Appendix for online publication: Attitudes toward automation and the demand for policies addressing job loss: the effects of information about trade-offs

Beatrice Magistro*, Peter John Loewen, Bart Bonikowski, Sophie Borwein, and Blake Lee-Whiting

Appendix

Information on case selection and survey experiment

To assess the role of cost-benefit information on the perceived fairness of a firm's decision to automate and on support for different policy responses, we fielded an online survey experiment in Australia, Canada, the UK, and the US. We chose the four countries for their similarities across several dimensions: they share the same language, are liberal market economies, have similar historical origins, and are all in an advanced stage of de-routinization, having adopted technology more intensely than other countries (as proxied by ICT use) (De La Rica and Gortazar, 2016).[1] Despite some variation across these cases in specific dimensions of technology adoption, at the aggregate level they are all among the top scorers on technology readiness (United Nations, 2021). All four are in the top 15 (out of 158 countries) on the United Nations' Readiness for Frontier Technologies Index, which measures a country's capacity to use, adopt, and adapt frontier technologies, considering the level of ICT infrastructure, skills, R&D activity, industry activity, and access to finance (United Nations, 2021). While technological progress is essential for a society's economic advancement and development, it can also lead to distributional consequences by exacerbating existing inequalities or creating new ones. For these reasons, governments often play a central role in trying to maximize the potential benefits of technology, while mitigating its most harmful costs. The latter task will be particularly challenging in this group of liberal market economies that feature less extensive, more residual welfare states than many of their continental European counterparts. In this context, the experience with trade may be particularly instructive: Rodrik (2018) argues that while various US administrations did not do a good job at redistributing the gains from trade, possibly unleashing the protectionist backlash observed in recent years, most European countries have long had strong social protections and generous welfare states, so openness to trade there has been accompanied by much greater redistribution and more generous social insurance. For these reasons, compared to mature welfare states where automation represents a new labor market risk in a relatively low-risk environment, focusing

*Corresponding author: magistro@caltech.edu

[1] By de-routinization we mean the displacement of labor from routine tasks and hence greater reallocation of low-skill workers from routine task-intensive occupations to service occupations.

on countries at the forefront of the technological frontier that also feature much less generous welfare states is of critical importance.

Assessing the political impacts of automation presents several empirical challenges, particularly when it comes to distinguishing the specific effects of technology from other factors influencing employment threats. While a majority of jobs may not be susceptible to being relocated overseas, a significant number of workers experience challenges arising from both trade and automation simultaneously. Furthermore, several recent studies find little to no correlation between objective and subjective perceptions of automation risk (Loewen and Allen Stevens, 2019; Gallego, Kuo, Manzano, and Fernández-Albertos, 2021), suggesting that most people are not aware of their risk of automation. As a result, to explore the causal relationship between the impacts of automation and perceptions of fairness and automation policy preferences, we conducted a survey experiment using a vignette designed to manipulate the costs and benefits of different hypothetical scenarios concerning automation. In doing this we follow existing vignette-based experimental studies (Di Tella and Rodrik, 2020; Gallego, Kuo, and Manzano, 2023; Ladreit, 2022; Wu, 2022; Zhang, 2022). One key difference across many of these studies, which limits their comparability, is that they use different control groups: while some compare automation's employment effects to a scenario which does not involve employment effects, others compare automation's employment shocks to other labor market shocks, such as offshoring or changes in consumer demand. Our study is the first to compare an automation prime emphasizing only the costs of automation, which acts as our baseline and is consistent with most studies' framing, to primes emphasizing both the costs and benefits of automation in either specific or generic terms. Finally, while the use of an experiment featuring a hypothetical firm deciding to automate some of its processes is consistent with much of the literature, we recognize that the resulting findings may not be generalizable to the entire labor market. That said, our study's conjoint experiment arm features a comparison of four different types of firms (producing smartphones, cars, airplanes, and vaccines) and this does not appear to affect respondents' views on automation, suggesting that the observed effects are not sector-specific.

Specific trade-offs information conjoint treatment group

Research design

In this section we provide more details on how the quantities presented in the conjoint tables were derived.

What happens after a firm introduces a new computer-based productivity-improving technology? Theoretically, we can think of a few different scenarios, which we use to motivate our experimental treatments.

First, assuming that we initially have a perfectly competitive market for the main good being produced by the firm in question, a new computer-based technology will make the firm more productive, shifting the supply curve out, which in turn will drive prices down for consumers. Provided that demand is elastic enough to prices, product demand will increase, which will result in net job growth.[2] However, the expectation is that low-skilled

[2] We are describing process (i.e., reducing marginal costs) rather than product (i.e., introducing a new product) innovation. The former shifts the supply curve out and leads to lower prices, gains in consumer

and high-skilled workers in the firm will be affected heterogeneously by a new computer-based productivity-improving technology. In this scenario, where demand is elastic enough to prices, after automation, a majority of high-skilled workers will benefit. These include workers performing certain technical skills, required to deploy, operate and maintain the new digital technologies, such as AI, big data, and machine learning specialists. However, a minority of low-skilled workers will lose their jobs, as automation will reduce the demand for jobs with more repetitive tasks that can be easily automated, such as assembly and factory workers (Centre for the New Economy and Society, 2018). In this hypothetical scenario, the gains for consumers, producers, and for high-skilled workers would be substantial enough that it would be more efficient to compensate the low-skilled workers through retraining programs, unemployment insurance, or other policy options than to stop innovation altogether.

What if demand is inelastic? In this scenario, as prices go down as a result of new innovative technologies, demand does not increase enough to result in net job growth. Again, we could consider heterogeneous effects, where only a minority of high-skilled workers benefit, while a majority of low-skilled workers lose their jobs.

If we relax the assumption that the market is perfectly competitive, we could also envision a scenario in which the firm chooses not to decrease prices as a result of the innovation. Alternatively, even in a perfectly competitive market, there could be a scenario where prices are sticky in the short run and hence may not decrease right away.

Analyzing these different scenarios, we can envision different outcomes for prices and high-skilled and low-skilled workers. We use a simplified version of the examples outlined here to build our survey experiment. We hold constant the information about a manufacturing firm introducing a new computer-based productivity-improving technology, which would lower production costs, while in the different treatment groups we vary information on prices of the final good and effects on high-skilled vs low-skilled workers, before and after the innovation.

For simplicity, we keep one job per type (one high-skilled—AI, big data, and machine learning specialists—and one low-skilled: factory and assembly workers). We do not include a scenario where low-skilled workers benefit. Theoretically, this could exist (we could think of non-routine manual workers), but if we did allow for the possibility that low-skilled workers gain and high-skilled lose, this would require different examples and types of jobs (since it would not make sense in the scenario of a computer-based productivity improving innovation). That possibility would introduce more complexity and a much higher number of scenarios, which would raise power concerns. Finally, while we allow for price change to be 0 and for the change in the number of high-skilled workers to be 0, we do not allow the change in the number of low-skilled workers to be 0 since it would imply a decision with no trade-offs.

We adjust the wages based on the average wage for the occupation in question for each country according to the source `talent.com`. The wages shown in Table 1 apply to the US and Canada. In the Australian case, the average wage for assembly workers is AUS$50,000 (and the two scenarios after innovation are as a result, AUS$30,000 or AUS$40,000), while

welfare, and depending on the elasticity of demand, jobs gains or losses. The latter could possibly lead to even larger gains for consumers if the demand curve is shifted out drastically enough, as quality-adjusted prices may decrease even more than production costs and consumer surplus may be significantly larger. Product innovation is historically responsible for larger increases in consumer welfare than process innovation (Menaldo, Forthcoming), hence our example and related treatments likely provide a lower bound on the benefits of automation and innovation.

the average wage for data scientists is around AUS$100,000; in the UK we adjust wages for both occupations. The average wage for data scientists is £60,000 (and the two scenarios after innovation are as a result, £75,000 or £90,000), while for assembly workers the average wage is £20,000 (and the two scenarios after innovation are as a result, £13,000 or £17,000).

For simplicity we keep the same prices across all four countries, while only changing the currencies. We believe the potential price changes as a result of innovation (up to 50% lower prices) are realistic. For instance, Ford's revolutionary assembly line allowed him to dramatically reduce the price of his cars. The first Model T in 1908 cost $850, half the price of existing automobiles. In 1914, its price dropped to $440, and by 1924 it was down to $240. Similarly, computers today are about one-1,100th of their price 35 years ago. The biggest price reduction took place in the 1980s, but even more recently, between 2014 and 2015, the price decreased by 10%. The same is true of televisions, cellphones, and cameras (Rosoff, 2015; Ito, 2015). The median price of a smartphone decreased from $325 to $200 between 2012 and 2014. This significant price reduction has been made possible by the declining cost of manufacturing smartphones, driven by standardized processors, efficient supply chains, economies of scale, and intensifying market competition among vendors offering more affordable options (The Economist, 2014). The cost of renewable technologies has experienced a drastic decline, making them cost-competitive or even cheaper than new fossil fuels due to advances in technology and economies of scale. Today, the cost of constructing a new solar plant is nearly three times lower than that of a new coal plant, and the price of solar electricity has decreased by 89% between 2009 and 2019 (Roser, 2020). Deployment and technological improvements have also made batteries cheaper and cheaper. The price of lithium-ion battery cells declined by 97% in the last three decades. A battery with a capacity of one kilowatt-hour that cost $7500 in 1991, was just $181 in 2018. And prices are still falling steeply: the cost halved between 2014 and 2018 (Ritchie, 2020). Finally, a more timely example comes from ChatGPT: In March 2023 OpenAI released APIs for its ChatGPT and Whisper models at a significantly reduced cost, with ChatGPT experiencing a 90% cost reduction since December 2022, in just under 3 months. This decreasing cost of large AI models is mainly due to the continuous advancement of technology and intensification of competition (Zhang, John, 2023). There are exceptions to these trends, of course. For instance, while cheaper smartphone brands have gained market share, Apple's unique value proposition, brand loyalty, ecosystem integration, product differentiation, and focus on user experience have allowed the company to maintain its competitive position in the market, allowing it to maintain higher prices than its competitors.

DV: Policy preferences

After each treatment, respondents were asked how much they agreed or disagreed with the following government policies (from Borwein et al. (2023)) on a five-point scale with a "don't know" option:

- Expand social spending to support laid-off workers, and workers in similar positions.
- Implement a basic income that gives every adult a set amount of money from the government on a regular basis.

- Pay to retain displaced workers and guarantee them jobs.
- Reduce the number of unskilled immigrants entering the country for work.
- Reduce the number of skilled immigrants entering the country for work.
- Restrict international competition by increasing trade barriers on goods and services to [Australia, Canada, the UK, the US].
- Fund programs to re-skill workers for new jobs.
- Directly tax companies that replace workers with machines and robots.

Objective and subjective knowledge

Here, we investigate the possibility that conjoint treatment effects may vary by respondents' economic literacy, which we measure in the specific information conjoint treatment group by asking respondents to compute the costs and benefits of the new innovation. We expect that people who display higher economic literacy should be more responsive to changes in the attributes, since they should have a better understanding of the trade-offs involved.

We include a series of questions aimed to measure both objective and subjective knowledge of automation.

After the first conjoint table respondents were asked the following multiple-choice questions to determine whether they understood the effects of the innovation:

- How much cheaper does the main product become after the innovation? [correct options are either 0%, 20% or 50%.]
- What is the total number of workers before the innovation? And after?

Using these questions we are able to build an index of objective knowledge for individuals in the specific information conjoint treatment group. The resulting index ranges from 0 to 2, to reflect the number of correct answers. Since these questions may be measuring attention rather than actual knowledge, we also validate our findings with an alternative variable that measures self-reported subjective knowledge of automation, which may make a respondent more likely to know that automation entails both costs and benefits and in turn may make them more sensitive to changes in these numbers. Individuals were asked:

- "How much would you say you understand automation" [I know nothing about it; I have heard the concept, but I don't understand it well; I am familiar with the concept; I have a basic understanding; I have a good understanding; I am an expert]

The answers are recoded into three categories:

- "Low knowledge" [I know nothing about it; I have heard the concept, but I don't understand it well];
- "Medium knowledge" [I am familiar with the concept; I have a basic understanding];

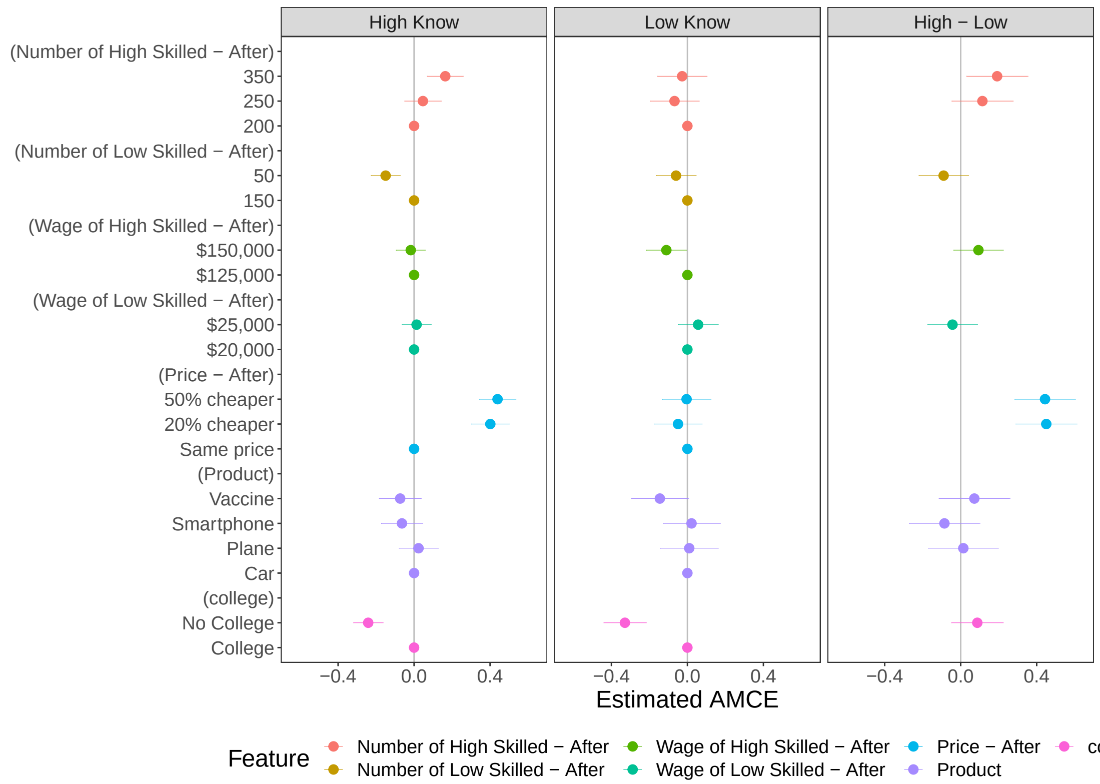

Figure A1: Average marginal component effects on fairness by high and low knowledge

- "High knowledge" [I have a good understanding; I am an expert].

