Learning to be Unbiased:

Evidence from the French Asylum Office

Supplemental Information

Mathilde Emeriau[‡‡]

The material is intended for online publication only.

[‡‡]Department of Government, London School of Economics and Political Science, and Immigration Policy Lab, Stanford University, Stanford, CA 94305-6044, USA. m.emeriau@lse.ac.uk

A Model

In this section, I provide additional details on the derivation of equation (1). The bureaucrat receives $-(v-(\omega-c_g))^2$ as payoff from evaluation v for an asylum seeker with characteristic g and persecution ω. He chooses the evaluation v that maximizes his expected payoff with respect to his posterior belief about the applicant's level of persecution.

$$v(s,g)^* \equiv \arg\max \mathbb{E}\left[-(v-(\omega-c_g))^2 \mid s,g\right]$$

His optimal evaluation is $v(s,g)^* = \mathbb{E}[\omega \mid s,g] - c_g$. To see this, let F be the conditional density function of ω and rewrite the bureaucrat's maximization problem as

$$v(s,g)^* = \arg\max \int_{-\infty}^{+\infty} -(v-(\omega-c_g))^2 dF(\omega \mid s,g)$$

and take the first-order condition of the objective function with respect to w and set it equal to 0.

$$\begin{aligned}
& \int_{-\infty}^{+\infty} -2(v-(\omega-c_g))dF(\omega \mid s,g) = 0 \\
\iff \quad & -2(v+c_g) + 2\int_{-\infty}^{+\infty} \omega dF(\omega \mid s,g) = 0 \\
\iff \quad & -2(v+c_g) + 2\,\mathbb{E}[\omega \mid s,g] = 0 \\
\iff \quad & -(v+c_g) + \mathbb{E}[\omega \mid s,g] = 0 \\
\iff \quad & v = \mathbb{E}[\omega \mid s,g] - c_g
\end{aligned}$$

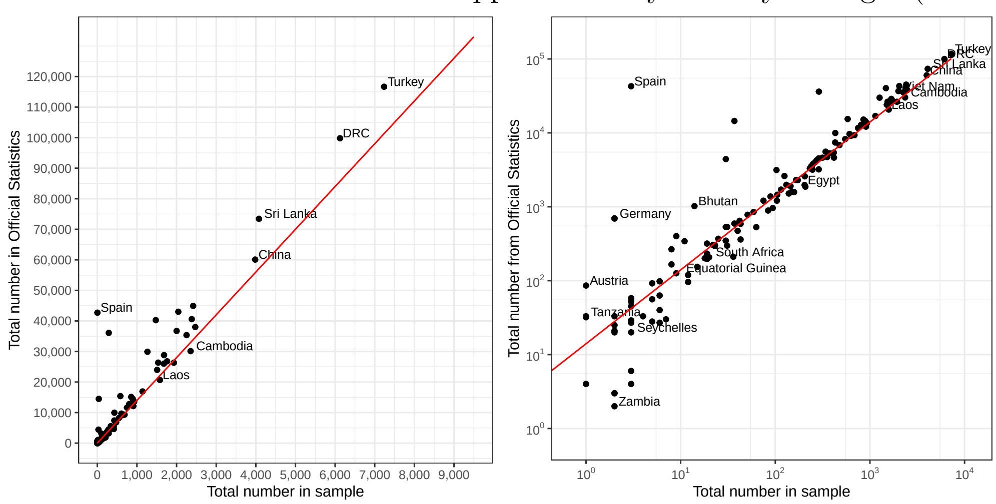
To derive $\mathbb{E}[\omega \mid s,g]$, note that the posterior distribution $p(\omega|s)$ is proportional to the signal distribution ($s|\omega \sim \mathcal{N}(\omega, \sigma_\epsilon^2 + \sigma_\eta^2)$) multiplied by the prior distribution for the applicant's level of persecution ($\omega \sim \mathcal{N}(\hat{\mu}_g, \sigma_\omega^2)$). Given that both the prior and the signal are normally distributed, the posterior distribution is also normally distributed with a mean equal to $\frac{\sigma_\omega^2}{\sigma_\omega^2+\sigma_\epsilon^2+\sigma_\eta^2} s + \frac{\sigma_\epsilon^2+\sigma_\eta^2}{\sigma_\omega^2+\sigma_\epsilon^2+\sigma_\eta^2}\hat{\mu}_g$ and variance $\frac{\sigma_\omega^2(\sigma_\epsilon^2+\sigma_\eta^2)}{\sigma_\omega^2+\sigma_\epsilon^2+\sigma_\eta^2}$.

B Sampling

B.1 Representativeness of the sampling frame

In July 2015, the French asylum office provided me with a list of 100,000 asylum applications filed between 1952 and 2014, randomly drawn from their administrative databases. In this section, I show that this list is indeed representative of the universe of asylum applications filed during this period. To do so, I use the official statistics published every year by the French asylum office that are accessible online (since 2001) or in the archives of the French asylum office (before 2001). I compiled a dataset of the total number of first-time applications by country of origin and year of application. In Figure B.1, I compare the total number of first-time asylum applications by country (1952–2014) in the administrative sample (x-axis) to the number published in the activity reports (y-axis).

Figure B.1: Total number of first-time applications by country of origin (1952–2014)



Notes: Each dot represents a country of origin in the administrative sample. The x axis represents the number of applications from that country in the administrative sample of 100,000 observations, and the y axis represents the number of applications in the official statistics. The same figure is displayed using a linear scale on the left and using a log scale on the right.

B.2 Sampling design and weights

From the list of 100,000 asylum applications, I selected 10,000 for in-depth data collection. I first excluded three perfect duplicates and 1,572 applications from the 81 nationalities that comprised fewer than 100 applications overall. I then split the dataset into four subsamples depending on (1) the year of application and (2) the database in which the application was recorded.

