Power Analysis

A power analysis was performed to determine the sample size needed for the proposed project with enough statistical power. To my knowledge, there is no existing research exploring how perceived and objective occupational risks, belief certainty, and indirect occupational risks affect policy opinions[1]. This means that power analyses could not rely on coefficient estimates from previous studies. As such, this project takes a conservative approach and assumes that the expected effect sizes for the coefficients under study will be small (.2) or medium (.5) using Cohen's D effect sizes[2]. Specifically, the coefficients β and the sample size vary between permutations of the power analysis s.t., $(N \in \{500, 600, 700, \ldots, 6000\}, \beta_1 \in \{.2, .5\}, \beta_2 \in \{.2, .5\}, \beta_3 \in \{.2, .5, .8\}, \beta_4 \in \{.2, .5\}, \beta_5 \in \{.2, .5\}, \beta_6 \in \{.2, .5\}, \beta_7 \in \{.2\})$.

$$\begin{aligned}\text{Policy Opposition}_{ip} =& \beta_1 \text{Perceived Ind. Risk}_{ip} + \beta_2 \sum_{j \in P \setminus \{p\}} \text{Objective Ind. Risk}_{ij} + \beta_3 \text{Certainty}_{ip} + \\ & \beta_4 \left(\text{Certainty}_{ip} * \text{Perceived Ind. Risk}_{ip}\right) + \beta_5 \left(\text{Certainty}_{ip} * \sum_{j \in P \setminus \{p\}} \text{Objective Ind. Risk}_{ij}\right) + \zeta_k + \epsilon_{ip}\end{aligned} \tag{1}$$

Each hypothesis will be tested against the four questions to account for potential different causal processes influencing policy opposition and to test hypothesis five, which posits that spillover from unrelated migration threats is greater than other options.

For each simulated individual i in the sample of size N, their opposition towards policy p (automation, outsourcing, migration, imports) was generated using Equation 1a above. This equation is identical to the equation that will be used in the methodology section, except for an included random error term $\epsilon_{ip} \sim \mathcal{N}(0, 1)$ in lieu of the vector of control variables Θ_i. The objective risk of the individual towards automation, outsourcing, migration, and imports was generated $\mathcal{N}(.5, .25)$, with a truncation at 0 and 1. This truncation was conducted to reflect that some respondents in the sample will either be completely at risk toward an option (1) or completely not at risk (0), but some respondents cannot have a risk greater than 1 or less than 0. In each generated sample, roughly 5% of individuals (±2SD) will be entirely at risk or not at all at risk from a given option. The certainty of the respondents in their perceived risk is also generated $\mathcal{N}(.5, .25)$, with truncation at 0 and 1.

Subsequently, the individuals in the sample were randomly assigned to a state (1-50) and a county (254). That county variable was used to generate randomly distributed county-level fixed effects, and the state variable was used to generate state-level averages in susceptibility to these options. Considering the clustering at the county and state-level economic variables, this analysis accounts for other sociotropic and community-level influences on policy preferences not captured by the sociotropic questions included in the vector of control variables Θ_i.

To account for the effect of union membership on the accuracy of perceived risks, the correlation between an individual's perceived risk and their objective risk increases for union members. Union membership is generated $B(\mathbf{n}, .1)$ to reflect the idea that only a small portion of the U.S. respondents in the sample will be union members[3]. Objective individual risk and perceived individual risk are

1. Many sources explore policy opinions towards automation, offshoring, migration, and imports, but none of which adopt the information and certainty belief of this project.

2. Gignac and Szodorai 2016.

3. Shierholz.

generated:

$$\begin{pmatrix}\text{Latent Objective Ind. Risks}\\ \text{Latent Perceived Ind. Risks}\end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix}.5\\ .5\end{pmatrix}, \begin{pmatrix}.25^2 & \rho\sigma_X\sigma_Y\\ \rho\sigma_X\sigma_Y & .25^2\end{pmatrix}\right) \tag{3}$$

where $\rho = .2$ for non-union members and $\rho = .5$ for union members. Following the generation of these variables, formula (2a) below is estimated.

$$\rho\left(7 - |\text{Objective Ind. Risk}_{ip} - \text{Perceived Ind. Risk}_{ip}|\right) = \beta_7\text{Union Membership}_i + \Theta_i + \zeta_k \quad \text{s.t.} \tag{2a}$$

To measure the accuracy of workers' perceptions of their risk, equation (2a) is used. It is identical to equation 2 from the methodology section, except that the accuracy of threat perceptions is replaced with the term $\left(7 - |\text{Objective Ind. Risk}_{ip} - \text{Perceived Ind. Risk}_{ip}|\right)$. This term measures the accuracy of threat perceptions in these data. When there are no differences between the perceived risk of a worker (e.g., 5) and the objective risk of the worker (e.g., 5), the accuracy term will have its highest value of 7. When there is the most difference between the perceived risk of a worker (e.g., 7) and their objective risk (e.g., 1), this accuracy term will be at its lowest value of 1.