In Figures A1 and A2 we test whether the observed effects differ by respondents' objective and subjective knowledge.[3] People who correctly estimated the costs and benefits of automation (who got two out of two correct answers), are more sensitive to price changes and to changes in the number of employed high-skilled workers than those who did not compute those numbers correctly (0 out of 2 correct), as Figure A1 illustrates.[4] Figure A2 shows that results are similar for self-reported as opposed to objective knowledge: People with higher self-reported knowledge of automation are more sensitive to price changes and to changes in the number of employed high-skilled workers than those with low self-reported knowledge.

DV: Would make the same decision if you were CEO of the company

In addition to assessing people's perceptions of fairness, we also examined respondents' likelihood of making the same decision if they were the CEO of the company, which takes into account considerations beyond fairness, such as efficiency. While there are some notable variations in responses compared to fairness, these differences do not appear to be substantively

[3]We present results by high and low subjective and objective knowledge here, since this is our comparison of interest. See figures A17 and A18 for the full results, which include moderate levels of knowledge. See tables A6 through A11 for complete results.

[4]These models hold education constant since it may be a proxy for math skills.

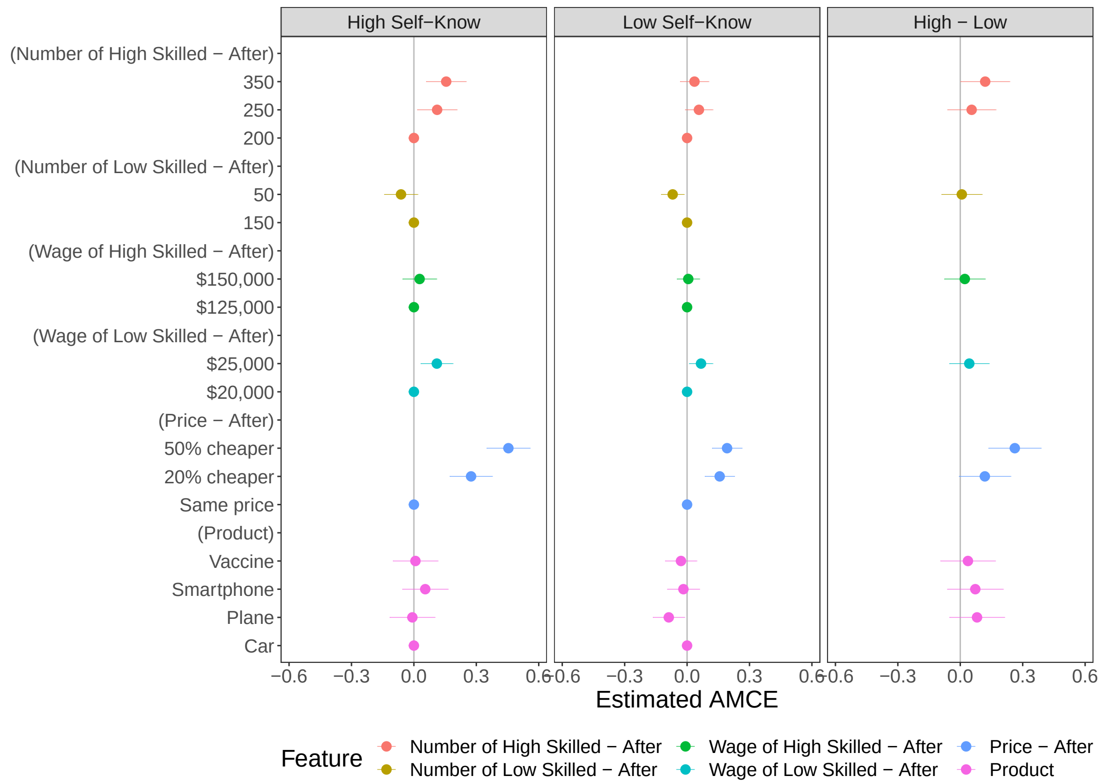

Figure A2: Average marginal component effects on fairness by high and low self-reported knowledge

consequential. Consistent with the findings on perceived fairness, respondents are more inclined to indicate that they would make the same decision if they were the CEO of the company when exposed to the generic information treatment compared to the news information treatment. The only difference is that the coefficient for specific information is not significantly different from the news information treatment at the 95% confidence level. However, the results from the conjoint analysis reveal that respondents are responsive to the same attributes, with effects consistently aligned in the same direction, irrespective of whether they are considering fairness or envisioning themselves as CEOs. This suggests that respondents did not approach the two questions with substantial differences in their decision-making considerations. For these reasons, we decided to focus on fairness and only report results with the CEO dependent variable here in the Appendix.

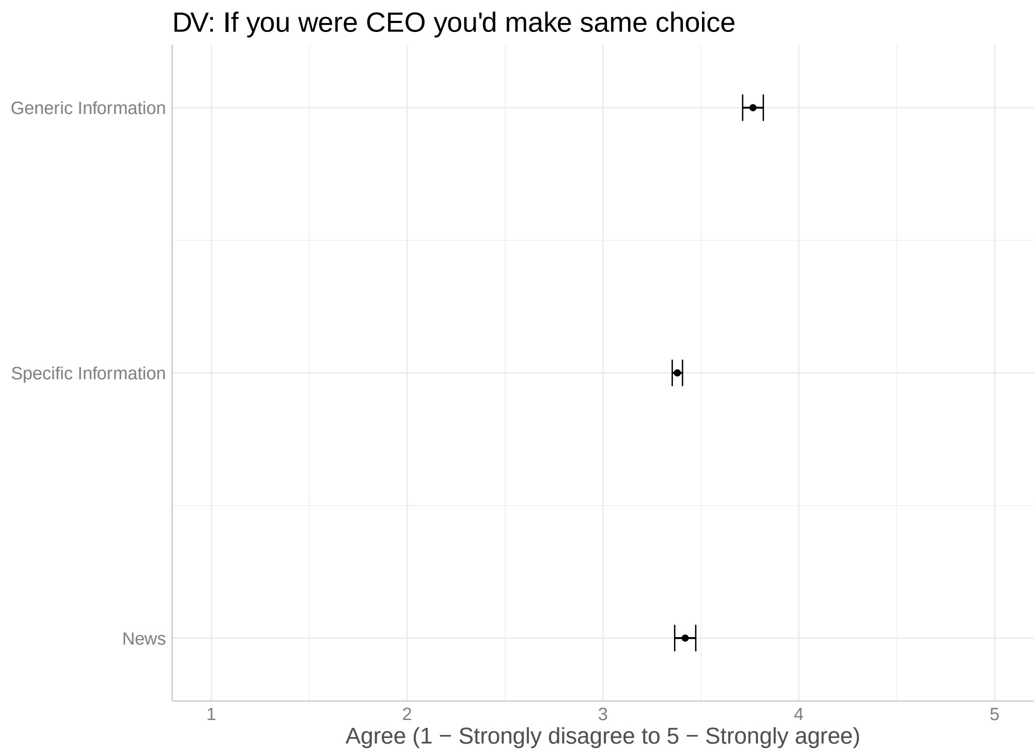

Figure A3: Predicted values of hypothetical CEO decision with 95% confidence intervals

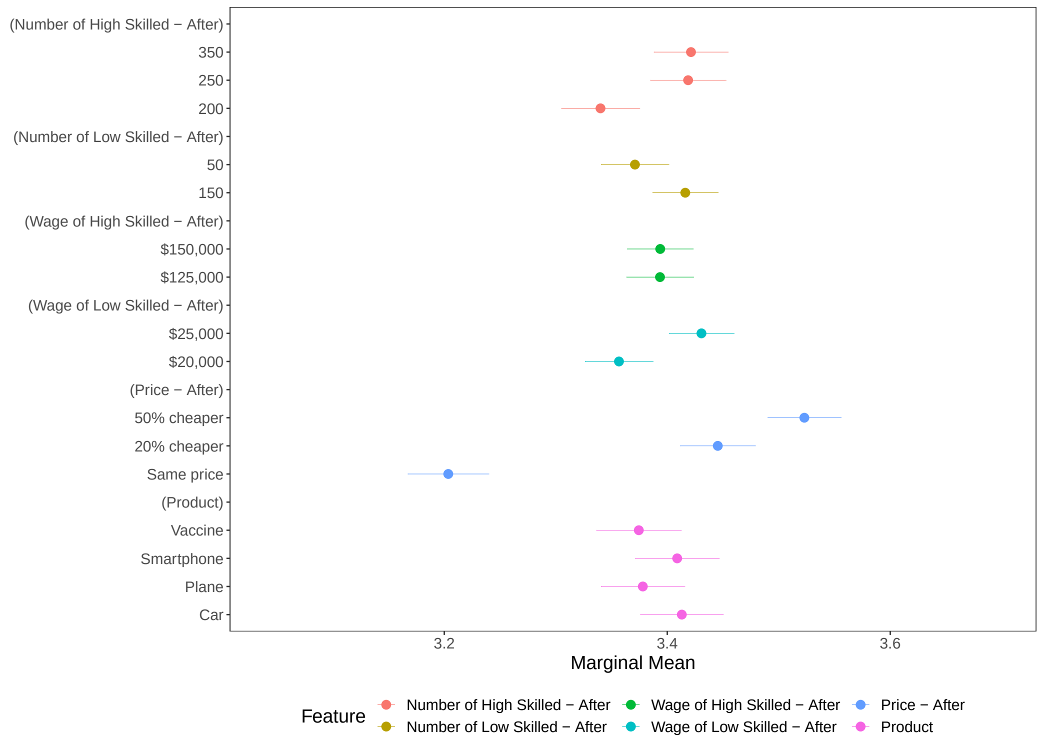

Figure A4: Marginal means of attributes on hypothetical CEO decision

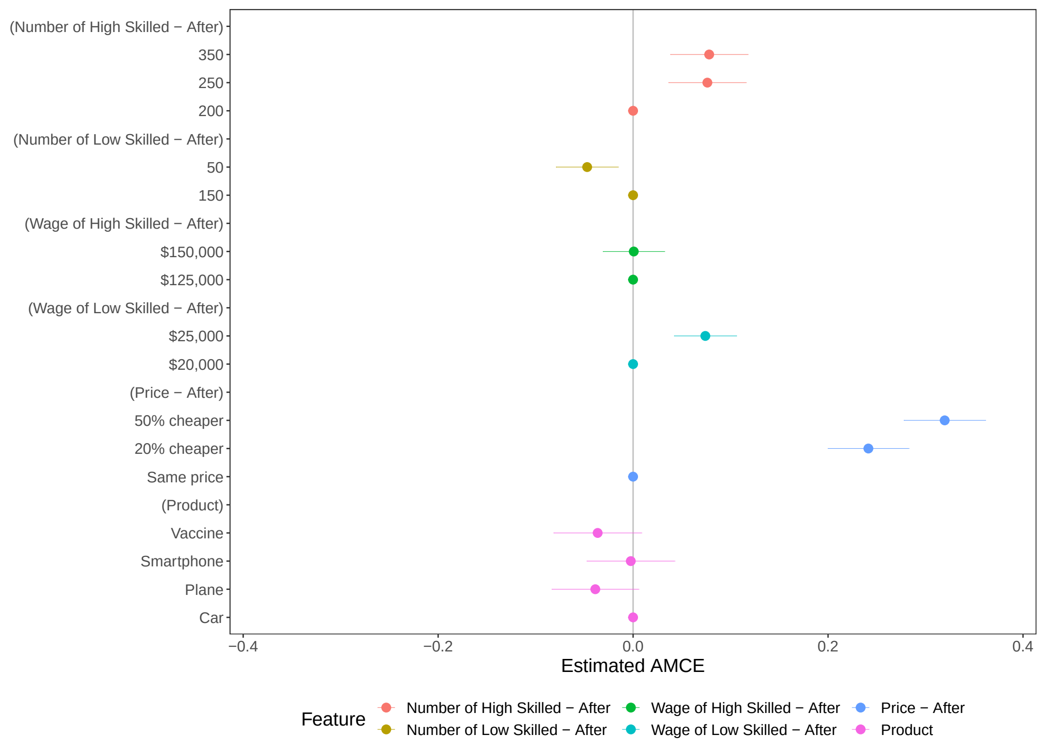

Figure A5: Average marginal component effects of attributes on hypothetical CEO decision