1. Applications from *Garonor* filed before January 1, 1990 (N=26,433). None of these had been destroyed by July 2015. For these applications, I only know the nationality of the applicant.

2. Applications from *Inerec* filed before January 1, 1990 (N=14,259). 40% of these had been destroyed by July 2015.

3. Applications from *Inerec* filed between January 1, 1990 and December 31, 2004 (N=35,398). 54% of these had been destroyed by July 2015.

4. Applications from *Inerec* filed between January 1, 2005 and December 31, 2014 (N=22,335). Only 13 had been destroyed July 2015.

To oversample applications filed after 1989, I drew 5% of the applications from subsamples 1 and 2 and 14% from subsamples 3 and 4. To account for the non-random destruction of folders (the asylum office only destroyed rejected applications), I proceeded as follows for each subsample. For each application, I first predicted the probability of still being in the archives using different linear models with a combination of the following variables: whether the applicant was granted refugee status, the year of application and the country of origin, as well as all possible interactions. For each model, I then drew several hundred samples, using the inverse of the predicted probability of still being in the archives as the selection probability. I used these samples to choose the model that minimizes the average distance between the sample and the population on the proportion of nationality, year of application, overall rejection rate, yearly rejection rate, and the proportion of the top 10 nationalities. Finally, for each model, I selected the sample that minimizes overall deviation. This strategy did not yield enough rejected applications for the period 1990–1992 since more than 68% of applications filed in these 3 years had already been destroyed. In May 2016, I requested an additional sample of 50,000 asylum applications filed between 1990 and 1992 and sampled an additional 500 folders from these 3 years. Finally, in June 2016, I requested an additional sample of 8,000 asylum applications filed in 2015 and 2016, and sampled an additional 500 applications.

In the analysis, I use weights to adjust for the fact that the sampling correction was not perfect, and to correct for the oversampling of applications filed after 1989. I first use entropy balancing (Hainmueller 2012) to match the proportion of accepted applications by year in the data collected to the proportion of accepted applications in the administrative sample. In order to match the total number of first-time applications, I then multiply these weights by 6.5 for observations prior to 1990, by 2 for observations between 1990 and 2015 included, and by 14.8 for observations from 2016. To illustrate, Figure B.2 displays the distribution of the year of application in the administrative sample (gray bar) to the density in the unweighted data (dashed) and in the weighted dataset (solid).

Figure B.2: Number of first-time applications (1976–2016)

Notes: This figure displays the number of first-time applications by year in the administrative sample (gray bar), in the unweighted sample (dashed line) and in the weighted sample (solid line).

B.3 Data Collection

The final sample included 10,995 applications. I randomly ordered applications and searched for the first 5,421 applications and found 5,220 of them (142 had been destroyed between the sampling and the data collection, and 59 were lost). Of these 5,220, 447 applications were excluded because they did not meet the criteria of being a first-time application for refugee status with an application form in French and a decision. With the help of a team of research assistants, I digitized 4,773 applications over the course of 21 months. The application form changed a few times over the study period but the questions remained similar. The application form contains questions about the applicant's origin (country of origin, nationality and ethnicity, which was added in the 1990s), marital status and family members, conditions of arrival in France (itinerary, past countries of residence, modality of entry on French territory, and whether entry was legal or illegal), religion, education and profession (in France and the last job in the country of origin), languages spoken, military service (date, role and country), and official documents (passport or diplomatic laissezpasser). Only a few questions were removed from the form. Among them were: “Are you planning on staying permanently in France?” and “Are you registered in the consulate of your country of origin?” To ensure the quality of the data collection, I checked each coded application for inconsistencies and missing values and resolved discrepancies manually on a daily basis. After these initial checks, the error rate among 210 randomly selected folders for double data entry was less than 5 percent. For this study, I further restrict the sample to applications filed after 1976 for two reasons. After an initial peak, the number of first-time applicants slowly trickled down to a couple thousand until France ratified the Bellagio protocol in 1976, an amendment that lifted the geographic and time limitations included in the Geneva Convention and opened the asylum process to non-European nationalities for events that happened after 1951 (Figure D.1). Moreover, between 1952 and 1976, the acceptance rate at the French asylum office was close to 100 percent.

Table B.1 presents summary statistics on additional variables used in the analysis reported in Table D.1 (column 2). The variable “Accelerated procedure” indicates whether the application was expedited or not. The Prefecture determines whether an application follows the normal or accelerated procedure; the Prefecture can refuse entry on the grounds that the country is deemed safe or that the application is deemed fraudulent. In this case, the applicant has to be notified of the decision within 15 days after the interview. The variables “Passport (reported)” and “Laissez-Passez (reported)” indicate whether the applicant reported providing these documents in the application. “Number of children” corresponds to the total number of children the applicant listed on the form. The variable “A family member is refugee in France” indicates whether the applicant listed a family member currently residing in France as a refugee. Finally, the variables “Military service” and “Arrival in France” code self-reported information by the applicant.

Table B.1: Summary statistics on additional independent variables

	N	Mean	Std. Dev.	Min	Max
Accelerated procedure	4,141	0.072	0.258	0	1
Passport (reported)	4,141	0.255	0.436	0	1
Laissez-Passez (reported)	4,141	0.033	0.180	0	1
Number of children	4,141	1.085	1.572	0	12
A family member is refugee in France	4,141	0.078	0.269	0	1
Military service					
No	4,141	0.687	0.464	0	1
Yes	4,141	0.162	0.368	0	1
Missing	4,141	0.152	0.359	0	1
Arrival in France (reported)					
Irregular	4,141	0.545	0.498	0	1
Regular	4,141	0.158	0.365	0	1
Missing	4,141	0.297	0.457	0	1

Notes: This table presents summary statistics on variables used as additional controls in the analysis reported in Table D.1 column 2.

