Gender, Incumbency, and Party List Nominations: Supplementary Appendix

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1 Supporting Information

1.1 Full Model Description

There is a set $I = \{1, 2, \ldots, n\}$ of potential nominees across all parties, with each potential nominee indexed by $i \in I$. For simplicity, we assume that parties make selections in list order—that they choose the candidate heading the party list first, and so on. Furthermore, we assume that a function, $f(\Theta_t^p, \Psi_t^p, \mathbf{x_p}, i) = \Pr(i_{pt} = i)$, probabilistically determines party p's choice of the candidate at list position t, where $\Theta_t^p \subset I$ is the set of candidates on party list p after choice $t-1$, $\Psi_t^p \subset I$ is the set of party p's potential candidates at choice t, $\mathbf{x_p}$ is a vector of covariates describing party p, and $i_{pt} \in I$ is the candidate that party p selects for list position t.[1]

Each element of Ψ_0^p, the party's pool of potential candidates, is associated with a K-vector, $\boldsymbol{\gamma_i}$, representing candidate i's membership in each of K ideal types, or groups. In this paper, we group potential candidates in terms of their gender and their incumbency status in the 2009 European election. We use an approach that assigns each candidate to one of

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[1] A number of technical assumptions complete the description of $f(\cdot)$: $\Theta_t^p \cap \Psi_t^p = \emptyset$, $\Theta_t^p \subset \Psi_0^p\ \forall t$, $\Psi_t^p \subset \Psi_0^p\ \forall t$, and $\Theta_0^p = \emptyset$.

the four following groups: male non-incumbent, female non-incumbent, male incumbent, or female incumbent. So, for example, we represent each male non-incumbent with the vector $\boldsymbol{\gamma}_{\mathbf{i}} = (1, 0, 0, 0)$.

In general, party p's choice of nominee for list place t might depend both on the characteristics of the remaining available potential candidates, Ψ_t^p, and those of the members already on the list at point t, Θ_t^p. For example, parties might wish to balance the composition of their lists. Nonetheless, in this work, we make the simplifying assumption that parties consider only their remaining potential candidates when making list selections (i.e. $f(\Theta_t^p, \Psi_t^p, \mathbf{x_p}, i) = f(\Psi_t^p, \mathbf{x_p}, i)$). Building on standard statistical models of choice, we assume that

$$f(\Psi_t^p, \mathbf{x_p}, i|\boldsymbol{\beta}) = \begin{cases} 0 & \text{if } i \notin \Psi_t^p \\ \frac{\sum_{k=1}^{K}\left(\gamma_{ik} \cdot e^{\mathbf{x_p}\boldsymbol{\beta}_{\mathbf{k}}}\right)}{\sum_{j \in \Psi_t^p}\left[\sum_{k=1}^{K}\left(\gamma_{jk} \cdot e^{\mathbf{x_p}\boldsymbol{\beta}_{\mathbf{k}}}\right)\right]} & \text{otherwise.} \end{cases} \tag{1}$$

Equation 1 implies that parties make nomination choices in terms of how much affinity they feel towards candidates of each type. Parties' characteristics determine their preferences, and, in particular, each $\boldsymbol{\beta}_{\mathbf{k}}$ is a vector of coefficients that captures the extent to which parties value candidates representing group k, as a function of party characteristics $\mathbf{x_p}$. We represent a party's overall bias towards a potential nominee in terms of the sum of the party's affinity towards each of the K types, weighted by the potential candidates membership—described by $\boldsymbol{\gamma}_{\mathbf{i}}$—in each group.[2] The probability that party p selects candidate i for list position p is simply this bias divided by the party's overall affinity towards the candidate pool that remains at choice t. Note that $\boldsymbol{\beta}_{\mathbf{k}}$ does not vary across choices and equation 1 implies that parties make identical and independent choices at each stage, conditional on the remaining supply of available candidates.

Note that this model is a generalization of multinomial logit.[3] Indeed, if, at every time t, every Ψ_t^p contains K candidates, each of which is a full member of just one of the K can-

[2]While the model is general enough to accommodate partial and multiple group membership, we do not take advantage of that feature here, except in the robustness check described by figure 7.

[3]See Long, 1997.

didate groups, and no two members of Ψ_t^p belong to the same group, equation 1 simplifies to the functional form assumed by multinomial logit. Therefore, one can interpret the coefficient matrix $\boldsymbol{\beta}$ in the model that we present here similarly to coefficients in a multinomial logit; specifically, they capture the relative affinity that parties sporting a particular set of characteristics have for full representatives of each of the K candidate groups, given the counterfactual situation in which party p has the opportunity to select a single candidate from a full set of ideal types.[4] This characteristic of the estimator is crucial to understanding how we use the model to examine European nomination behavior. In particular, we do not directly address questions of candidate supply in this paper. Rather, we ask: who is at the top of the list, and why, given the menu of candidates available to the party?[5] Put another way, the quantity of interest here is not who, on aggregate, different types of parties place into European office. Instead, we ask who they would prioritize were they given the chance to choose their ideal type. Of course, because we cannot explicitly model the construction of the set of candidates on the list—we cannot know, for example, if parties wished to include other candidates who made themselves unavailable—our analysis is potentially vulnerable to selection effects. Nonetheless, our results will be consistent so long as that selection process is explained by our measured covariates; indeed, sample selection biases coefficient estimates only when unobserved variables predict both selection into the sample and the outcome variable, and when selection into the sample is correlated with explanatory variables .[6] Thus, we face a standard omitted variable bias problem and have worked to

[4]In reality, parties forming lists never face the choice structure implied by the multinomial logit at each—and sometimes even at any—list position. The model we describe here takes this complicated choice structure into account, adjusting coefficient and error estimates to reflect the empirical data structure. Nonetheless, it provides predictions of the choices that parties would be likely to make given an idealized choice structure.

[5]See Lawless & Fox, 2010 for a discussion of why women do not run for office in single member district systems. Note also, while we do not model the process that generates the pool of potential viable nominees, the model can capture the relationship between variables that affect the quality of supply and party ranking decisions. In particular, the background characteristics of potentially viable female candidates—that is, women on the list—may covary with factors such as female workforce participation and how common it is for women to hold high-level government and private sector positions within a given country. Thus, the model could potentially capture the tendency of parties to place women in viable spots more often when available women tend to be better qualified.