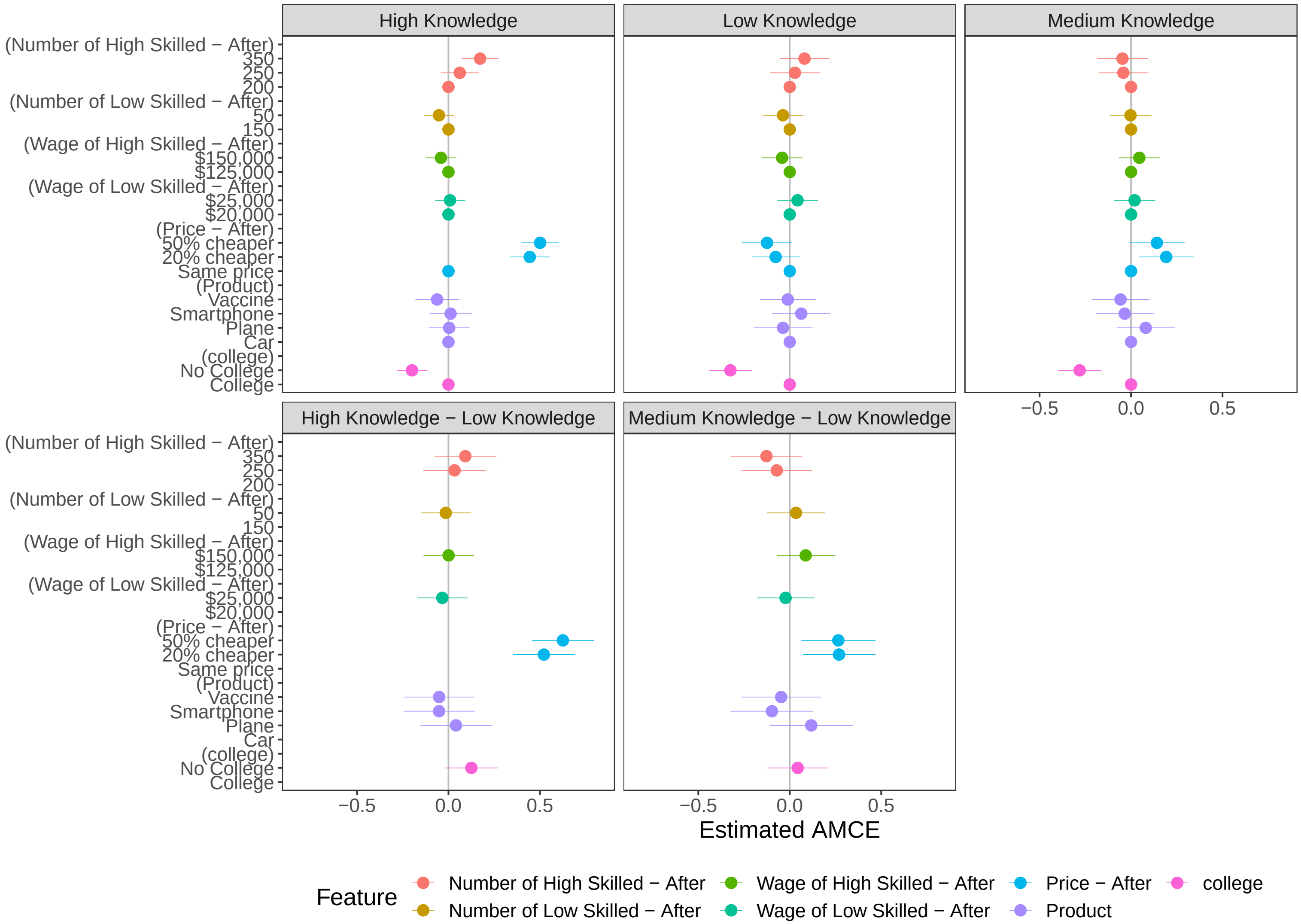

Figure A6: Average marginal component effects on hypothetical CEO decision by degree of knowledge

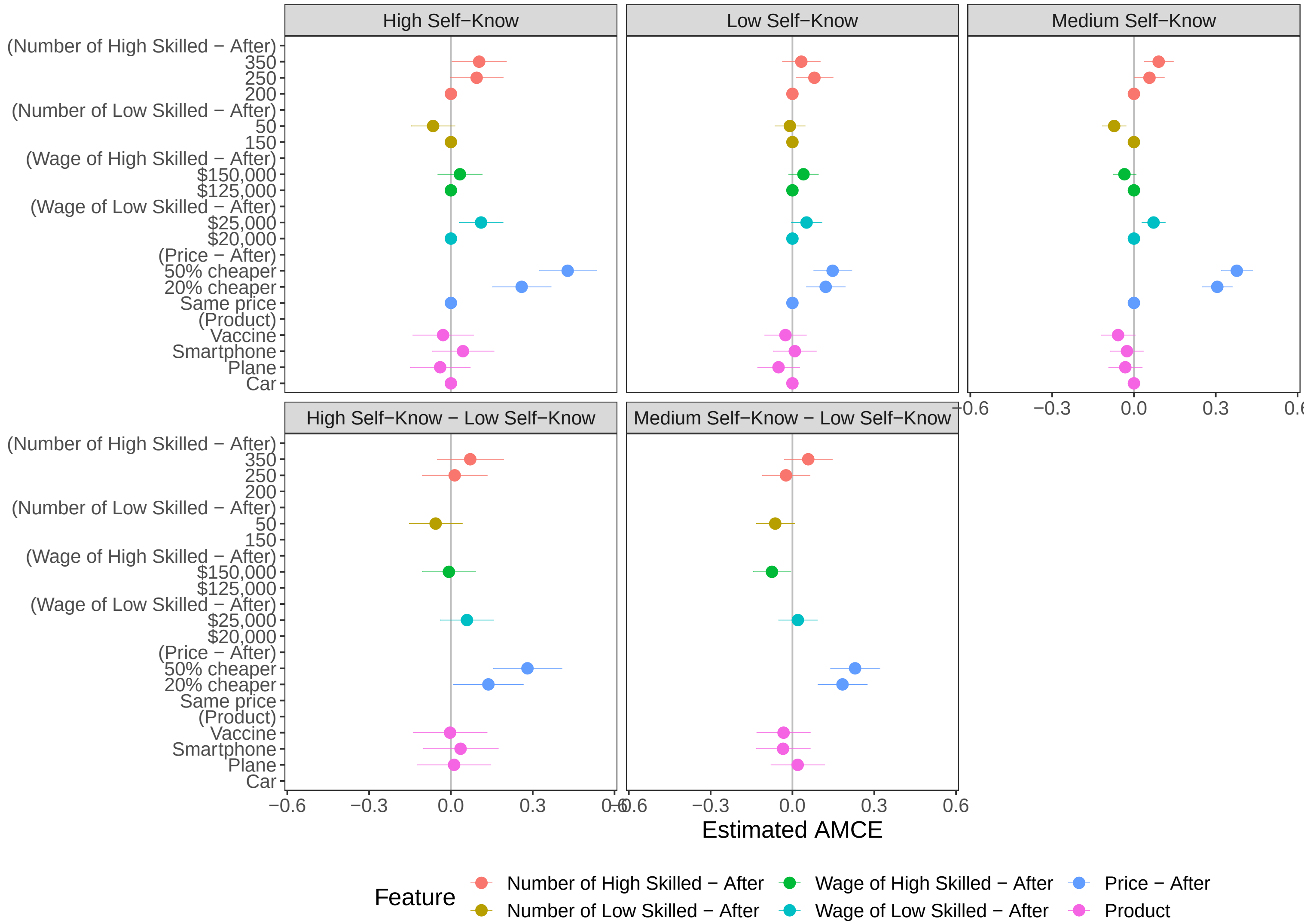

Figure A7: Average marginal component effects on hypothetical CEO decision by self-reported knowledge

Alternative explanations

An alternative explanation is that the lower perceived fairness of automation in the specific information treatment may be driven by the vignette's identification of winners and losers (i.e., we clearly state that low-skilled workers lose out and high-skilled workers win), rather than respondents' envisioning larger net gains for workers in general in the generic treatment compared to the average conjoint. If so, this could be due to two mechanisms: all respondents may be more sensitive to low-skilled job loss or respondents with different skill levels may respond in different ways to the treatment. While we can't directly test the former mechanism, if it were driving the results, respondents in the conjoint would should be significantly more sensitive to changes in the number of low-skilled rather than high-skilled workers. That does not appear to be the case. Regarding the latter mechanism, while we expand further on the question of differential treatment effects by subjective and objective exposure to automation elsewhere, our findings suggest that there are no differential treatment effects by automation threat or education level. Objective automation threat is measured both by the conventional RTI (routine task intensity) measure and by a task-based measure developed by Gallego, Kuo, Manzano, and Fernández-Albertos (2021). Taken together, these findings suggest that our results are not primarily driven by the identification of winners and losers in the specific information condition.

Figures and Tables

Table A1: Regression analyses predicting perceived fairness and hypothetical CEO decision. Standard errors are given in parentheses.

	Dependent variable:	
	Fairness	Would do same if CEO
	(1)	(2)
Specific Information (ref. News)	0.143^{***}	-0.040
	(0.029)	(0.031)
Generic Information	0.451^{***}	0.346^{***}
	(0.037)	(0.038)
Constant	3.231^{***}	3.420^{***}
	(0.026)	(0.027)
Observations	7,655	7,523
Note:	* p<0.05; ** p<0.01; *** p<0.001	

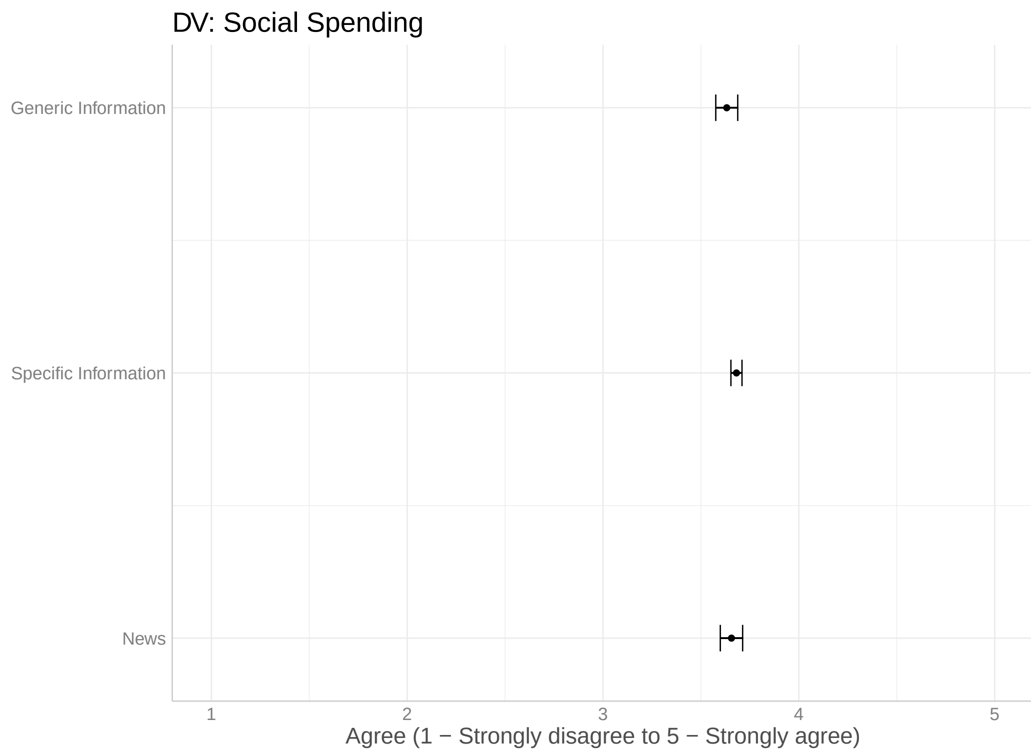

Figure A8: Predicted values of social spending with 95% confidence intervals.

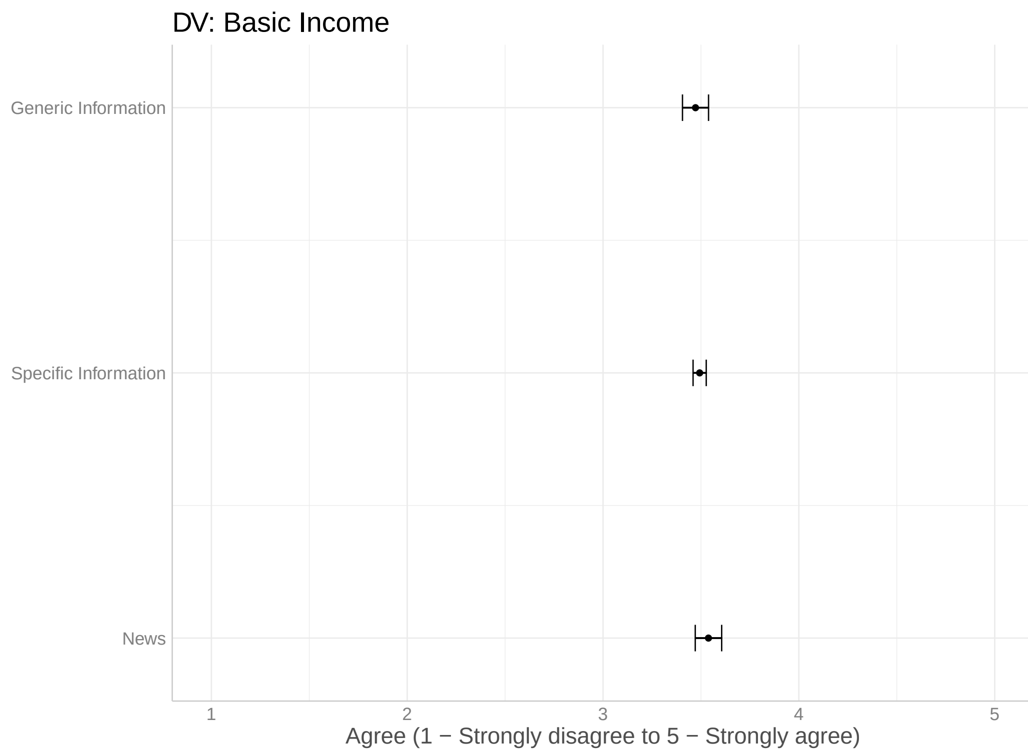

Figure A9: Predicted values of basic income with 95% confidence intervals.