C Measuring the credibility of the narrative

C.1 Construction of narrative features

In this section, I describe the construction of the distance measure and the topic proportions reported in Table 2. I start by converting the corpus of narratives into a document-term matrix. I first remove capitalization, punctuation, word order and stop words. I then stem words and drop unigrams that are too uncommon (those that occur in less than 1 percent of the narratives) or too common (those that appear in more than 99 percent of the narratives) (Hopkins and King 2010). For each of the 2,842 remaining unigrams, I compute the term frequency in each document weighted by the inverse document frequency (tf-idf). Using this document-term matrix which represents each narrative as a vector of weighted term frequencies for 2,842 different unigrams, I can compute the Euclidean distance (defined as the square root of the sum of squares of differences between corresponding vector elements) between each narrative and all other narratives from applicants from the same country of origin and take their average, which I use as a measure of the narrative's originality.

I also use this document-term matrix to estimate a structural topic model with 20 different topics and allow topic prevalence to vary by country of origin. This model associates words with each topic (Table C.1) and estimates the frequency with which each topic is discussed in each narrative. I then code narratives as discussing a topic substantially if the proportion of the narrative discussing the topic exceeds 0.20. I use these estimates to control for the content of the narrative in the empirical strategy.

Table C.1: Topical content

Topic								
Family members	mar	fill	mer	enfant	fil	mari	soeur	frer
Bangladesh	awam	bangladesh	ligu	bnp	malfaiteur	terror	inde	commissariat
Student protest	régim	opposit	étudi	social	populair	démocrat	manifest	professeur
Escape	voitur	argent	environ	passeur	soudan	pai	emmen	puis
Sri Lanka	ltte	sri	tamoul	tigr	lank	colombo	jaffn	camp
RDC	kabil	kinshas	congo	congol	brazzavill	udp	congolais	cellul
Live in France	vivr	pay	franc	veux	peux	vi	peut	espoir
Former Yugoslavia	serb	kosovo	alban	yougoslav	albanais	rom	bosn	guerr
China	chin	chinois	ouvri	usin	fonctionnair	entrepris	licenci	démocrat
Ethnic minority	russ	armen	appart	arménien	tchétchen	moscou	géorg	azerbaïdjan
Kurds in Turkey	kurd	turqu	turc	kurdistan	istanbul	pkk	tortur	villag
Political instability	etait	president	apre	sassou	arret	decid	mem	haït
Political opposition	guin	mauritan	sénégal	mauritanien	conakry	rebel	gendarm	élect
Court hearing	joint	alger	lettr	journal	convoc	tribunal	univers	écrit
Narrative	dit	dis	c'et	qu'il	quand	rien	dir	ça
Angola	militair	angol	prison	titr	unit	fronti	camp	soldat
Salutation	agré	statut	ofpra	madam	monsieur	salut	express	distingu
Family at risk	épous	époux	agress	menac	domicil	syr	physiqu	2012
Zaire	rwand	mobutu	zaïr	président	ministr	zair	zaïrois	annex
Religion	conseil	religion	chrétien	islam	musulman	religi	églis	communaut

Notes: This table presents, for each of the 20 topics in the structural topic model, the eight words that scored the highest on the FREX metric (Roberts et al. 2014).

C.2 Comparing the narratives by religion

In this section, I compare the narratives of Christians vs. Muslims (Table C.2), those with a post-secondary education vs. a secondary or primary education (Table C.3), those who are highly skilled vs. middle or low skill levels (Table C.4), and those who are proficient in French vs. those who are not (Table C.5).

Table C.2: Differences between the narratives of Christian and Muslim applicants

	Christians			Muslims			t-test	
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Diff.	p
Level of detail								
Number of words	834.365	823.903	1,426	770.640	738.646	1,679	-63.72	0.047
Number of dates	7.443	8.795	1,435	7.126	7.645	1,681	-0.32	0.359
Number of location	6.775	8.244	1,435	6.470	6.959	1,681	-0.30	0.290
Personal								
Number of personal pronouns	35.569	35.366	1,359	36.331	32.727	1,611	0.76	0.582
Originality								
Distance	49.159	24.170	1,423	48.082	21.927	1,679	-1.08	0.226
Topics								
Family members	0.091	0.287	1,426	0.100	0.300	1,677	0.01	0.384
Bangladesh	0.002	0.041	1,426	0.074	0.262	1,677	0.07	0.000
Student protest	0.084	0.278	1,426	0.062	0.241	1,677	-0.02	0.052
Escape	0.071	0.256	1,426	0.135	0.342	1,677	0.06	0.000
Sri Lanka	0.019	0.138	1,426	0.005	0.068	1,677	-0.01	0.000
RDC	0.110	0.314	1,426	0.000	0.021	1,677	-0.11	0.000
Life in France	0.221	0.415	1,426	0.184	0.388	1,677	-0.04	0.035
Former Yugoslavia	0.048	0.215	1,426	0.123	0.328	1,677	0.07	0.000
China	0.021	0.145	1,426	0.007	0.081	1,677	-0.01	0.006
Ethnic minorities	0.086	0.280	1,426	0.028	0.165	1,677	-0.06	0.000
Kurds in Turkey	0.003	0.057	1,426	0.136	0.343	1,677	0.13	0.000
Political instability	0.088	0.284	1,426	0.023	0.149	1,677	-0.07	0.000
Political opposition	0.023	0.150	1,426	0.106	0.308	1,677	0.08	0.000
Court hearing	0.023	0.150	1,426	0.020	0.141	1,677	-0.00	0.647
Narrative	0.176	0.381	1,426	0.148	0.356	1,677	-0.03	0.051
Angola	0.086	0.280	1,426	0.031	0.175	1,677	-0.05	0.000
Salutation	0.051	0.220	1,426	0.064	0.244	1,677	0.01	0.190
Family at risk	0.042	0.200	1,426	0.056	0.229	1,677	0.01	0.070
Zaire	0.073	0.261	1,426	0.006	0.076	1,677	-0.07	0.000
Religion	0.022	0.147	1,426	0.020	0.140	1,677	-0.00	0.667