[6]Wooldridge, 2013, 17.5.

include relevant predictors—both of party preference and selection—into the model.

We model the selection of n_p top list positions from N_p total list spots for each party, p.[7] In so doing, we assume that the universe of potential nominees to top list positions, Ψ_0^p, is captured by each party's full list.[8] Combined with equation 1, this strategy leads to the observed data likelihood

$$\prod_{p\in P}\prod_{t=1}^{n_p}\frac{\sum_{k=1}^{K}\left(\gamma_{c(p,t)k}\cdot e^{\mathbf{x_p}\boldsymbol{\beta}_\mathbf{k}}\right)}{\sum_{j\in\Psi_t^p}\left[\sum_{k=1}^{K}\left(\gamma_{jk}\cdot e^{\mathbf{x_p}\boldsymbol{\beta}_\mathbf{k}}\right)\right]}, \tag{2}$$

where $c(p,t)$ is a function mapping party p's nominee at list position t into I.

We estimated the model using a Bayesian approach and adopted diffuse normal priors on the coefficients, $\boldsymbol{\beta}$. Specifically, after making the identifying restriction that the first row of the parameter matrix $\boldsymbol{\beta}_\mathbf{1}=0$, we assumed that each $\boldsymbol{\beta}_\mathbf{2},\boldsymbol{\beta}_\mathbf{3},\ldots,\boldsymbol{\beta}_\mathbf{K}\sim N_m(0,25\cdot\mathbf{I}_m)$, a priori. We fit the model using Markov chain Monte Carlo (MCMC) methods. We used a basic Metropolis-Hastings algorithm and implemented the sampler using the Scythe Statistical Library.[9] The algorithm generates a chain of values for the $K\times m$ coefficient matrix $\boldsymbol{\beta}$ that, at convergence, represents a random walk over the posterior probability distribution of the coefficient matrix, based on the model in this section. The algorithm begins with an arbitrary starting matrix $\boldsymbol{\beta}^0$, subject to the identifying constraint that the first row of the coefficient matrix $\boldsymbol{\beta}_\mathbf{1}=0$. Next, at each iteration s, the sampler generates a draw from the proposal distribution,

$$\boldsymbol{\beta}_{\mathbf{-1}}{}^{p}\sim\mathcal{N}_{m(K-1)}\left(\boldsymbol{\beta}_{\mathbf{-1}}{}^{s-1},c^2\mathbf{I}_{m(K-1)}\right), \tag{3}$$

where $\boldsymbol{\beta}_{\mathbf{-1}}$ is the submatrix of $\boldsymbol{\beta}$ that excludes $\boldsymbol{\beta}$'s first row, $\boldsymbol{\beta}_\mathbf{1}$, and c is a tuning parameter

[7] In general, parties in EP elections nominate substantially more candidates to their lists than can possibly expect to obtain seats in the Parliament, such that $N_p > n_p$ by some measure. In fact, many parties maintain lists that are longer than the total number of EP seats allocated to representatives of their countries.

[8] It is certainly possible to conceive of situations when this assumption might break down. For instance, some potential nominees, failing to attain viable positions, might refuse any list spot, and thus escape our notice. Nonetheless, this approach represents perhaps the only practical way to approximate the full viable nominee pool.

[9] Pemstein, Quinn, & Martin, 2011.

that we set to 0.1 in practice. Next, using equation 2 and our assumed prior distribution for $\boldsymbol{\beta}$, the sampler computes an acceptance probability,

$$r = \min\left(1, \frac{g(\boldsymbol{\beta}^p|\Psi, \mathbf{X})}{g(\boldsymbol{\beta}^{s-1}|\Psi, \mathbf{X})}\right), \tag{4}$$

where Ψ is the set of all party sublists Ψ_t^p, $\mathbf{X}$ is the full matrix of party covariate vectors $\mathbf{x_p}$, and $g(\cdot)$ represents the posterior probability of the parameter matrix given the observed data. Finally, with probability r, the sampler sets $\boldsymbol{\beta}^s = \boldsymbol{\beta}^p$; otherwise, it sets $\boldsymbol{\beta}^s = \boldsymbol{\beta}^{s-1}$. We ran eight chains for the sampler, for one million iterations each, and discarded the first half of the run to allow the sampler ample time to reach convergence. We saved every hundredth draw from the second half of each chain, recording 5000 draws per chain (40,000 total draws) to summarize the posterior distribution of $\boldsymbol{\beta}$ given our observed data. Standard MCMC diagnostics for the sample are consistent with Markov chain convergence. In particular, the Gelman and Rubin potential scale reduction factors (PSRF) for every model parameter, and the multivariate PSRF are all less than 1.1.[10]

1.2 Additional Data Details and Discussion

Our candidate lists represent PR candidates from different types of electoral systems. For the purposes of the descriptive statistics and tests presented in the paper, we consider candidates lower than four positions below the lowest successfully elected candidate on national lists as unlikely to win seats and non-viable candidates. For regional PR lists with smaller district magnitude and much more predictable election outcomes and seat distributions, we label candidates lower than one position below the lowest successfully elected candidate non-viable.

Furthermore, there is variation in the list systems used to elect candidates to the EP—some countries use closed lists while others allow voters to perturb their lists with preference

[10]Gelman & Rubin, 1992.

votes—the party list placements almost always determine electoral success in EP elections. In practice, party list orderings are a near-perfect predictor of final seat allocations in the open list systems in our sample, save for Italy, where voters routinely cast consequential preference votes. Figure 5, in this appendix, shows that our results are robust to including an indicator for list type in the analysis. A few countries, such as Ireland and Malta, use the single transferable vote, rather than a list-based system. We order Irish candidates, who are in our sample, by relative vote share. As a robustness check of this decision, we ran an alternate specification of the model without Ireland, presented in the supporting information in Figure 4.

In order to code the characteristics of candidates, we collected native language biographical information from party websites and other electronic sources in the months preceding EP elections for all national parties predicted by Hix, Marsh and Vivyan to receive a single seat in EP and hired fluent language speakers to code a variety of candidate characteristics including gender, political experience, educational background, and employment history.[11] Limited resources, and practical constraints in recruiting translators from a university student population, restricted our ability to code every country that participated in the election. We sought a regionally representative sample, including countries from both eastern and western Europe, and both northern and southern countries from the West. The sample includes 3085 candidates from 73 national parties in 12 countries: Bulgaria, Czech Republic, France, Germany,[12] Greece, Hungary, Ireland, Italy, the Netherlands, Romania, Spain and the United Kingdom. Table 1 shows the number of candidates in the sample, broken down by country and gender. We were unable to find lists and/or biographies for a subset of parties. This was quite rare, only occurring for 4 parties in the sample.