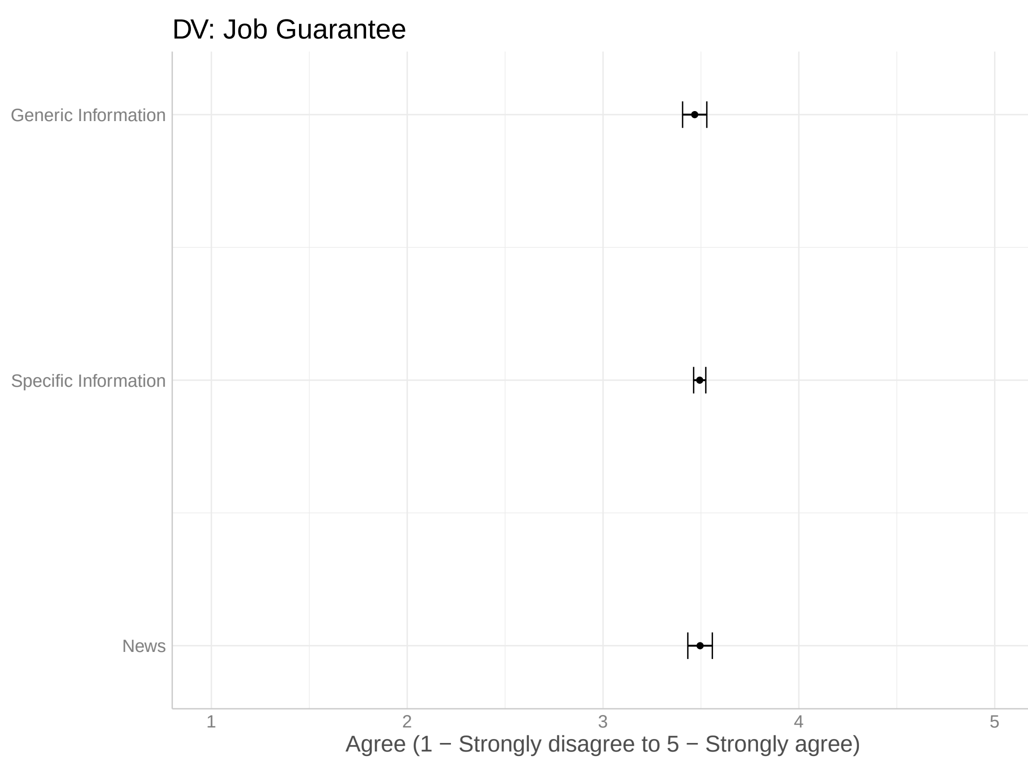

Figure A10: Predicted values of job guarantee with 95% confidence intervals.

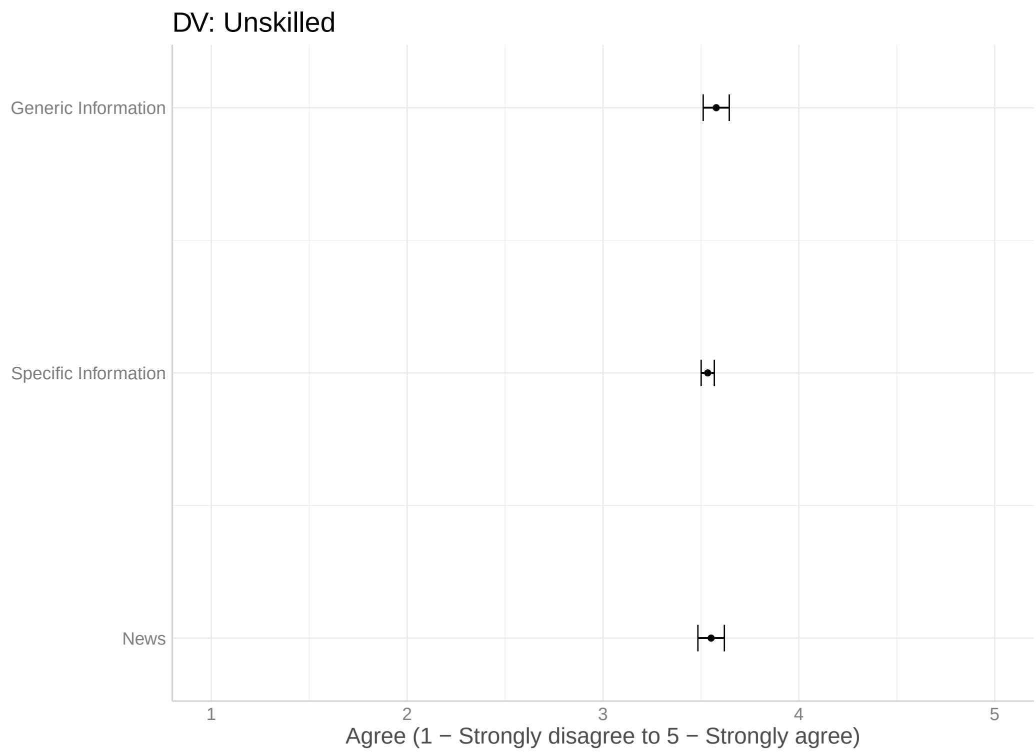

Figure A11: Predicted values of restricting unskilled migration with 95% confidence intervals.

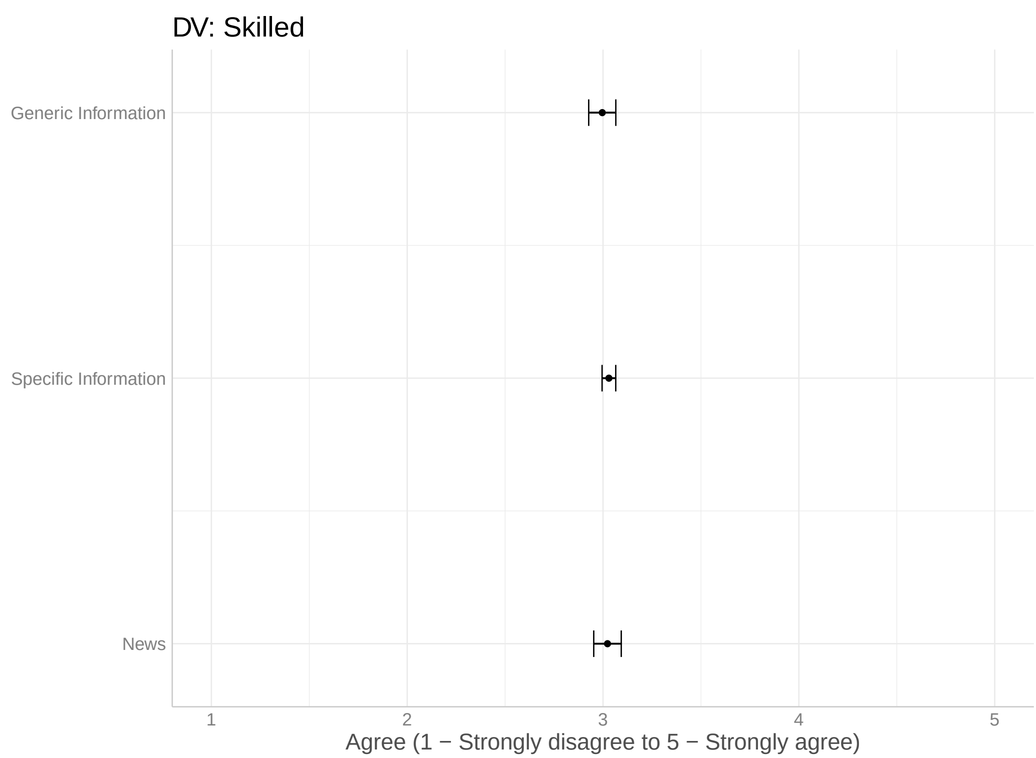

Figure A12: Predicted values of restricting skilled migration with 95% confidence intervals.

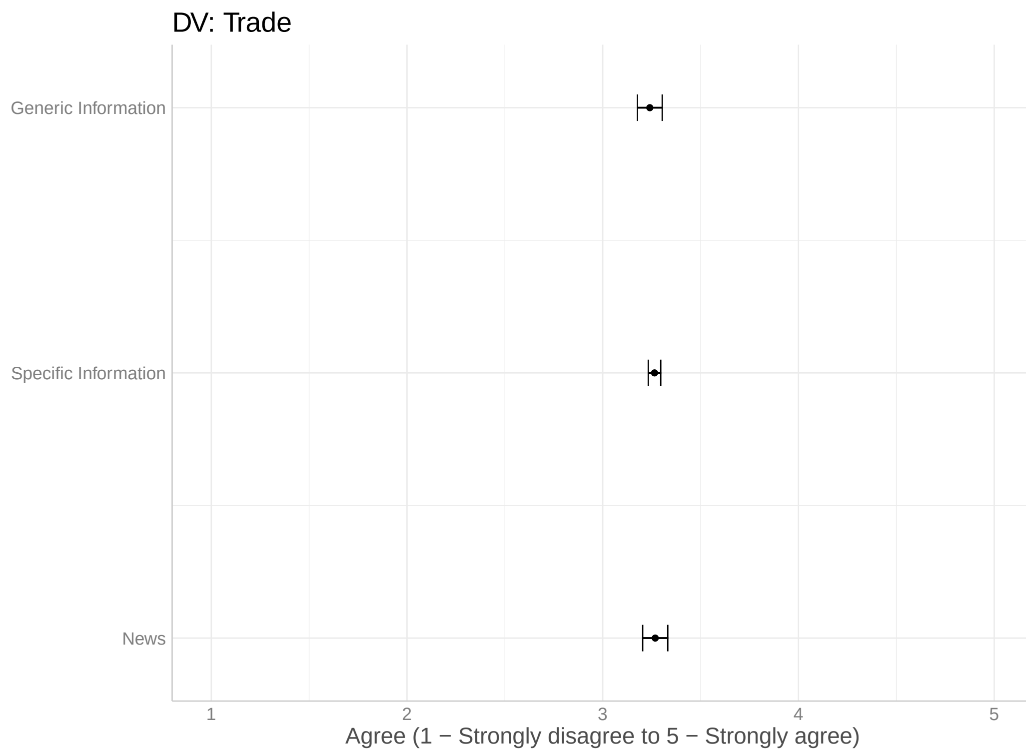

Figure A13: Predicted values of restricting trade with 95% confidence intervals.

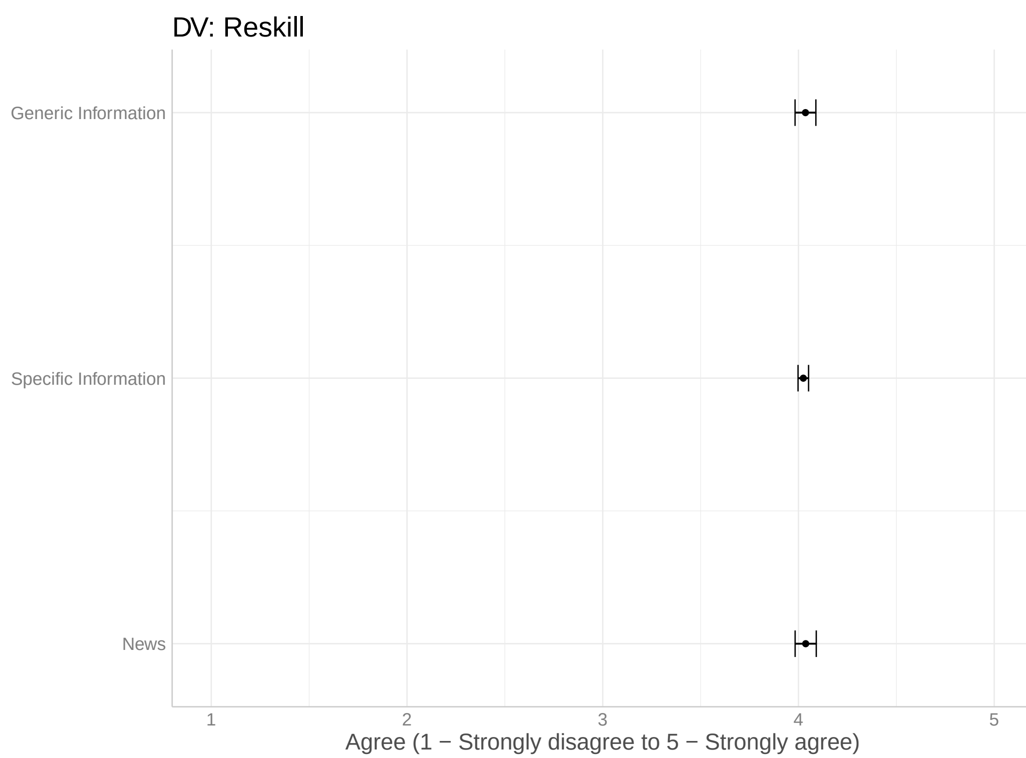

Figure A14: Predicted values of retraining workers with 95% confidence intervals.