Table C.3: Differences between the narratives of highly educated applicants vs. applicants with secondary or primary education

	Post-secondary			Secondary/Primary			t-test	
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Diff.	p
Level of detail								
Number of words	1106.708	1069.892	558	807.107	733.840	2,367	-299.60	0.000
Number of dates	10.312	11.586	560	7.517	7.889	2,388	-2.80	0.000
Number of location	8.029	9.073	560	6.816	7.595	2,388	-1.21	0.005
Personal								
Number of personal pronouns	44.124	41.598	530	36.397	33.539	2,277	-7.73	0.001
Originality								
Distance	51.623	24.354	558	48.140	23.598	2,363	-3.48	0.007

Table C.4: Differences between the narratives of applicants who are highly skilled vs. middle or low levels of skills

	Highly skilled			Middle and Low			t-test	
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Diff.	*p*
Level of detail								
Number of words	907.546	958.730	563	772.758	744.589	2,308	-134.79	0.010
Number of dates	7.882	9.383	574	7.111	7.672	2,322	-0.77	0.099
Number of location	6.953	8.341	574	6.380	7.386	2,322	-0.57	0.163
Personal								
Number of personal pronouns	36.002	35.933	541	35.438	34.006	2,213	-0.56	0.783
Originality								
Distance	45.554	23.817	563	47.236	23.340	2,303	1.68	0.199

Table C.5: Differences between the narratives of applicants who are proficient in French and those who are not

	Proficient in French			Not proficient in French			t-test	
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Diff.	*p*
Level of detail								
Number of words	770.670	890.089	1,044	779.995	711.894	2,888	9.32	0.796
Number of dates	6.401	8.752	1,044	7.517	8.100	2,916	1.12	0.003
Number of location	6.354	8.169	1,044	6.515	7.219	2,916	0.16	0.592
Personal								
Number of personal pronouns	32.778	36.257	1,001	35.272	31.792	2,759	2.49	0.094
Originality								
Distance	45.565	24.816	1,042	47.739	22.728	2,885	2.17	0.025

C.3 Hand coding the credibility of the narrative

In this section, I provide additional information regarding the hand coding of the credibility of the narratives. Table C.6 reports summary statistics on all variables collected by the research assistants. Questions about the content and objective features of the text, like the level of detail and the cohesiveness of the text, were designed to prime coders to think fully about the different aspects of the text before rating a narrative's credibility. I assess the inter-coder reliability in Table C.7 using Krippendorff's alpha coefficient. In Table C.8, I show that a positive correlation between different features of the text (as coded by a research assistant) and a binary indicator of whether the coders "agreed" or "somewhat agreed" that the asylum seeker is entitled to claim the right to asylum, suggesting reasonable internal validity of this measure.

Table C.6: Summary statistics on the narratives

	N	Mean	Std. Dev.	Min	Max
Persecution					
Is persecuted	459	0.797	0.402	0	1
For reasons related to					
Race	459	0.172	0.378	0	1
Political opinion	459	0.418	0.494	0	1
Religion	459	0.063	0.244	0	1
Nationality	459	0.048	0.214	0	1
Social group	459	0.070	0.255	0	1
None	459	0.346	0.476	0	1
Narrative was coded as					
Believable	459	2.597	0.831	1	4
Convincing	459	2.307	0.817	1	4
Detailed	459	2.235	0.992	1	4
Individualized	459	2.399	0.815	1	4
Coherent	459	2.593	0.752	1	4
The narrative mentions					
A historical event	459	0.455	0.499	0	1
Family in France	459	0.109	0.312	0	1
Credibly claims the Geneva Convention					
No	459	0.209	0.407	0	1
Somewhat no	459	0.292	0.455	0	1
Somewhat yes	459	0.353	0.478	0	1
Yes	459	0.146	0.353	0	1

Notes: This table reports summary statistics on the main variables collected by coders for a representative sample of 459 narratives. The unit of observation is narrative/coder.

Table C.7: Assessment of inter-coder agreement for the measure of the credibility of the narrative using Krippendorff's alpha coefficient

	Indicator if Agree (0-1)	Indicator if Agree or Somewhat Agree (0-1)
Between coder 1 and 2	0.291	0.381
Between coder 1 and 3	0.036	0.623
Between coder 2 and 3	0.120	0.428
Between all three coders	0.186	0.483

Table C.8: Assessing the internal validity of the credibility measure in the set of hand-coded narratives

	(1) Credible Narrative
Is persecuted	0.113*
	(0.055)
Probable	0.120**
	(0.036)
Convincing	0.200**
	(0.039)
Detailed	0.053†
	(0.028)
Singular	-0.047
	(0.030)
Coherent	0.083*
	(0.034)
Constant	-0.603**
	(0.069)
Observations	459
R^2	0.450

Notes: $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$. This table shows point estimates and standard errors in parentheses from an ordinary least squares (OLS) regression of the main credibility variable collected in the narrative hand coding on other leading questions focused on features of the text such as the level of detail. The unit of observation is narrative/coder.

C.4 Predicting the credibility of the narrative

Using the set of hand-coded narratives, I compare the performance of three classification algorithms to predict the credibility of the narrative for the rest of the corpus using weighted word frequencies and additional text features. Using the training set, I tune and evaluate the performance of three classification algorithms (Gradient Boosted Trees, Random Forests, and the Lasso) using the following procedure:

- I partitioned the labeled set of 341 hand-coded documents into the labeled training set (75 percent) and the labeled test set (25 percent).
- I trained three different algorithms using tenfold cross validation to tune the model and used the tf-idf of unigrams and additional narrative covariates as predictors (e.g., length, number of pronouns, number of dates and locations mentioned, and an indicator for whether one of the 20 topics covers more than 20 percent of a narrative).
- For each of these models, I calculated the predicted probabilities and computed AUC, Brier Score and accuracy (Table C.9), as well as the calibration plots (Figure C.1).