[11] Hix, Marsh, & Vivyan, 2009.

[12] We did not fully code German lists because of excessive lengths. Specifically, we coded either as many candidates as each party listed, or approximately twice as many candidates per party, in list order,than were actually elected to the EP, whichever was smaller. As a result, unlike other countries, the current German data excludes some minor candidates at the bottom of lists.

1.3 Sample/Non-Sample Country Level Descriptive Statistics

Table 1: Number and Gender of Candidates per Country

Country	Number of Men	Number of Women	Percent Women
Bulgaria	31	20	39%
Czech Republic	125	63	34%
France	502	489	49%
Germany	118	81	41%
Greece	81	50	38%
Hungary	59	19	24%
Ireland	20	10	33%
Italy	269	159	37%
Netherlands	115	69	38%
Romania	119	34	22%
Spain	152	148	49%
UK	231	121	34%
Total	1822	1263	41%

Table 2: Descriptive Statistics, In-Sample EU Countries

	Mean	Std. Deviation	Min	Max
Log District Mag	2.92	0.93	1.10	4.60
Central Selection	3.95	0.47	3.20	4.46
Female Labor	0.50	0.06	0.38	0.60
LR Ideology	-4.76	6.81	-19.08	6.11
EU Ideology	2.35	4.74	-8.45	9.67
Gender Quota	0.25	0.45	0	1
Women Leaders	0.18	0.15	0	0.5
Female Elites	0.33	0.04	0.28	0.40

To ensure that the EU countries in our sample were not significantly different than the EU countries outside our sample, we gathered descriptive statistics of our independent variables, aggregated to averages at the country level, shown in tables 2 and 3.[13] Based on these tables, it does not appear that the EU countries in our sample represent a truncated subset with

[13]Woman Leaders, which is a dummy variable at the party level has a country maximum of 0.5 in both samples because no more than half the parties in any country had woman leaders.

Table 3: Descriptive Statistics, Out-of-Sample EU

	Mean	Std. Deviation	Min	Max
Log District Mag	2.22	0.52	1.35	3.09
Central Selection	4.11	0.41	2.96	4.65
Female Labor	0.54	0.08	0.33	0.68
LR Ideology	-4.36	8.84	-18.30	10.30
EU Ideology	6.40	7.84	-5.42	25.31
Gender Quota	0.20	0.41	0	1
Women Leaders	0.20	0.21	0	0.5
Female Elites	0.30	0.08	0.12	0.43

respect to our independent variables. T-tests of difference in means yield only one statistically significant difference at the 0.05 level, log of district magnitude.[14] In-sample countries have larger average district magnitude than out-of-sample countries, a characteristic that is largely driven by our decision to disproportionately sample the largest countries in the EU, who have many more seats to allocate than small countries.

1.4 Supplemental Results

1.5 Regression Plots and Robustness Checks

We first provide three alternative plots of the regression shown in the paper, one for each possible baseline category. While these three plots and figure 1 all provide the same information, certain comparisons are easier to visualize depending on the baseline category.

Figures 4, 5, 6 describe three robustness checks. In the first, we dropped Ireland from the sample because it relies on STV, rather than electoral lists. Figure 4 shows that our results are robust to removing Ireland from the analysis. Figure 5 examines the role that list-type—open or closed—has on our findings, again excluding Ireland from the analysis. We find no statistically significant effect for open list, nor does including an open list dummy in the

[14] Of course, we have almost a 34 per cent chance of erroneously rejecting the null at least once in the process of conducting these eight tests.

analysis substantively alter our findings. Figure 6 adds a further control, the percentage of seats held by women in national parliament.[15] Adding this control produces little change in our coefficient estimates and standard errors. Finally, figure 7 displays coefficient estimates for a model which includes information about candidates' experience in national elected office, also drawn from candidate biographies, to control for candidate quality. Specifically, in addition to membership in the four mutually exclusive groups (male non-incumbent, female non-incumbent, male incumbent, female incumbent), we also code whether or not candidates belong to the group of nationally experienced candidates. Figure 7 shows that controlling for this form of experience does little to alter the substantive implications of the model; coefficient estimates for the four types are robust to the inclusion of this information.

1.5.1 European Integration

Figure 1 in the paper, figure 2 and 3 from the supplementary appendix make the result more clear—shows that there is a statistically significant, and negative, relationship between support for European integration and parties' tendency to rank male incumbents in viable list positions. Parties become more likely to prioritize the placement of novices over male incumbents as party support for integration grows. While in the same direction, the corresponding relationships between novices and female incumbents do not reach traditional statistical significance.[16] Yet, the posterior probability that the effect for women incumbents is less than the effect for male incumbents is only 0.83. Thus, we hesitate to argue that incumbency interacts with gender in this context. Rather, we have some evidence that parties that support European integration are less incumbent-oriented than eurosceptics, and that evidence is stronger for male incumbents than for female incumbents. At first glance it might seem surprising that pro-integration parties value incumbents less than eurosceptic parties, but it is important to point out that supporting Europe is not the same thing as prioritizing influence within European institutions. Eurosceptics may have an incentive to

[15]We use PIREDEU's contextual dataset variable 7.25.
[16]For the clearest picture of this finding, see 3.

Figure 1: Regression coefficients: female non-incumbents are the reference category; plotted coefficients describe selection effects for non-incumbent men (**M**), incumbent men (**MI**), and incumbent women (**FI**), relative to female novices.