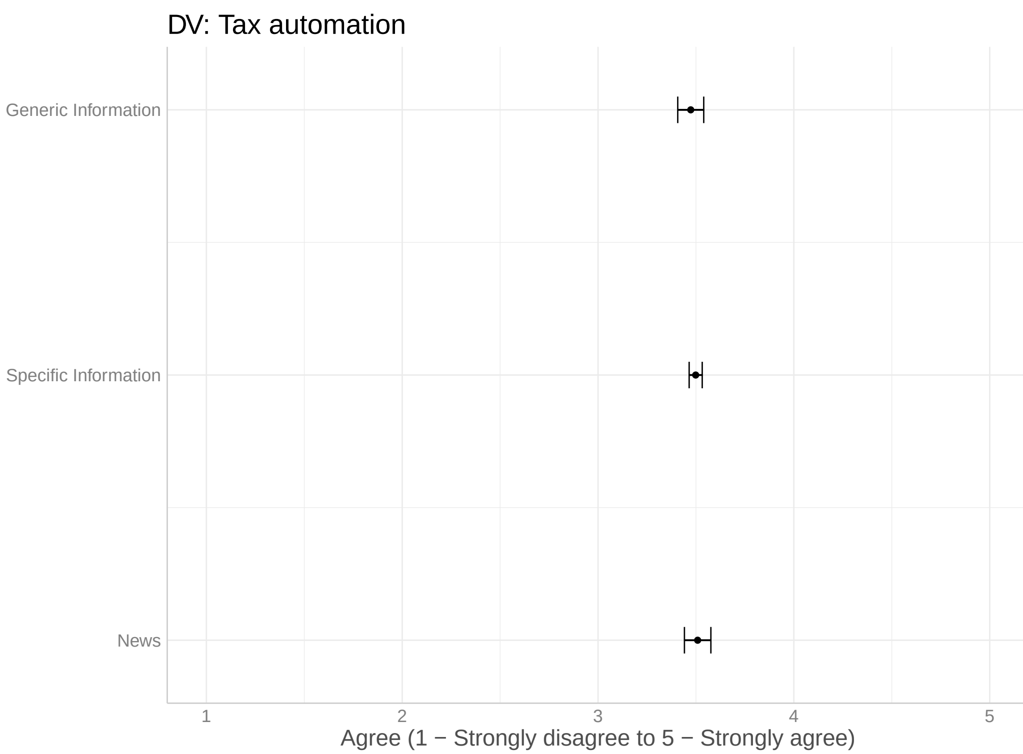

Figure A15: Predicted values of taxing automation with 95% confidence intervals.

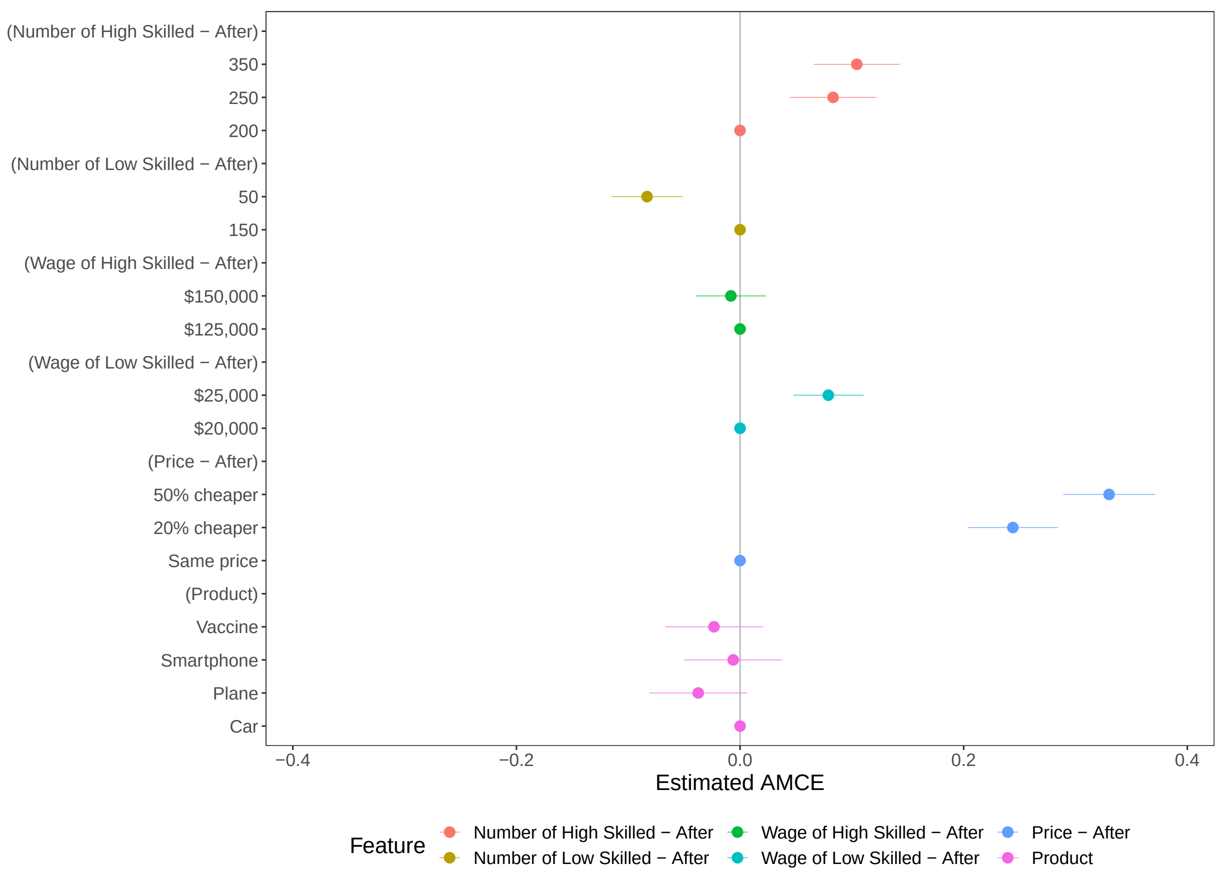

Figure A16: Average marginal component effects on perceived fairness

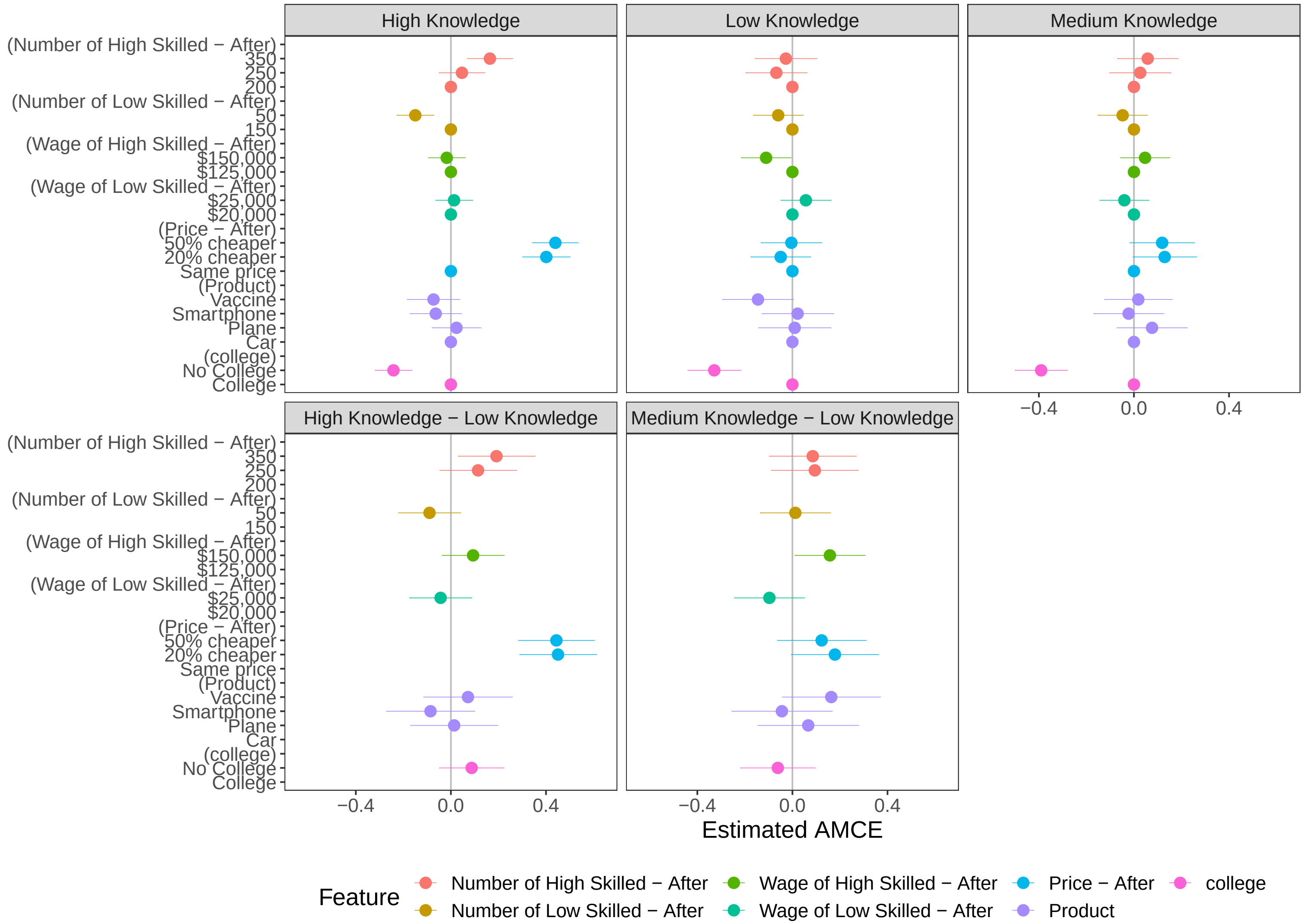

Figure A17: Average marginal component effects on perceived fairness by knowledge

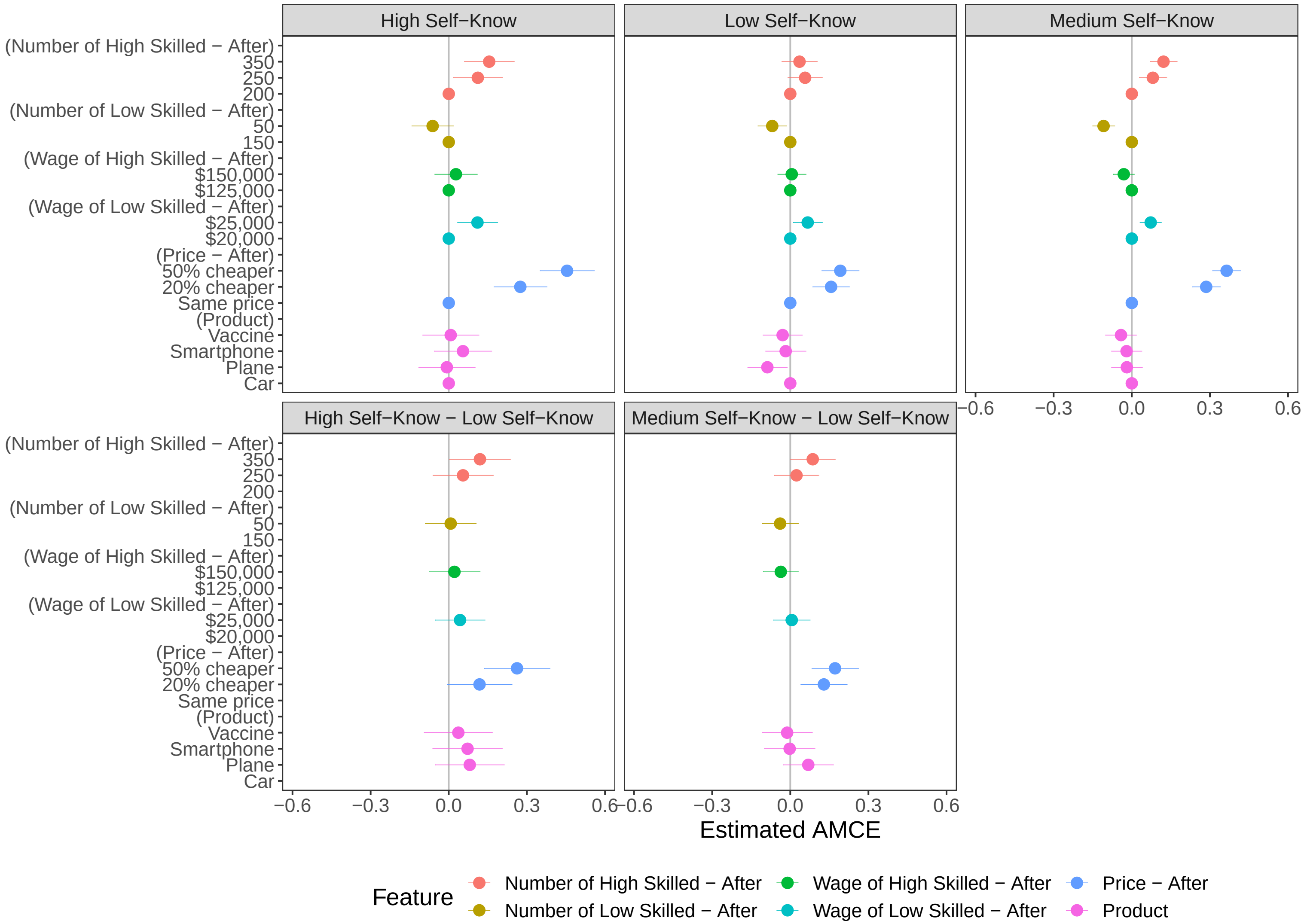

Figure A18: Average marginal component effects on perceived fairness by self-reported knowledge

Table A2: Regression analyses of treatment effects on policy support. Standard errors in parentheses.