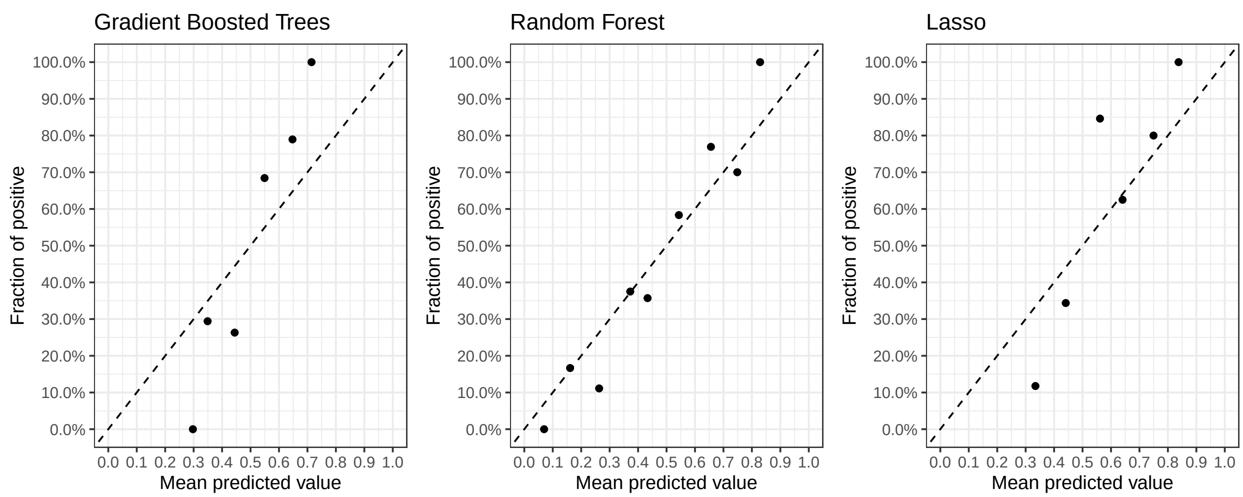
All three algorithms perform relatively well on standard metrics (Table C.9), but predicted probabilities from Random Forest are better calibrated (Figure C.1). Using Random Forest, I am able to accurately predict the quality measure 75 percent of the time in the left-out sample of 81 narratives, a substantial reduction in error compared to a baseline of 48 percent. In addition, Table C.10 shows that the predicted measure of credibility correlates as expected with extracted features of the text.

Table C.9: Model performance

Model	AUC	Accuracy	Brier Score
Gradient Boosted trees	0.817	0.762	0.196
Random Forest	0.823	0.750	0.176
Lasso	0.830	0.762	0.194

Notes: This table presents three performance statistics for three different algorithms computed on the left-out sample of 85 narratives.

Figure C.1: Calibration plots



Notes: This figure plots the calibration of predicted probabilities from three different algorithms in a left-out sample of 85 narratives. After dividing the predicted probabilities into 10 equally spaced intervals, I compute, within each bin, the average of the predicted probabilities (x-axis) and the fraction of observations in that bin with a true positive (y-axis).

Table C.10: Assessing the correlation between the credibility measure and features of the narratives

	Credibility of the narrative	
	(1) Hand Coded	(2) Predicted
Number of words ('000)	0.211*	0.255**
	(0.089)	(0.024)
Distance ('000)	0.259	1.359**
	(1.057)	(0.299)
# of dates mentioned ('000)	13.996*	9.679**
	(6.209)	(1.331)
# of places mentioned ('000)	-1.544	2.510*
	(3.966)	(1.220)
Number of personal pronouns ('000)	-1.405	0.254
	(1.447)	(0.419)
Constant	0.274**	0.186**
	(0.053)	(0.016)
Observations	320	3472

Notes: $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$. This table displays the results of an OLS regression in the subsample of hand-coded narratives in column 1 and the full sample of narratives in column 2 (excluding hand-coded narratives). The dependent variable is coded 1 if the predicted credibility was above 50 percent. No additional controls were included in this regression.

D Additional tables and figures

Figure D.1: Number of first-time applications filed at the French asylum office (1952–2016)

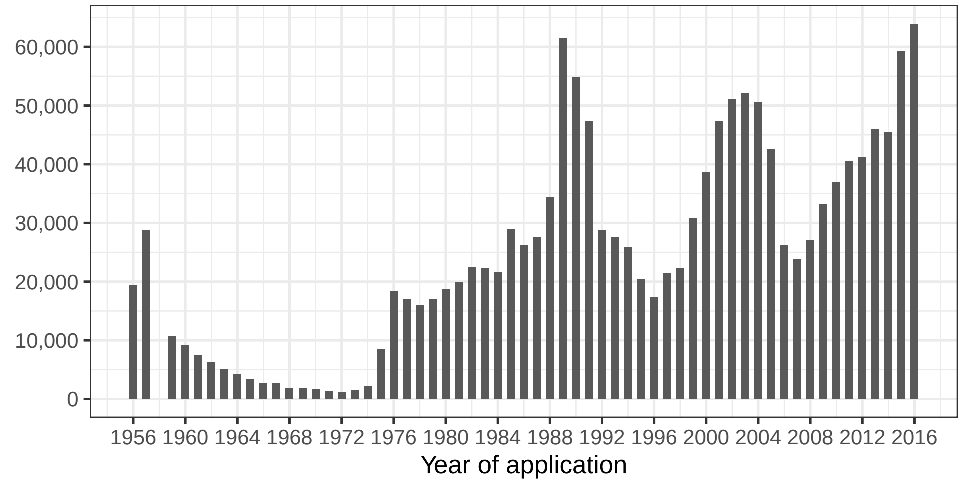
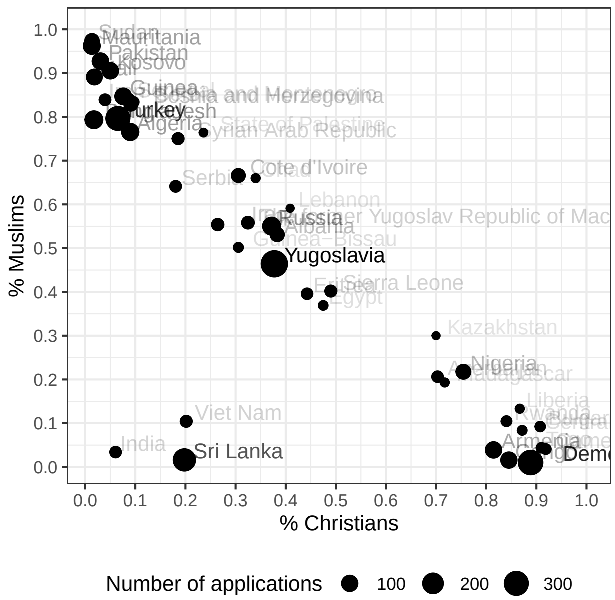