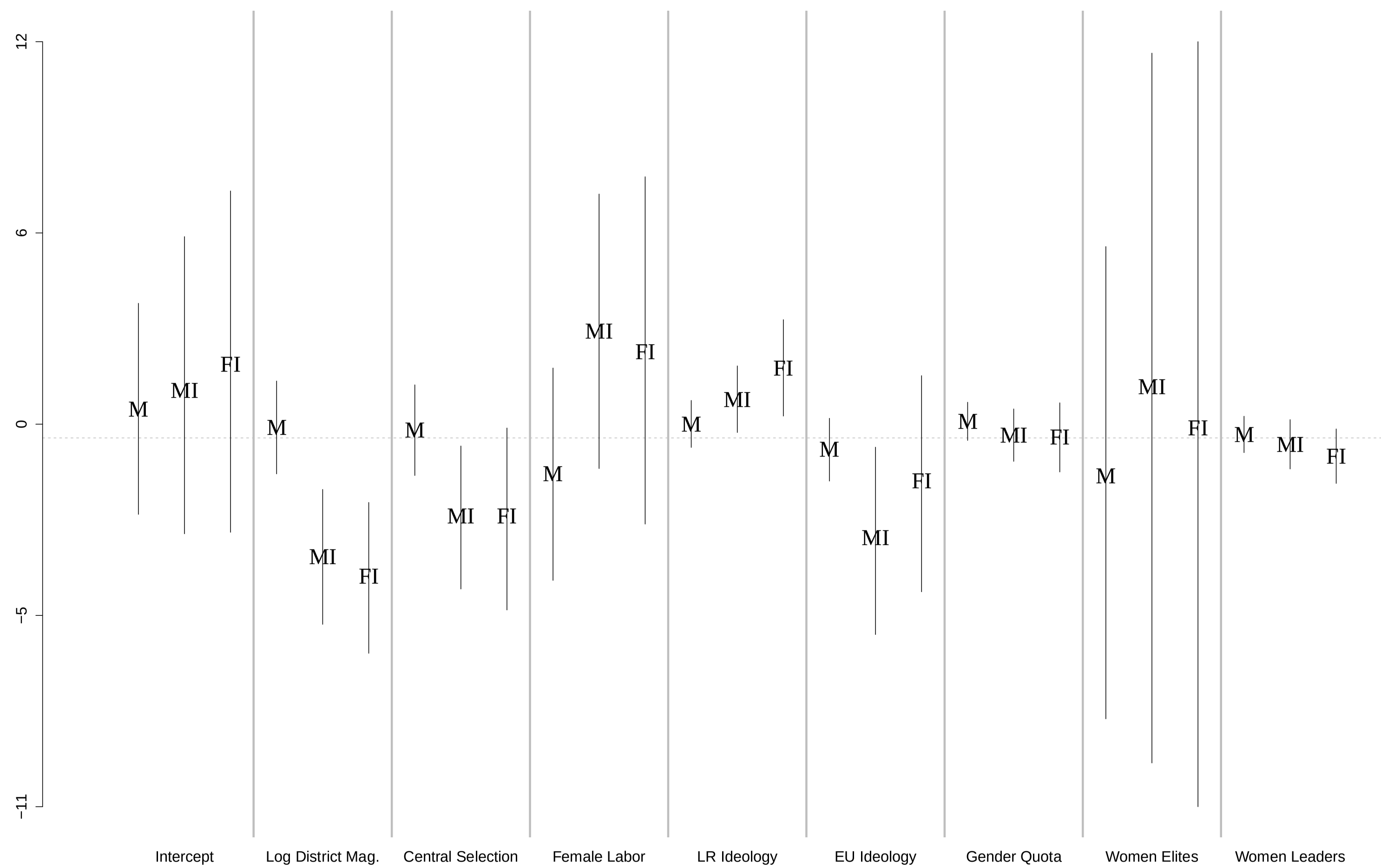


Figure 2: Regression coefficients: male incumbents are the reference category; plotted coefficients describe selection effects for non-incumbent women (**F**), non-incumbent men (**M**), and incumbent women (**FI**), relative to male incumbents.