	Dependent variable:							
	Social Spending	Basic Income	Job Guarantee	Unskilled	Skilled	Trade	Reskilling	Tax Automation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specific Information (ref. News)	0.026	−0.045	−0.002	−0.017	0.007	−0.004	−0.012	−0.010
	(0.032)	(0.038)	(0.036)	(0.038)	(0.040)	(0.037)	(0.031)	(0.038)
Generic Information	−0.024	−0.066	−0.028	0.026	−0.027	−0.028	−0.001	−0.035
	(0.041)	(0.048)	(0.045)	(0.048)	(0.050)	(0.046)	(0.039)	(0.048)
Constant	3.656***	3.538***	3.496***	3.552***	3.023***	3.268***	4.037***	3.509***
	(0.029)	(0.034)	(0.032)	(0.034)	(0.036)	(0.033)	(0.028)	(0.034)
Observations	7,461	7,513	7,514	7,470	7,474	7,251	7,571	7,436

Note: * p<0.05; ** p<0.01; *** p<0.001

Table A3: Marginal means of perceived fairness for best-case and worst-case scenarios

outcome	statistic	feature	level	estimate	std.error	z	p	lower	upper	price after	num. low skilled after
fairness	mm	Number of High Skilled - After	350	3.5984321	0.03174347	113.359774	0	3.5362160	3.6606481	50% cheaper	150
fairness	mm	Number of High Skilled - After	200	3.0865724	0.03640994	84.772801	0	3.0152103	3.1579346	Same price	50

Note: Number of observations is 21,208 and number of clusters is 5,302. Robust standard errors are clustered at the subject level.

Table A4: Marginal means of attributes on perceived fairness

outcome	statistic	feature	level	estimate	std.error	z	p	lower	upper
fairness	mm	Number of High Skilled - After	200	3.319682	0.0173853	190.9479	0	3.285608	3.353757
fairness	mm	Number of High Skilled - After	250	3.406216	0.0167775	203.0235	0	3.373333	3.439099
fairness	mm	Number of High Skilled - After	350	3.427936	0.0163460	209.7109	0	3.395898	3.459973
fairness	mm	Number of Low Skilled - After	150	3.426191	0.0145481	235.5074	0	3.397677	3.454705
fairness	mm	Number of Low Skilled - After	50	3.343826	0.0151642	220.5075	0	3.314105	3.373547
fairness	mm	Wage of High Skilled - After	$125,000	3.389576	0.0148954	227.5584	0	3.360382	3.418771
fairness	mm	Wage of High Skilled - After	$150,000	3.380286	0.0146666	230.4748	0	3.351540	3.409032
fairness	mm	Wage of Low Skilled - After	$20,000	3.345414	0.0151108	221.3918	0	3.315797	3.375031
fairness	mm	Wage of Low Skilled - After	$25,000	3.424581	0.0144444	237.0868	0	3.396270	3.452892
fairness	mm	Price - After	Same price	3.190380	0.0179977	177.2660	0	3.155105	3.225654
fairness	mm	Price - After	20% cheaper	3.435280	0.0167235	205.4158	0	3.402502	3.468057
fairness	mm	Price - After	50% cheaper	3.520337	0.0162418	216.7454	0	3.488504	3.552171
fairness	mm	Product	Car	3.402233	0.0182552	186.3703	0	3.366454	3.438013
fairness	mm	Product	Plane	3.368293	0.0185339	181.7373	0	3.331968	3.404619
fairness	mm	Product	Smartphone	3.394149	0.0186754	181.7444	0	3.357546	3.430752
fairness	mm	Product	Vaccine	3.375127	0.0188677	178.8839	0	3.338147	3.412107

Note: Number of observations is 21,208 and number of clusters is 5,302. Robust standard errors are clustered at the subject level.

Table A5: Average marginal component effects (AMCE) of attributes on perceived fairness

outcome	statistic	feature	level	estimate	std.error	z	p	lower	upper
fairness	amce	Number of High Skilled - After	200	0.0000000	NA	NA	NA	NA	NA
fairness	amce	Number of High Skilled - After	250	0.0831862	0.0195574	4.2534472	0.0000211	0.0448545	0.1215179
fairness	amce	Number of High Skilled - After	350	0.1044012	0.0196094	5.3240464	0.0000001	0.0659675	0.1428349
fairness	amce	Number of Low Skilled - After	150	0.0000000	NA	NA	NA	NA	NA
fairness	amce	Number of Low Skilled - After	50	-0.0832044	0.0160837	-5.1732100	0.0000002	-0.1147278	-0.0516809
fairness	amce	Wage of High Skilled - After	$125,000	0.0000000	NA	NA	NA	NA	NA
fairness	amce	Wage of High Skilled - After	$150,000	-0.0082164	0.0158129	-0.5195991	0.6033430	-0.0392090	0.0227763
fairness	amce	Wage of Low Skilled - After	$20,000	0.0000000	NA	NA	NA	NA	NA
fairness	amce	Wage of Low Skilled - After	$25,000	0.0789175	0.0158975	4.9641579	0.0000007	0.0477590	0.1100759
fairness	amce	Price - After	Same price	0.0000000	NA	NA	NA	NA	NA
fairness	amce	Price - After	20% cheaper	0.2439888	0.0204527	11.9294212	0.0000000	0.2039023	0.2840754
fairness	amce	Price - After	50% cheaper	0.3300810	0.0207957	15.8725244	0.0000000	0.2893221	0.3708399
fairness	amce	Product	Car	0.0000000	NA	NA	NA	NA	NA
fairness	amce	Product	Plane	-0.0374456	0.0221268	-1.6923150	0.0905859	-0.0808133	0.0059222
fairness	amce	Product	Smartphone	-0.0061212	0.0221711	-0.2760877	0.7824807	-0.0495758	0.0373335
fairness	amce	Product	Vaccine	-0.0233167	0.0222310	-1.0488369	0.2942532	-0.0668888	0.0202553

Note: Number of observations is 21,208 and number of clusters is 5,302. Robust standard errors are clustered at the subject level.

Table A6: Average marginal component effects (AMCE) of attributes on perceived fairness by low knowledge

BY	outcome	statistic	feature	level	estimate	std.error	z	p	lower	upper
Low Knowledge	fairness	amce	Number of High Skilled - After	200	0.0000000	NA	NA	NA	NA	NA
Low Knowledge	fairness	amce	Number of High Skilled - After	250	-0.0677401	0.0660876	-1.0250059	0.3053604	-0.1972694	0.0617891
Low Knowledge	fairness	amce	Number of High Skilled - After	350	-0.0275603	0.0665310	-0.4142479	0.6786926	-0.1579588	0.1028381
Low Knowledge	fairness	amce	Number of Low Skilled - After	150	0.0000000	NA	NA	NA	NA	NA
Low Knowledge	fairness	amce	Number of Low Skilled - After	50	-0.0598090	0.0537313	-1.1131129	0.2656599	-0.1651205	0.0455024
Low Knowledge	fairness	amce	Wage of High Skilled - After	$125,000	0.0000000	NA	NA	NA	NA	NA
Low Knowledge	fairness	amce	Wage of High Skilled - After	$150,000	-0.1108209	0.0537342	-2.0623922	0.0391704	-0.2161379	-0.0055039
Low Knowledge	fairness	amce	Wage of Low Skilled - After	$20,000	0.0000000	NA	NA	NA	NA	NA
Low Knowledge	fairness	amce	Wage of Low Skilled - After	$25,000	0.0564873	0.0538612	1.0487576	0.2942897	-0.0490787	0.1620534
Low Knowledge	fairness	amce	Price - After	Same price	0.0000000	NA	NA	NA	NA	NA
Low Knowledge	fairness	amce	Price - After	20% cheaper	-0.0492643	0.0644842	-0.7639749	0.4448822	-0.1756510	0.0771224
Low Knowledge	fairness	amce	Price - After	50% cheaper	-0.0043450	0.0653185	-0.0665197	0.9469641	-0.1323670	0.1236770
Low Knowledge	fairness	amce	Product	Car	0.0000000	NA	NA	NA	NA	NA
Low Knowledge	fairness	amce	Product	Plane	0.0096818	0.0777787	0.1244788	0.9009362	-0.1427616	0.1621252
Low Knowledge	fairness	amce	Product	Smartphone	0.0218634	0.0770904	0.2836075	0.7767112	-0.1292310	0.1729579
Low Knowledge	fairness	amce	Product	Vaccine	-0.1449653	0.0766809	-1.8905011	0.0586910	-0.2952570	0.0053265
Low Knowledge	fairness	amce	college	College	0.0000000	NA	NA	NA	NA	NA
Low Knowledge	fairness	amce	college	No College	-0.3288148	0.0571368	-5.7548644	0.0000000	-0.4408010	-0.2168287

Note: Number of observations is 21,208 and number of clusters is 5,302. Robust standard errors are clustered at the subject level.

Table A7: Average marginal component effects (AMCE) of attributes on perceived fairness by high knowledge

BY	outcome	statistic	feature	level	estimate	std.error	z	p	lower	upper
High Knowledge	fairness	amce	Number of High Skilled - After	200	0.0000000	NA	NA	NA	NA	NA
High Knowledge	fairness	amce	Number of High Skilled - After	250	0.0464651	0.0494011	0.9405696	0.3469255	-0.0503592	0.1432894
High Knowledge	fairness	amce	Number of High Skilled - After	350	0.1641694	0.0488604	3.3599713	0.0007795	0.0684049	0.2599340
High Knowledge	fairness	amce	Number of Low Skilled - After	150	0.0000000	NA	NA	NA	NA	NA
High Knowledge	fairness	amce	Number of Low Skilled - After	50	-0.1497832	0.0396799	-3.7747860	0.0001601	-0.2275544	-0.0720120
High Knowledge	fairness	amce	Wage of High Skilled - After	$125,000	0.0000000	NA	NA	NA	NA	NA
High Knowledge	fairness	amce	Wage of High Skilled - After	$150,000	-0.0175282	0.0396711	-0.4418391	0.6586057	-0.0952821	0.0602256
High Knowledge	fairness	amce	Wage of Low Skilled - After	$20,000	0.0000000	NA	NA	NA	NA	NA
High Knowledge	fairness	amce	Wage of Low Skilled - After	$25,000	0.0132587	0.0398238	0.3329345	0.7391837	-0.0647945	0.0913119
High Knowledge	fairness	amce	Price - After	Same price	0.0000000	NA	NA	NA	NA	NA
High Knowledge	fairness	amce	Price - After	20% cheaper	0.4012206	0.0512696	7.8257088	0.0000000	0.3007341	0.5017071
High Knowledge	fairness	amce	Price - After	50% cheaper	0.4394185	0.0489922	8.9691492	0.0000000	0.3433955	0.5354415
High Knowledge	fairness	amce	Product	Car	0.0000000	NA	NA	NA	NA	NA
High Knowledge	fairness	amce	Product	Plane	0.0234934	0.0527746	0.4451644	0.6562009	-0.0799429	0.1269297
High Knowledge	fairness	amce	Product	Smartphone	-0.0638418	0.0557234	-1.1456903	0.2519233	-0.1730576	0.0453741
High Knowledge	fairness	amce	Product	Vaccine	-0.0731731	0.0568625	-1.2868423	0.1981493	-0.1846215	0.0382754
High Knowledge	fairness	amce	college	College	0.0000000	NA	NA	NA	NA	NA
High Knowledge	fairness	amce	college	No College	-0.2414920	0.0397888	-6.0693413	0.0000000	-0.3194766	-0.1635073

Note: Number of observations is 21,208 and number of clusters is 5,302. Robust standard errors are clustered at the subject level.

Table A8: Difference in average marginal component effects (AMCE) of attributes on perceived fairness by high and low knowledge

BY	outcome	statistic	feature	level	estimate	std.error	z	p	lower	upper
High - Low	fairness	amce_difference	college	No College	0.0873228	0.0696113	1.2544355	0.2096837	-0.0491127	0.2237584
High - Low	fairness	amce_difference	Number of High Skilled - After	250	0.1142053	0.0824938	1.3844096	0.1662331	-0.0474797	0.2758902
High - Low	fairness	amce_difference	Number of High Skilled - After	350	0.1917298	0.0825282	2.3232040	0.0201682	0.0299775	0.3534820
High - Low	fairness	amce_difference	Number of Low Skilled - After	50	-0.0899742	0.0667811	-1.3473008	0.1778834	-0.2208626	0.0409143
High - Low	fairness	amce_difference	Price - After	20% cheaper	0.4504849	0.0823654	5.4693475	0.0000000	0.2890517	0.6119181
High - Low	fairness	amce_difference	Price - After	50% cheaper	0.4437635	0.0816334	5.4360515	0.0000001	0.2837649	0.6037621
High - Low	fairness	amce_difference	Product	Plane	0.0138116	0.0939730	0.1469739	0.8831527	-0.1703722	0.1979953
High - Low	fairness	amce_difference	Product	Smartphone	-0.0857052	0.0951014	-0.9011983	0.3674829	-0.2721004	0.1006901
High - Low	fairness	amce_difference	Product	Vaccine	0.0717922	0.0954439	0.7521922	0.4519355	-0.1152745	0.2588589
High - Low	fairness	amce_difference	Wage of High Skilled - After	$150,000	0.0932927	0.0667781	1.3970555	0.1623969	-0.0375900	0.2241753
High - Low	fairness	amce_difference	Wage of Low Skilled - After	$25,000	-0.0432286	0.0669710	-0.6454828	0.5186143	-0.1744894	0.0880321

Note: Number of observations is 21,208 and number of clusters is 5,302. Robust standard errors are clustered at the subject level.