Within each sample of the power analysis, regression models were run using the specifications of Equation 1a and Equation 2a. Each model was run concerning the policy opinions of all four options: automation, offshoring, migration, and imports. The results of these power analyses can be seen in full in Section C1 of the appendix. Assuming that the coefficients are all at their weakest, this power analysis suggests that an effective sample of 3,500 respondents is needed to test the hypotheses of this project. To account for potential never-takers in the sample, which attention checks may not remove, a sample of 3,850 respondents is requested[4].

Survey Provider

The Prolific Platform Survey will be used to conduct the proposed survey. Prolific was selected for several reasons. The first is data quality. Douglas, Ewell, and Brauer (2023) has found that, compared to M-Turk and Qualtrics, the quality of survey respondents[5] was the highest among Prolific[6]. These findings of Prolific's data quality in comparison to other online survey platforms are also supported by Eyal et al. (2021) who found that Prolific, compared to Cloud Research and Mechanical Turk consistently had high-quality data (measured through attention checks, comprehension checks, and the honesty and internal consistency of respondents' answers)[7].

Furthermore, since many of the contributions of this project are descriptive and seek to explain how perceived job threats and the precision of perceived job threats vary across populations within the United States, a nationally representative sample is required. Unfortunately, due to a skewed demographic distribution among the Mechanical Turk survey participants, it is doubtful that a

4. Marbach and Hangartner 2020.
5. The quality of participation was measured by the proportion of the sample that passed attention checks, followed survey instructions, provided meaningful responses, remembered previously presented information, and worked at a pace where they could read the survey.
6. Douglas, Ewell, and Brauer 2023.
7. Eyal et al. 2021.

Mechanical Turk sample can obtain a nationally representative sample[8].

Provider	Total Costs	Cost per Respondents	Respondents	Sampling	Sampling Fee	Service Fee
Mechanical Turk	$11,200	$2	3850	Criteria Sampling[9]	NA	3,080
Prolific	$11,920.00	$2	3850	Nationally Representative	$1,653	$2,567
Cloud Research	$11,550.00	NA[10]	3850	Nationally Representative	$5,775.00	$5,775.00

TABLE 1. *Survey Providers*

8. Levay, Freese, and Druckman 2016.
8. Specifically full-time or part-time employed non-students.
8. You cannot edit how much each respondent is paid through Cloud Research's Panel when looking to sample a particular subset of the population

References

Douglas, Benjamin D, Patrick J Ewell, and Markus Brauer. 2023. Data quality in online human-subjects research: Comparisons between MTurk, Prolific, CloudResearch, Qualtrics, and SONA. *Plos one* 18 (3): e0279720.

Eyal, Peer, Rothschild David, Gordon Andrew, Evernden Zak, and Damer Ekaterina. 2021. Data quality of platforms and panels for online behavioral research. *Behavior research methods,* 1–20.

Gignac, Gilles E, and Eva T Szodorai. 2016. Effect size guidelines for individual differences researchers. *Personality and individual differences* 102:74–78.

Levay, Kevin E, Jeremy Freese, and James N Druckman. 2016. The demographic and political composition of Mechanical Turk samples. *Sage Open* 6 (1): 2158244016636433.

Marbach, Moritz, and Dominik Hangartner. 2020. Profiling compliers and noncompliers for instrumental-variable analysis. *Political Analysis* 28 (3): 435–444.

Shierholz, Heidi. Workers want unions, but the latest data point to obstacles in their path: Private-sector unionization rose by more than a quarter million in 2023, while unionization in state and local governments fell. Available at <https://www.epi.org/publication/union-membership-data/#:~:text=the%20public%20sector-,In%202023%2C%2016.2%20million%20workers%20in%20the%20United%20States%20were,from%2011.3%25%20to%2011.2%25.>.