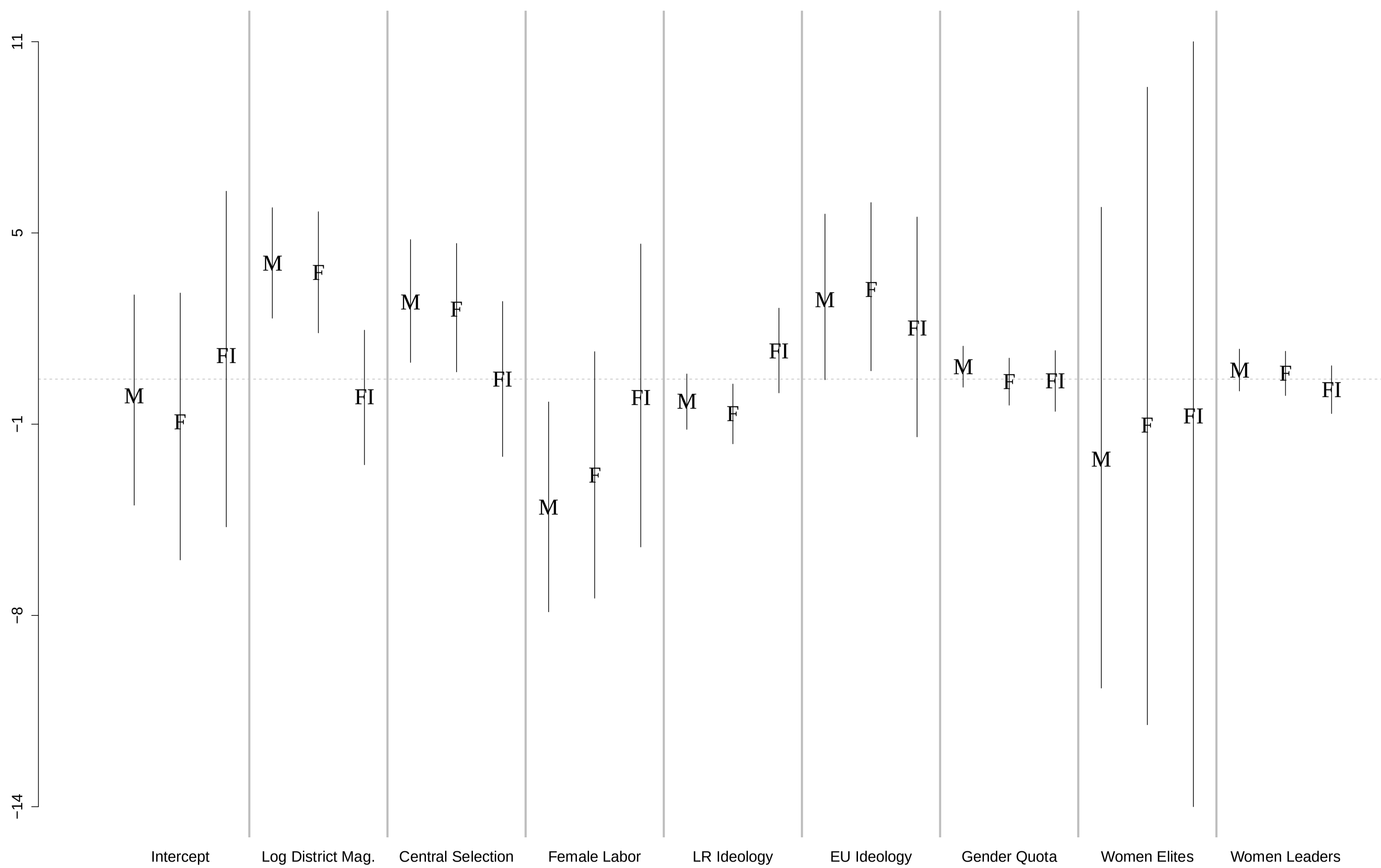


Figure 3: Regression coefficients: female incumbents are the reference category; plotted coefficients describe selection effects for non-incumbent women (**F**), non-incumbent men (**M**), and incumbent men (**MI**), relative to female incumbents.

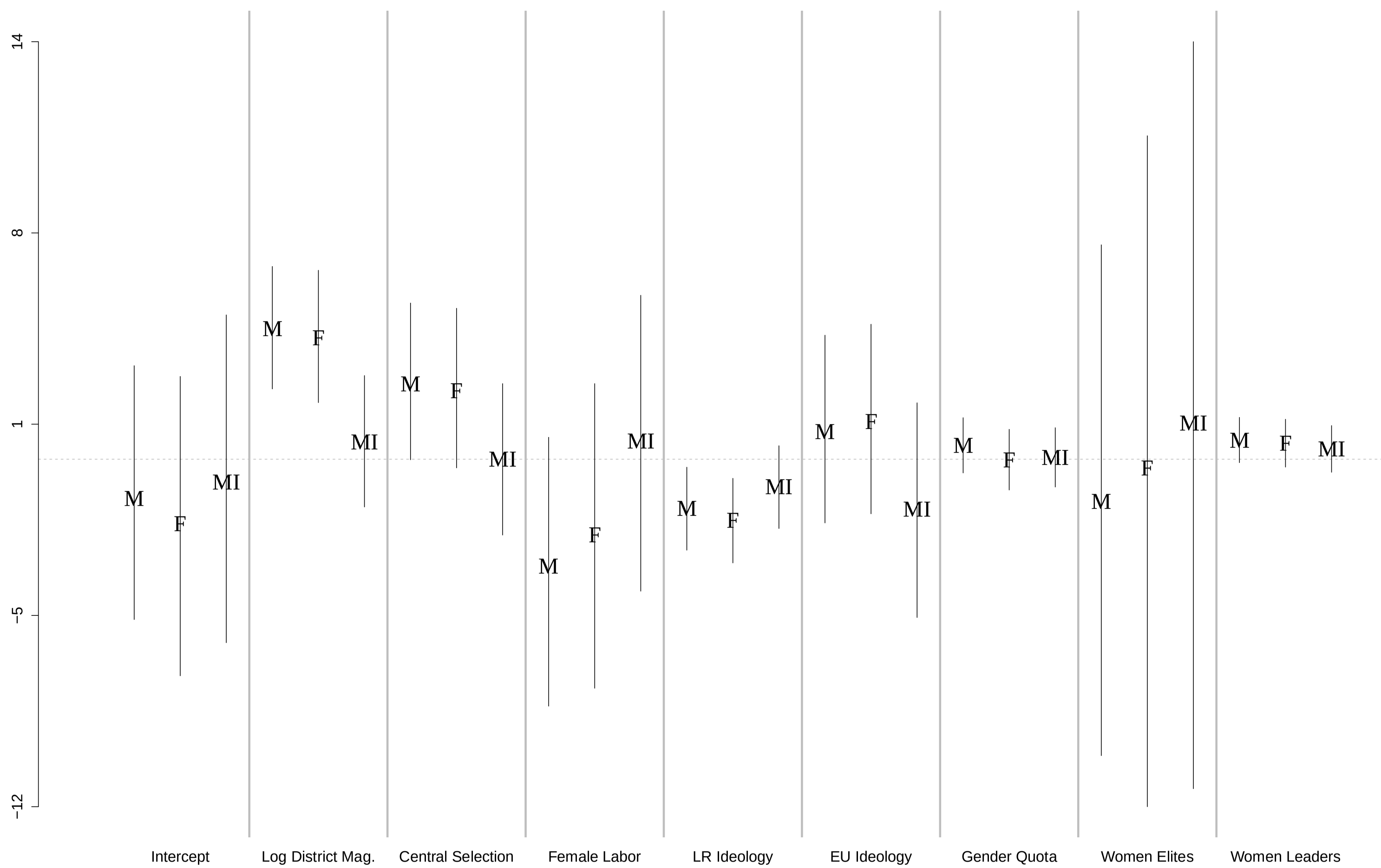


Figure 4: Regression coefficients with Ireland removed from sample: male non-incumbents are the reference category; plotted coefficients describe selection effects for non-incumbent women (**F**), incumbent men (**MI**), and incumbent women (**FI**), relative to male novices.