Table A9: Average marginal component effects (AMCE) of attributes on perceived fairness by low self-knowledge

BY	outcome	statistic	feature	level	estimate	std.error	z	p	lower	upper
Low Self-Knowledge	fairness	amce	Number of High Skilled - After	200	0.0000000	NA	NA	NA	NA	NA
Low Self-Knowledge	fairness	amce	Number of High Skilled - After	250	0.0568954	0.0341065	1.6681672	0.0952825	-0.0099522	0.1237429
Low Self-Knowledge	fairness	amce	Number of High Skilled - After	350	0.0355088	0.0350206	1.0139388	0.3106120	-0.0331304	0.1041480
Low Self-Knowledge	fairness	amce	Number of Low Skilled - After	150	0.0000000	NA	NA	NA	NA	NA
Low Self-Knowledge	fairness	amce	Number of Low Skilled - After	50	-0.0692884	0.0283003	-2.4483270	0.0143521	-0.1247560	-0.0138208
Low Self-Knowledge	fairness	amce	Wage of High Skilled - After	$125,000	0.0000000	NA	NA	NA	NA	NA
Low Self-Knowledge	fairness	amce	Wage of High Skilled - After	$150,000	0.0057150	0.0277881	0.2056649	0.8370527	-0.0487486	0.0601786
Low Self-Knowledge	fairness	amce	Wage of Low Skilled - After	$20,000	0.0000000	NA	NA	NA	NA	NA
Low Self-Knowledge	fairness	amce	Wage of Low Skilled - After	$25,000	0.0669080	0.0288316	2.3206513	0.0203057	0.0103992	0.1234169
Low Self-Knowledge	fairness	amce	Price - After	Same price	0.0000000	NA	NA	NA	NA	NA
Low Self-Knowledge	fairness	amce	Price - After	20% cheaper	0.1567041	0.0362974	4.3172315	0.0000158	0.0855626	0.2278456
Low Self-Knowledge	fairness	amce	Price - After	50% cheaper	0.1921663	0.0365343	5.2598814	0.0000001	0.1205603	0.2637723
Low Self-Knowledge	fairness	amce	Product	Car	0.0000000	NA	NA	NA	NA	NA
Low Self-Knowledge	fairness	amce	Product	Plane	-0.0879934	0.0388542	-2.2647076	0.0235306	-0.1641463	-0.0118406
Low Self-Knowledge	fairness	amce	Product	Smartphone	-0.0176219	0.0395553	-0.4454993	0.6559589	-0.0951488	0.0599051
Low Self-Knowledge	fairness	amce	Product	Vaccine	-0.0293556	0.0387125	-0.7582986	0.4482723	-0.1052306	0.0465194

Note: Number of observations is 21,208 and number of clusters is 5,302. Robust standard errors are clustered at the subject level.

Table A10: Average marginal component effects (AMCE) of attributes on perceived fairness by high self-knowledge

BY	outcome	statistic	feature	level	estimate	std.error	z	p	lower	upper
High Self-Knowledge	fairness	amce	Number of High Skilled - After	200	0.0000000	NA	NA	NA	NA	NA
High Self-Knowledge	fairness	amce	Number of High Skilled - After	250	0.1115999	0.0486879	2.2921479	0.0218971	0.0161733	0.2070264
High Self-Knowledge	fairness	amce	Number of High Skilled - After	350	0.1552551	0.0489496	3.1717320	0.0015153	0.0593156	0.2511946
High Self-Knowledge	fairness	amce	Number of Low Skilled - After	150	0.0000000	NA	NA	NA	NA	NA
High Self-Knowledge	fairness	amce	Number of Low Skilled - After	50	-0.0619218	0.0410948	-1.5068043	0.1318608	-0.1424661	0.0186225
High Self-Knowledge	fairness	amce	Wage of High Skilled - After	$125,000	0.0000000	NA	NA	NA	NA	NA
High Self-Knowledge	fairness	amce	Wage of High Skilled - After	$150,000	0.0275059	0.0417122	0.6594220	0.5096248	-0.0542485	0.1092604
High Self-Knowledge	fairness	amce	Wage of Low Skilled - After	$20,000	0.0000000	NA	NA	NA	NA	NA
High Self-Knowledge	fairness	amce	Wage of Low Skilled - After	$25,000	0.1102485	0.0393581	2.8011597	0.0050919	0.0331079	0.1873890
High Self-Knowledge	fairness	amce	Price - After	Same price	0.0000000	NA	NA	NA	NA	NA
High Self-Knowledge	fairness	amce	Price - After	20% cheaper	0.2748093	0.0521424	5.2703568	0.0000001	0.1726120	0.3770066
High Self-Knowledge	fairness	amce	Price - After	50% cheaper	0.4542648	0.0531854	8.5411568	0.0000000	0.3500234	0.5585063
High Self-Knowledge	fairness	amce	Product	Car	0.0000000	NA	NA	NA	NA	NA
High Self-Knowledge	fairness	amce	Product	Plane	-0.0074143	0.0553600	-0.1339282	0.8934593	-0.1159179	0.1010893
High Self-Knowledge	fairness	amce	Product	Smartphone	0.0545564	0.0561059	0.9723831	0.3308600	-0.0554091	0.1645219
High Self-Knowledge	fairness	amce	Product	Vaccine	0.0074248	0.0551333	0.1346696	0.8928731	-0.1006344	0.1154840

Note: Number of observations is 21,208 and number of clusters is 5,302. Robust standard errors are clustered at the subject level.

Table A11: Difference in average marginal component effects (AMCE) of attributes on perceived fairness by high and low self-knowledge

BY	outcome	statistic	feature	level	estimate	std.error	z	p	lower	upper
High - Low	fairness	amce_difference	Number of High Skilled - After	250	0.0547045	0.0594249	0.9205664	0.3572768	-0.0617661	0.1711751
High - Low	fairness	amce_difference	Number of High Skilled - After	350	0.1197463	0.0601665	1.9902477	0.0465637	0.0018221	0.2376706
High - Low	fairness	amce_difference	Number of Low Skilled - After	50	0.0073666	0.0498794	0.1476879	0.8825891	-0.0903952	0.1051284
High - Low	fairness	amce_difference	Price - After	20% cheaper	0.1181052	0.0635101	1.8596293	0.0629380	-0.0063723	0.2425826
High - Low	fairness	amce_difference	Price - After	50% cheaper	0.2620985	0.0645023	4.0634008	0.0000484	0.1356764	0.3885206
High - Low	fairness	amce_difference	Product	Plane	0.0805792	0.0676107	1.1918107	0.2333355	-0.0519354	0.2130937
High - Low	fairness	amce_difference	Product	Smartphone	0.0721783	0.0686238	1.0517962	0.2928930	-0.0623219	0.2066785
High - Low	fairness	amce_difference	Product	Vaccine	0.0367804	0.0673438	0.5461586	0.5849569	-0.0952110	0.1687717
High - Low	fairness	amce_difference	Wage of High Skilled - After	$150,000	0.0217909	0.0501031	0.4349218	0.6636192	-0.0764093	0.1199911
High - Low	fairness	amce_difference	Wage of Low Skilled - After	$25,000	0.0433404	0.0487718	0.8886362	0.3741986	-0.0522506	0.1389315

Note: Number of observations is 21,208 and number of clusters is 5,302. Robust standard errors are clustered at the subject level.

Results by country

Our study deals with relatively similar countries: all are liberal market economies, in which respondents were selected using comparable age, gender, and regional quotas, and received the same information treatments. It is possible, however, that a pooled analysis may average over significant cross-country heterogeneity. Hence, we also run the analyses by country and report the results below. Findings are not significantly or substantively different, with a few exceptions. Looking at the effects of the generic information treatment on attitudes toward automation relative to the news article condition, we see that there are no significant differences across countries: people in the generic information treatment group have more positive attitudes toward automation than those in the news article group. In contrast, there is some variation when it comes to the specific information treatment group. In Australia and the UK, respondents in the specific information group are no more or less likely to think the company's decision to automate is fair, compared to those in the news article treatment group. Conversely, this effect is positive and significant in Canada and the US: individuals in the specific information group are more likely to think that the company's decision to automate is fair than those in the news article group. When it comes to what the respondents would do if they were the CEO of the company, there's some variation as well. In Australia and the UK respondents in the specific information group are less likely to think they would make the same decision to automate if they were CEO of the company compared to people in the news treatment group, while specific information respondents in the US are more likely to do so, relative to the news condition. Finally, the effect of specific information in Canada is not significantly different from that of the news article for the CEO dependent variable.

When it comes to policy preferences in response to job loss due to automation, respondents in the US display lower support for any policy response relative to the other three countries, except for restrictions on skilled migration and on trade, which they favor relatively more. Furthermore, while at the aggregate level there are no significant treatment effects on policy preferences, there is some variation at the country-level. In the US, people in the generic information treatment group are less supportive of social spending in response to job loss due to automation than respondents in the news article group. Similarly, in Canada, people in the generic information treatment group are less supportive of trade restrictions than those in the news article group.

The conjoint analysis allows us to compare the effects of different attributes within the specific information treatment condition. Overall, in Australia, Canada, and the UK respondents appear to be the most sensitive to prices, but also to changes in wages and in the number of jobs, consistent with the aggregate results. Respondents in the US are only sensitive to price changes, and not to any number of employment or wage changes. This suggests that in the American context prices are more salient than other attributes when labor market changes are a result of automation, rather than of other forces, such as offshoring. Finally, when looking at the conjoint analyses by knowledge and by country, while the effects are in the same direction as those in the pooled models, whereby more knowledgeable people are more sensitive to price changes, in most cases the coefficients fail to reach statistical significance: this may be simply due to power limitations at the individual country level. Overall, the country-by-country analysis shows that, with a few exceptions, respondents in the four different countries do not display substantially different attitudes towards automation or demand different policies in response to job loss when presented with the same type of information.

Table A12: Regression analyses predicting perceived fairness by country. Standard errors in parentheses.

	Dependent variable:			
	Fairness			
	Australia	Canada	UK	US
	(1)	(2)	(3)	(4)
Specific Information (ref. News)	-0.021	0.225^{***}	0.042	0.323^{***}
	(0.058)	(0.058)	(0.057)	(0.061)
Generic Information	0.331^{***}	0.595^{***}	0.349^{***}	0.522^{***}
	(0.072)	(0.074)	(0.071)	(0.079)
Constant	3.365^{***}	3.168^{***}	3.255^{***}	3.142^{***}
	(0.052)	(0.052)	(0.051)	(0.055)
Observations	1,903	1,895	1,972	1,885
Note:	* p<0.05; ** p<0.01; *** p<0.001			

Table A13: Regression analyses predicting hypothetical CEO decision by country. Standard errors in parentheses.

	Dependent variable:			
	Would do the same if CEO			
	Australia	Canada	UK	US
	(1)	(2)	(3)	(4)
Specific Information (ref. News)	-0.149^{*}	-0.013	-0.149^{*}	0.151^{*}
	(0.060)	(0.061)	(0.059)	(0.064)
Generic Information	0.282^{***}	0.408^{***}	0.261^{***}	0.428^{***}
	(0.075)	(0.076)	(0.074)	(0.083)
Constant	3.505^{***}	3.429^{***}	3.464^{***}	3.284^{***}
	(0.054)	(0.054)	(0.053)	(0.058)
Observations	1,875	1,847	1,940	1,861
Note:	* p<0.05; ** p<0.01; *** p<0.001			