Figure D.2: Proportion of Muslim and Christian applicants by country of origin (1976–2016)



Notes: This figure plots, for each country of origin included in the sample, the proportion of applicants from this country that are Christian (x-axis) and Muslim (y-axis).

In Table D.1 column 4, I report estimates from the main regression on a matched sample. I used coarsened exact matching (Iacus et al. 2012) to first group applicants from the same country of origin (exact matching) who arrived within up to 4 years of each other (coarsened exact matching). The algorithm next discards all applicants from strata with only Christians or only Muslims, keeping 1,577 applicants from strata with both Muslims and Christians. For each of the remaining units, the algorithm assigns a weight of 1 to Muslims and a weight of $\frac{m_C}{m_T}\frac{m_T^s}{m_C^s}$ to Christians, with m_C (m_T) being the number of Christians (Muslims) in the matched sample, and m_C^s (m_T^s) the number of Christians (Muslims) in the stratum. I then use a weighted OLS regression to estimate the effect of being a Muslim on the decision, controlling, as before, for all standard covariates except the country of origin.

Table D.1: Determinants of the attribution of refugee status (robustness tests)

	Granted refugee status				
	(1)	(2)	(3)	(4)	(5)
	Main specification	Additional covariates	Country-year interaction	Matched Sample	Omitting credibility
Credible narrative	0.058**	0.057**	0.048**	0.096**	
	(0.013)	(0.013)	(0.014)	(0.017)	
Gender (Ref: Male)					
Female	0.019	0.005	0.002	0.014	0.018
	(0.014)	(0.014)	(0.014)	(0.020)	(0.014)
Age (Ref: Less than 20)					
Between 20 and 40	-0.084**	-0.065**	-0.084**	-0.090**	-0.087**
	(0.024)	(0.024)	(0.026)	(0.028)	(0.024)
More than 40	-0.067*	-0.060*	-0.083**	-0.102**	-0.062*
	(0.028)	(0.029)	(0.029)	(0.035)	(0.028)
Marital status (Ref: Single)					
Married	0.063**	0.051**	0.055**	0.114**	0.060**
	(0.013)	(0.014)	(0.014)	(0.017)	(0.013)
Time in France (Ref: < 1 year)					
> 1 year in France	0.003	0.007	0.012	0.022	0.001
	(0.016)	(0.016)	(0.017)	(0.022)	(0.015)
Religion (Ref: Christian)					
Muslim	-0.062**	-0.049*	-0.059**	-0.104**	-0.055**
	(0.020)	(0.020)	(0.022)	(0.017)	(0.020)
Other	0.061*	0.060*	0.080**		0.047†
	(0.027)	(0.027)	(0.029)		(0.027)
None/Missing	-0.017	-0.020	-0.017		-0.015
	(0.022)	(0.021)	(0.024)		(0.022)
Education (Ref: University)					
Secondary	-0.024	-0.024	-0.015	-0.024	-0.014
	(0.020)	(0.019)	(0.018)	(0.028)	(0.019)
Primary	-0.063*	-0.058*	-0.066*	-0.088*	-0.062*
	(0.028)	(0.027)	(0.027)	(0.036)	(0.027)
None/Missing	-0.033	-0.022	-0.018	-0.022	-0.033
	(0.022)	(0.022)	(0.022)	(0.031)	(0.022)
Skill level (Ref: High)					
Middle	-0.061**	-0.060**	-0.043*	-0.020	-0.061**
	(0.021)	(0.020)	(0.021)	(0.029)	(0.021)
Low	-0.082**	-0.080**	-0.068**	-0.105**	-0.087**
	(0.022)	(0.021)	(0.022)	(0.031)	(0.021)
None/Missing	-0.025	-0.022	-0.005	0.018	-0.031
	(0.022)	(0.021)	(0.022)	(0.030)	(0.021)
Speaks French (Ref: Yes)					
No/Missing	-0.033†	-0.028†	-0.015	-0.054*	-0.033†
	(0.018)	(0.017)	(0.018)	(0.022)	(0.018)
Observations	3,930	3,930	3,930	1,525	4,140
R^2	0.360	0.380	0.612	0.226	0.353
Mean acceptance rate	0.153	0.153	0.153	0.129	0.153

Notes: $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$. The dependent variable is a dummy variable indicating whether the applicant received refugee status upon first examination at the French asylum office. All regressions include country-of-origin and year-of-application fixed effects.