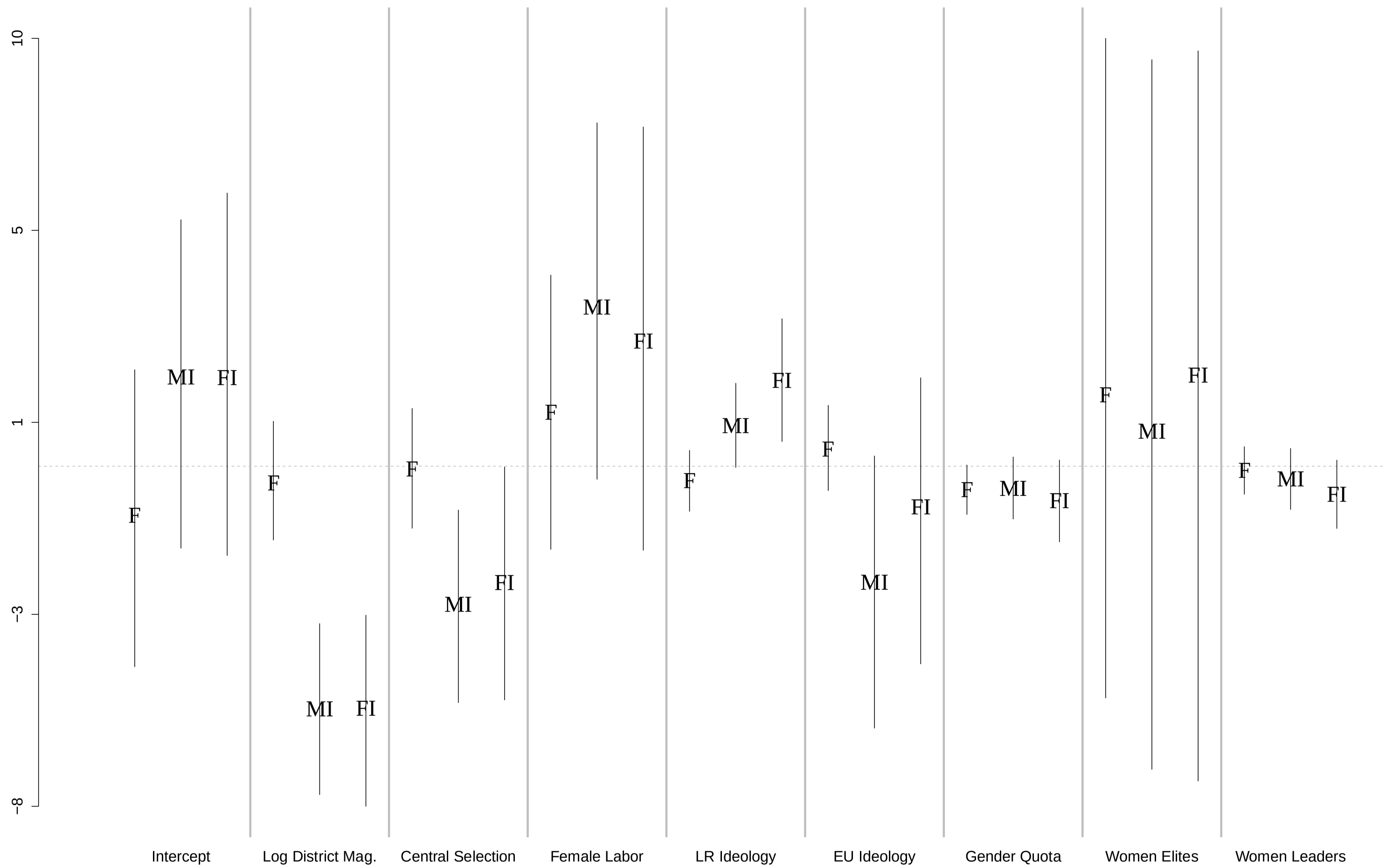


Figure 5: Regression coefficients including an open list dummy, with Ireland removed from the sample: male non-incumbents are the reference category; plotted coefficients describe selection effects for non-incumbent women (**F**), incumbent men (**MI**), and incumbent women (**FI**), relative to male novices.

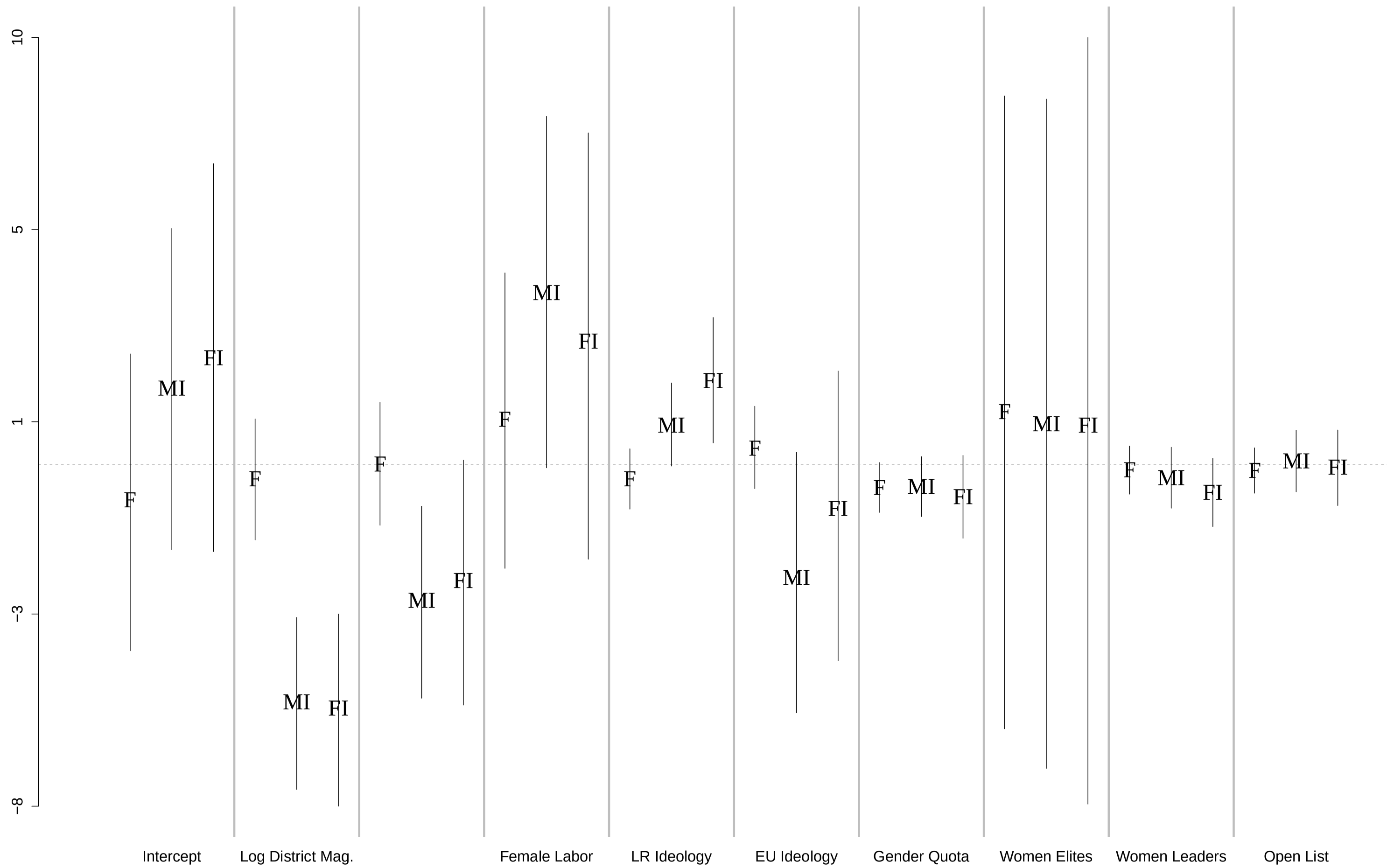


Figure 6: Regression coefficients including % women in national parliament: male non-incumbents are the reference category; plotted coefficients describe selection effects for non-incumbent women (**F**), incumbent men (**MI**), and incumbent women (**FI**), relative to male novices.

