 but then dips on reaching Index 4. This particular trend replicates exactly what I had observed manually in the earlier 96 cases.
  - The Win Rate shows a clear increasing trend as it moves from Sophistication Index 1 to Sophistication Index 4. Also, the increase is very significant since the Win Rate grows from 13% for Sophistication Index 1 to 49% for Sophistications Index 4. This is again expected and in line with prior findings since with an improvement in the sophistication argument of the claimant there should be a higher chance of getting some grant.
20. The linear regression model has been used for the initial analysis for better interpretability of the coefficient of each variable used in the equation.
21. The  $R^2$  is a statistical measurement of fit that indicates how much variation of a dependent variable is explained by the variation of independent variables.
22. The p-value measures the statistical significance of an observed effect to test a hypothesis.
23. Among the various experiments performed, the following were the best  $R^2$  scores achieved:
  - Recovery Rate: The best  $R^2$  score achieved using a linear model was 0.953. This was using the following variables: Claim *Quantum*, Sophistication Index, and Length of Negotiation.
  - Win Rate: The best  $R^2$  score achieved using a linear model was 0.998. This was using the following variables: Claim *Quantum*, Sophistication Index and Reputation.

## REFERENCES

- Atiyah, P.S. (1995). *An Introduction to the Law of Contract* (5<sup>th</sup> Ed.). Oxford: Clarendon Press.
- Barnes, D.W. (1996). The Meaning of Value in Contract Damages and Contract Theory, 46 am. *American University Law Review*.
- Barnes, D.W., & Stout, L.A. (1992). *Cases and Materials on Law and Economics*. St Paul: West Group.
- Briggs, A. (2013). *The Conflict of Laws*. Oxford University Press.
- Bussani, M., & Palmer, V.V. (2003). *Pure Economic Loss in Europe*. Cambridge: Cambridge University Press.
- Chen-Wishart, M. (2008). *Contract Law*. Oxford University Press.
- Collins, H. (1995). *The Law of Contract* (4<sup>th</sup> Ed.). Oxford: Clarendon Press.
- Dobbs, D.B. (2008). *The Law of Torts, Hornbook Series*. West Group.
- Farnsworth, E.A. (1991). *United States Contract Law*. Transnational Juris Publications Inc.
- Ferrarese M.R. (1997). An entrepreneurial conception of law? The American model through Italian eyes. In D. Nelken (Ed.), *Comparing Legal Cultures*.
- Fuller, L.L., & Perdue, W.R. (1936). The reliance interest in contract damages. *The Yale Law Journal*.
- Giaoui, F., Aggarwal, L., Lobo, D., Gondolo, J., Lachkeur, P., & Jain, S. (2023). Applying NLLP and ML to predict damages as a remedy for contract breach. *Proceedings of the Nineteenth International Conference on Artificial Intelligence and Law (ICAAIL)*, pp. 468–469.
- Giaoui, F.S. (2019). Indemnisation du Préjudice Economique. *L'Harmattan*.
- Giaoui, F.S. (2020). Towards legally reviewable damage awards. *Arizona State, 1 Corp. & Bus. L.J.*, 173, 173–229.
- Giaoui, F.S. (2022). Breaches of agreements to negotiate: Comparative analysis of damages. *American Journal of Trade and Policy*, 9(2), 77–98.

- Giaoui, F.S. (2023a). Damage to reputation: Comparative Analysis of compensation for non-pecuniary harm. *Loyola of Los Angeles International and Comparative Law Review*, 46(1).
- Giaoui, F.S. (2023b). Predicting damages award: Comparative analysis on contract breach litigations. *Journal of Complex Litigations*, 9(1).
- Harris D., Campbell D., & Halson R. (2002). *Remedies in Contract & Tort* (2<sup>nd</sup> Ed.). London: Butterworths.
- Kahneman, D., & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. *Heuristics and Biases: The Psychology of Intuitive Judgment*, pp. 49–81.
- Klerman, D., & Lee, Y.-H.A. (2014). Inferences from litigated cases. *The Journal of Legal Studies*, 4(2), 209–248.
- Koch, B.A., & Helmut, K. (2002). *Unification of Tort Law: Strict liability, European Centre of Tort and Insurance Law*. Kluwer Law International.
- Laycock, D., & Hasen, L.R. (2018). *Modern American Remedies: Cases and Materials*. Insert 693.
- Lee, Y.-H.A., & Klerman, D. (2016). The Priest-Klein hypotheses: Proofs and generality. *International Review of Law and Economics*, 48, 59–76.
- Posner, R.A. (1998). *Economic Analysis of Law* (5<sup>th</sup> Ed.). New York: Aspen Publishers Inc.
- Priest, G.L., & Klein, B. (1984). The selection of disputes for litigation. *Journal of Legal Studies*, 13(1), 1–55.
- Scarso, A.P. (2005). *Tort Law and Liability Insurance*. Wien/New York.
- Schweizer, U. (2016). Litigated cases: The selection effect revisited. *Journal of Institutional and Theoretical Economics (JITE) / Zeitschrift für die gesamte Staatswissenschaft*, 172(3), 409–416.
- Scott, R., & Triantis, G. (2004). *Embedded Options in the Case Against Compensation in Contract Law*. 104 Colum. L. Rev. 1428.
- Voorheis, P. (1903). *A Treatise on the Law of the Measure of Damages for Personal Injuries, Including Suggestions on Pleading, Evidence, and Province of Court and Jury, Applicable to the Trial of this Class of Cases*, 577. The Laning Co. Publishers.