Table D.2: Determinants of the attribution of refugee status (logistic regression)

	Average Predicted Probability	[95% Conf. Interval]	
Religion			
Christian	0.154	0.128	0.179
Muslim	0.108	0.090	0.126
Education			
University	0.171	0.136	0.206
Secondary	0.141	0.125	0.158
Primary	0.110	0.080	0.139
None/Missing	0.135	0.112	0.158
Skill level			
High	0.186	0.152	0.220
Middle	0.125	0.107	0.143
Low	0.103	0.078	0.127
None/Missing	0.157	0.134	0.180

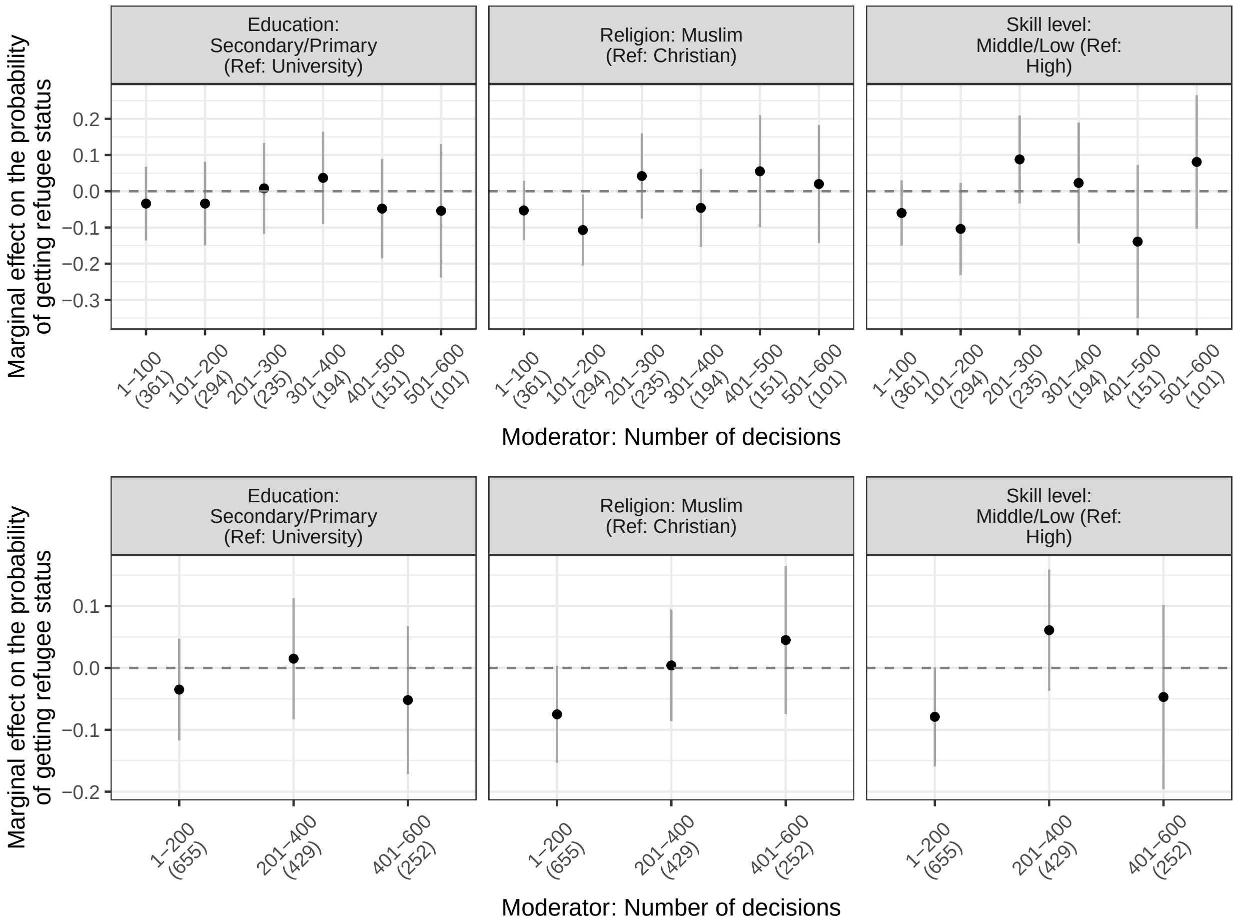
Notes: This table reports the average predicted probability of being granted refugee status for different subgroups using estimates from a logit regression model that includes all individual covariates and fixed effects from the main specification. For each of the characteristics listed in the table, I predict the probability of being granted asylum for each applicant in the sample holding all characteristics fixed except the one listed, assigning in turn all applicants to be Christian, Muslim, having some university, etc.

Table D.3: Comparing applications examined by experienced vs. inexperienced bureaucrats

	Inexperienced Bureaucrats			Experienced Bureaucrats			t-test	
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Diff.	p
Level of experience								
Months since first decision	9.083	10.900	610	26.526	15.095	609	17.443	0.000
Age								
Less than 20	0.058	0.233	610	0.056	0.230	609	-0.002	0.903
Between 20 and 40	0.779	0.416	610	0.768	0.423	609	-0.011	0.654
More than 40	0.164	0.370	610	0.176	0.382	609	0.013	0.568
Marital status								
Single	0.543	0.499	610	0.483	0.500	609	-0.060	0.038
Married	0.457	0.499	610	0.517	0.500	609	0.060	0.038
Education								
University	0.162	0.369	610	0.155	0.362	609	-0.007	0.727
Secondary	0.564	0.496	610	0.553	0.498	609	-0.011	0.708
Primary	0.089	0.285	610	0.126	0.332	609	0.037	0.041
None/Missing	0.185	0.389	610	0.166	0.372	609	-0.019	0.391
Religion								
Christian	0.390	0.488	610	0.361	0.481	609	-0.028	0.312
Muslim	0.406	0.491	610	0.418	0.494	609	0.012	0.672
Other	0.092	0.289	610	0.100	0.301	609	0.009	0.611
None/Missing	0.113	0.317	610	0.120	0.325	609	0.007	0.683
Skill level								
High	0.136	0.344	610	0.118	0.323	609	-0.018	0.347
Middle	0.347	0.476	610	0.391	0.488	609	0.044	0.119
Low	0.225	0.418	610	0.219	0.414	609	-0.006	0.820
None/Missing	0.292	0.455	610	0.272	0.445	609	-0.020	0.444
Proficiency in French								
Yes	0.259	0.439	610	0.225	0.418	609	-0.035	0.163
No/Missing	0.741	0.439	610	0.775	0.418	609	0.035	0.163
Narrative								
Provided a narrative	0.978	0.146	610	0.975	0.156	609	-0.003	0.718
Credibility of the narrative	0.653	0.476	597	0.669	0.471	593	0.016	0.568
Number of words	993.119	937.561	597	965.637	775.523	593	-27.482	0.594
Distance	52.631	23.503	597	51.109	20.570	593	-1.522	0.242
Number of dates	9.166	8.858	598	9.519	8.145	595	0.353	0.485
Number of location	8.103	9.357	598	8.093	8.399	595	-0.010	0.985