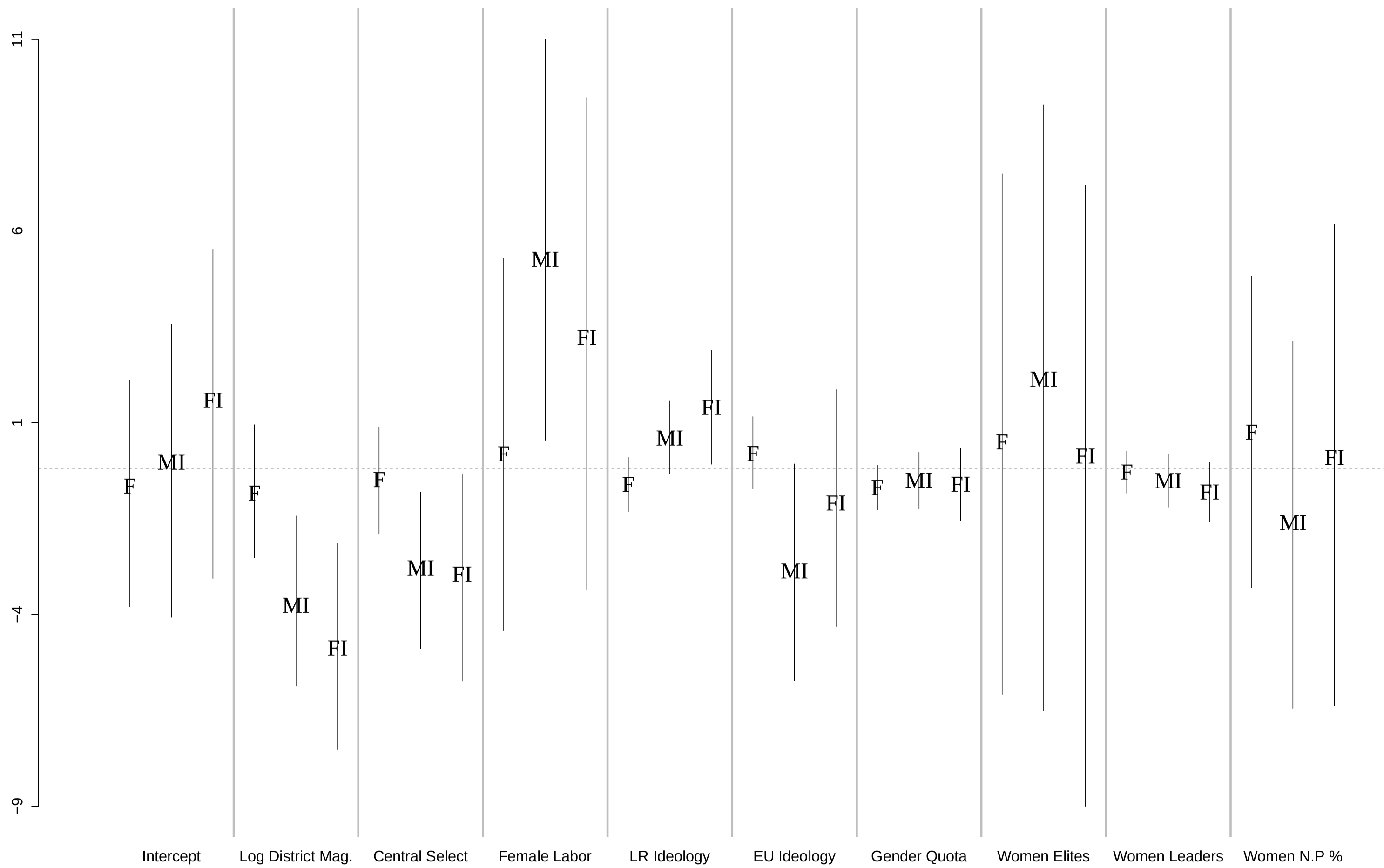


Figure 7: Regression coefficients: male non-incumbents are the reference category; plotted coefficients describe selection effects for non-incumbent women (**F**), incumbent men (**MI**), incumbent women (**FI**), and prior holders of national office (**N**), relative to male novices.

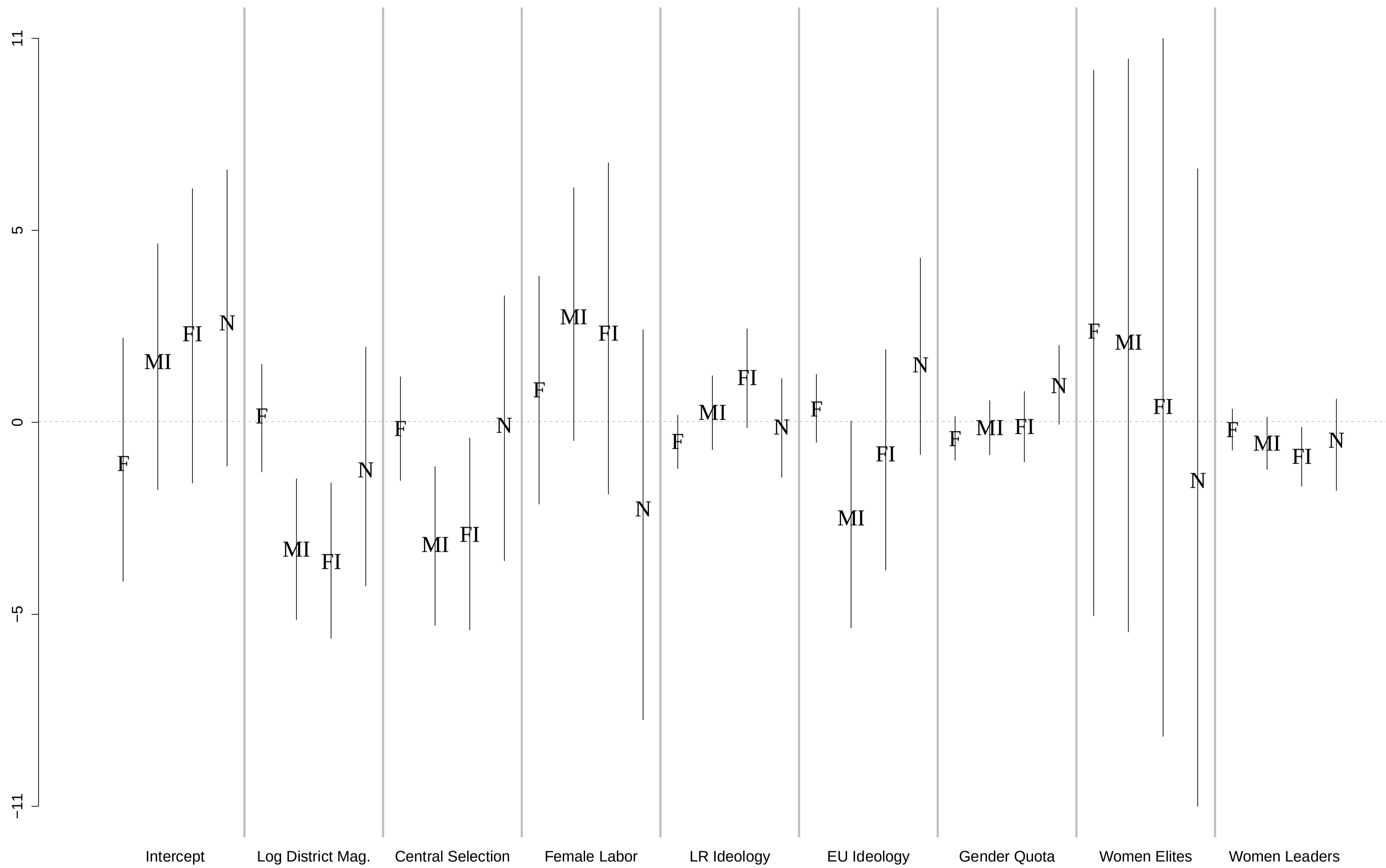
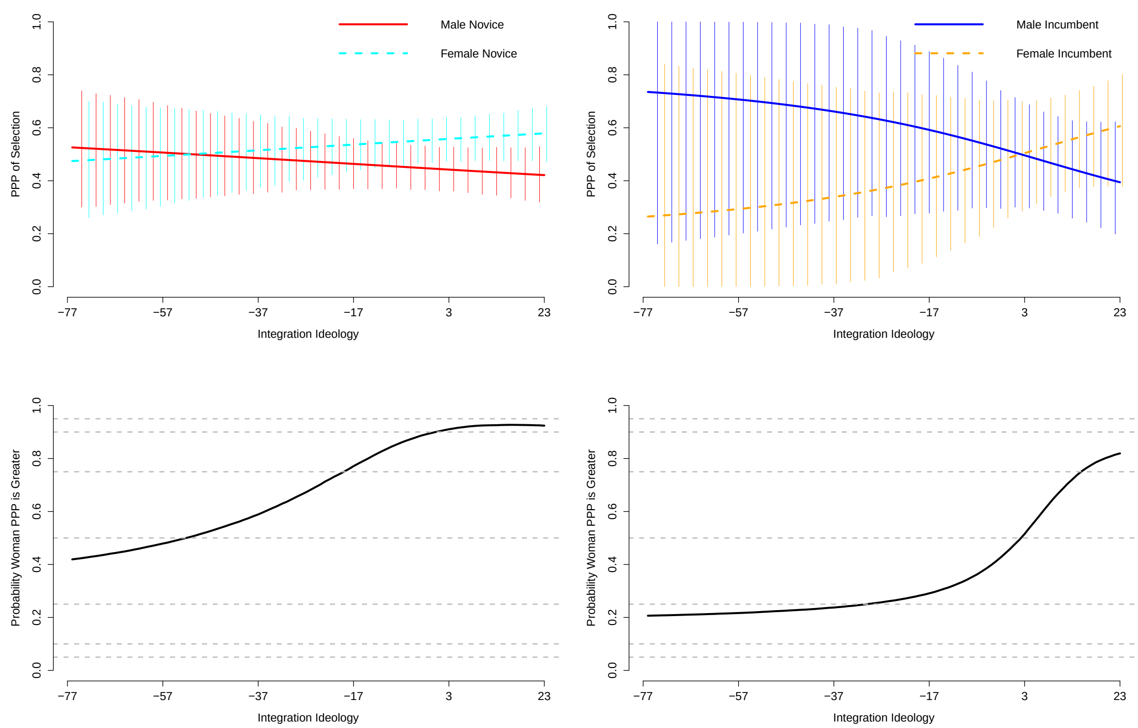


Figure 8: The posterior predicted probability of choosing candidates of each gender, across observed integration ideology scores. The left panels examine contests between novices, while the right panels depict choices between incumbents. The upper panels depict posterior predicted probabilities while the lower panels show the posterior probability that the woman candidate is more likely to obtain the nomination.



cultivate expertise in the EP specifically because they hope to effectively undermine the expansion of European influence. Similarly, because they often are competitive only on the European stage, such parties have little incentive to use the EP as a training ground for inexperienced candidates; thus they have less reason to drop an incumbent in favor of fresh blood than do nationally competitive parties. Focusing on gendered choices within novices and incumbents, we find limited evidence that pro-integration parties show a preference for women candidates, both among novices and incumbents. While such a result would not be terribly surprising—many euroskeptic parties also reject cosmopolitan values—we do not, as a whole, find strong statistical relationships between attitudes towards Europe and gender choices in candidate nominations.

Focusing on gendered choices within novices and incumbents, figure 8 shows limited evidence that pro-integration parties show a preference for women candidates, both among novices and incumbents. While such a result would not be terribly surprising—many euroskeptic parties also reject cosmopolitan values—we do not, as a whole, find strong statistical relationships between attitudes towards Europe and gender choices in candidate nominations.

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