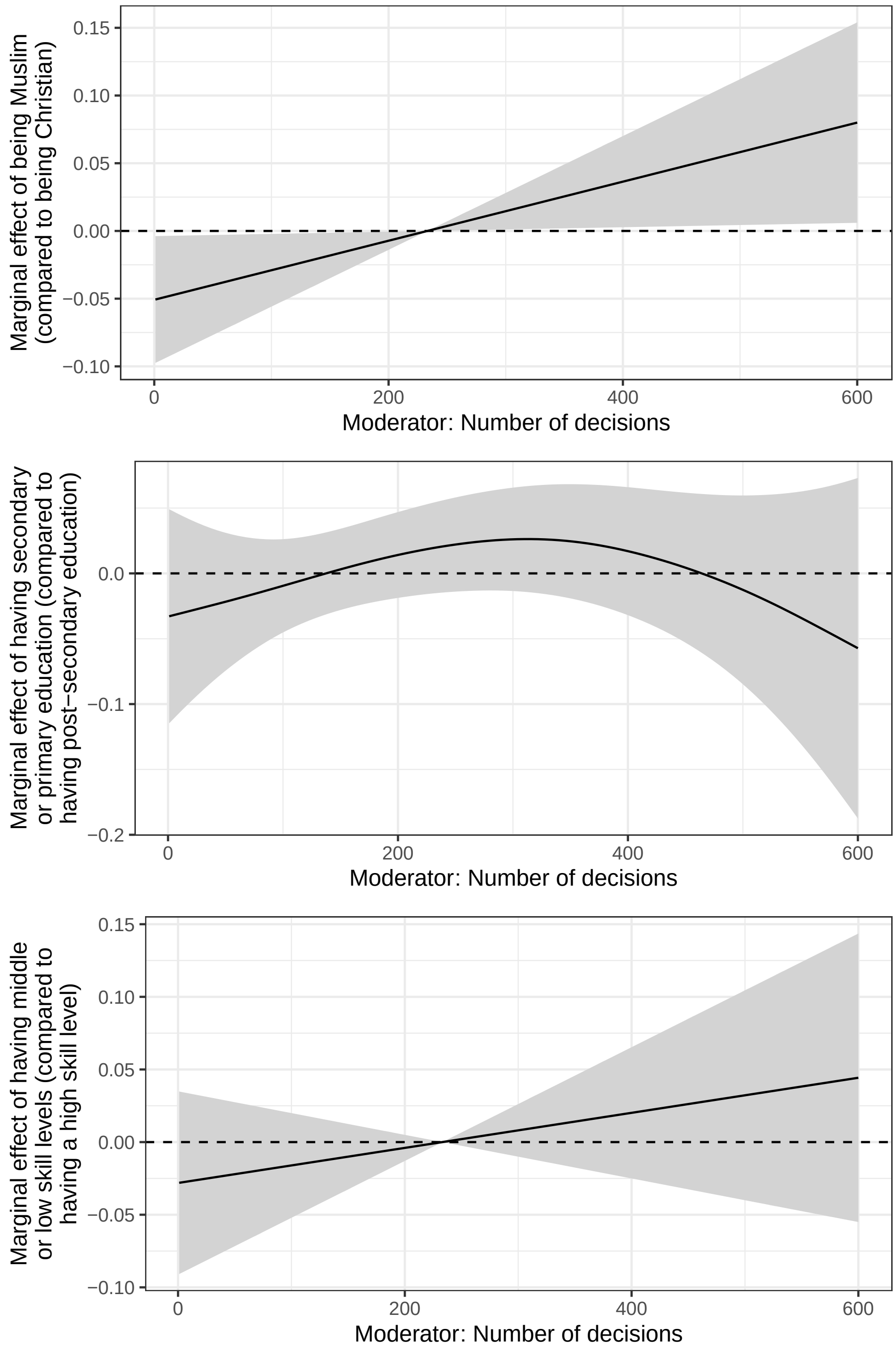
Notes: This table presents, for a selection of individual characteristics, the difference in means between applications decided by inexperienced bureaucrats (less than 185 decisions) and experienced bureaucrats (more than 185 decisions) in the subsample of the first 486 applications decided by bureaucrats.

Figure D.3: Discrimination by bureaucrats' experience (robustness)



Notes: This figure shows the estimated conditional marginal effect, and 95 percent confidence intervals based on standard errors clustered by bureaucrats, and the number of observations in each bin in parentheses. These conditional marginal effects are estimated by interacting a bin indicator (every 100 cases on the top and every 200 cases on the bottom) with the individual characteristics of interest. All specifications include covariates and fixed effects for year of application and country of origin.

Figure D.4: Discrimination by bureaucrats' experience (robustness)



Notes: This figure shows the estimated conditional marginal effect and 95 percent confidence intervals. These conditional marginal effects are estimated using three general additive models that include all the covariates and fixed effects from the main specification and two smooth functions of the number of past decisions, one for each value of each characteristic under consideration.