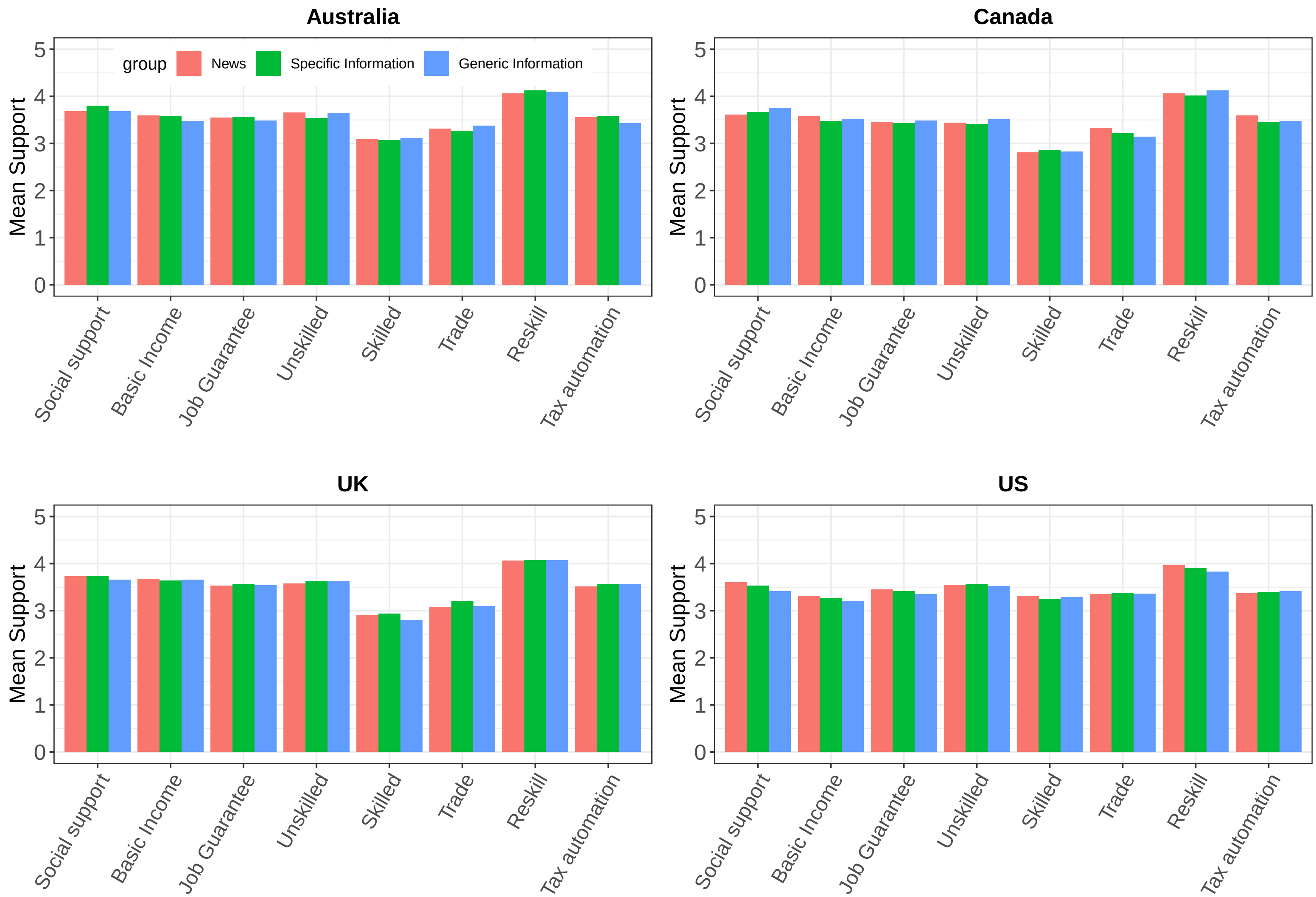

Figure A19: Mean policy support by country and treatment group

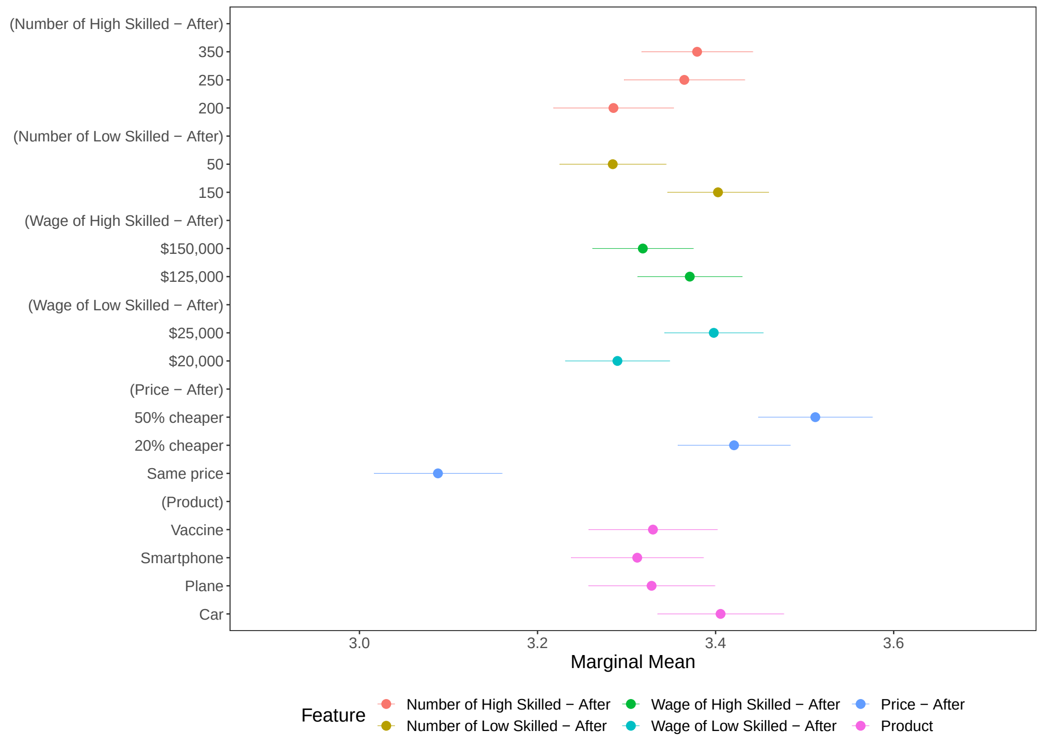

Figure A20: Marginal means for fairness DV: Australia

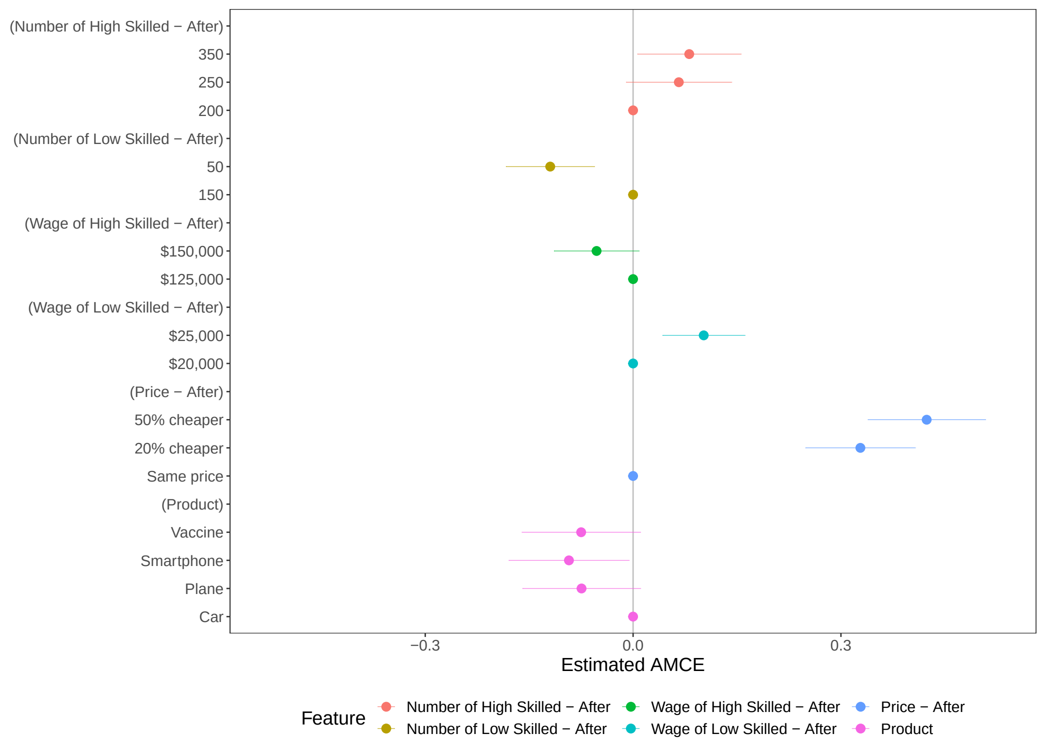

Figure A21: Average marginal component effects for fairness DV: Australia

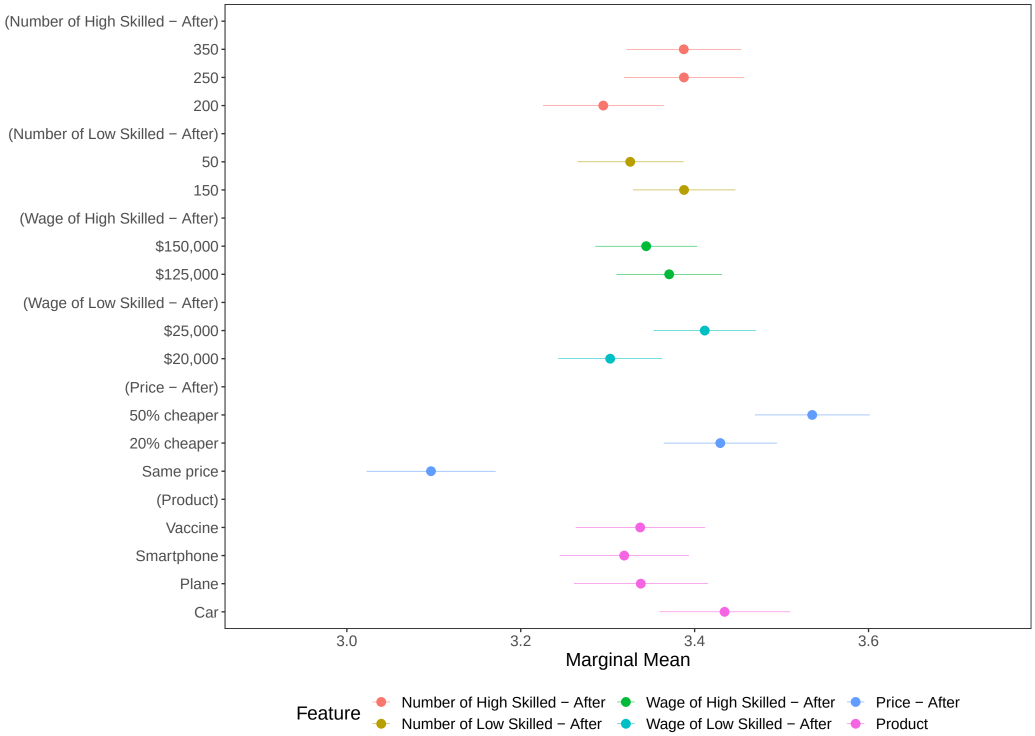

Figure A22: Marginal means for CEO DV: Australia

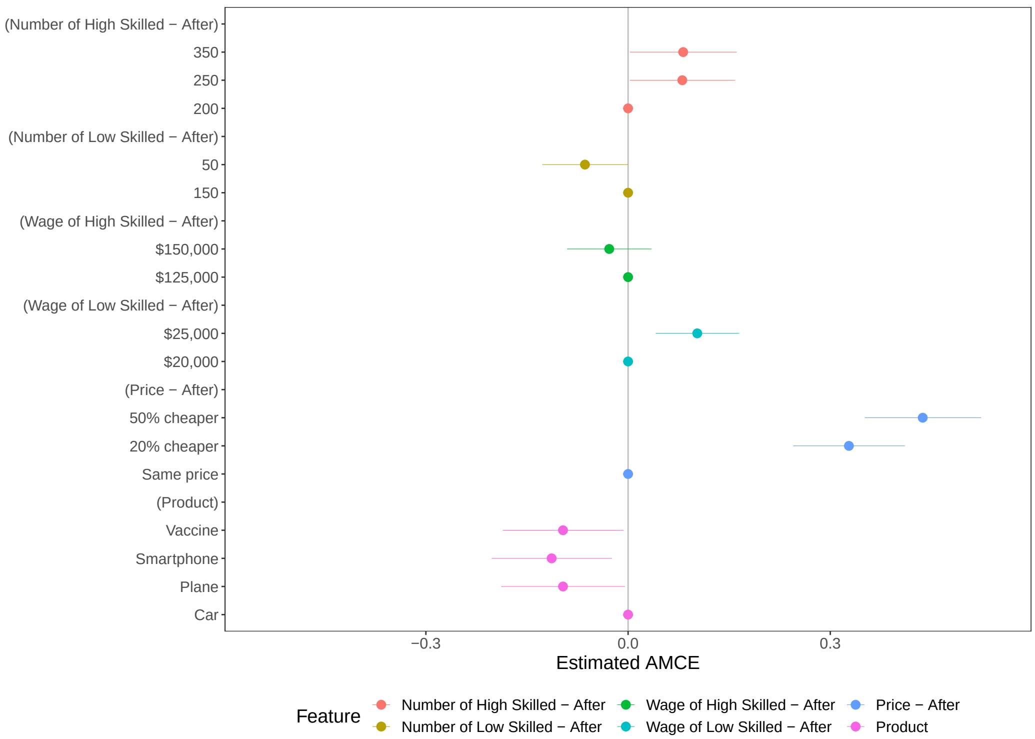

Figure A23: Average marginal component effects for CEO DV: Australia

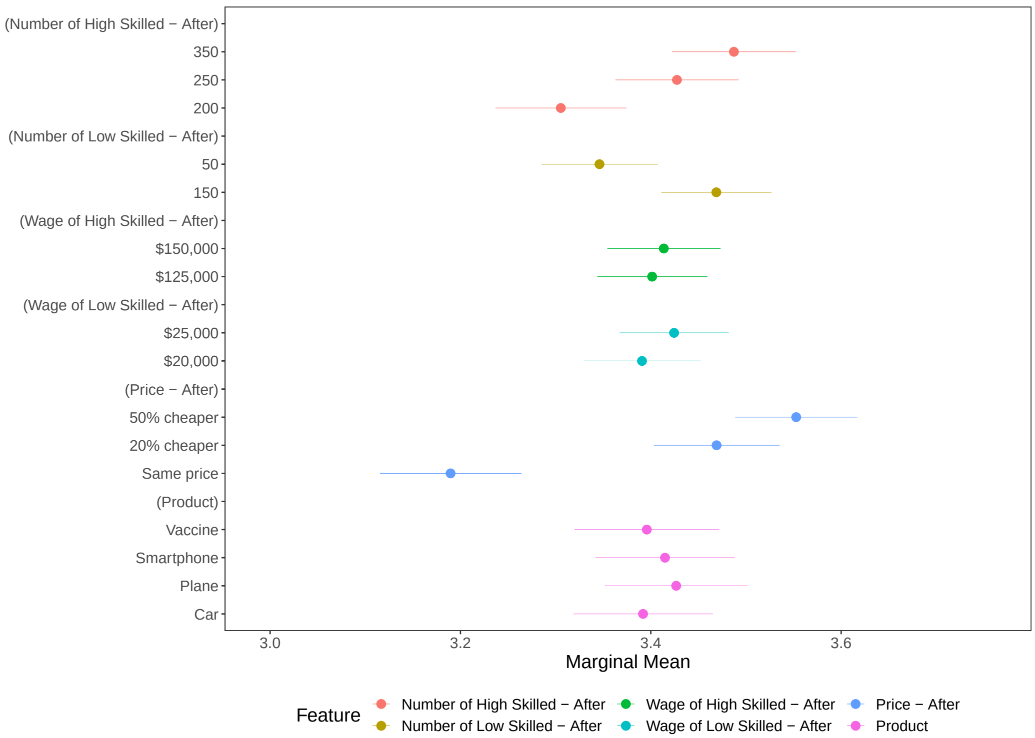

Figure A24: Marginal means for fairness DV: Canada

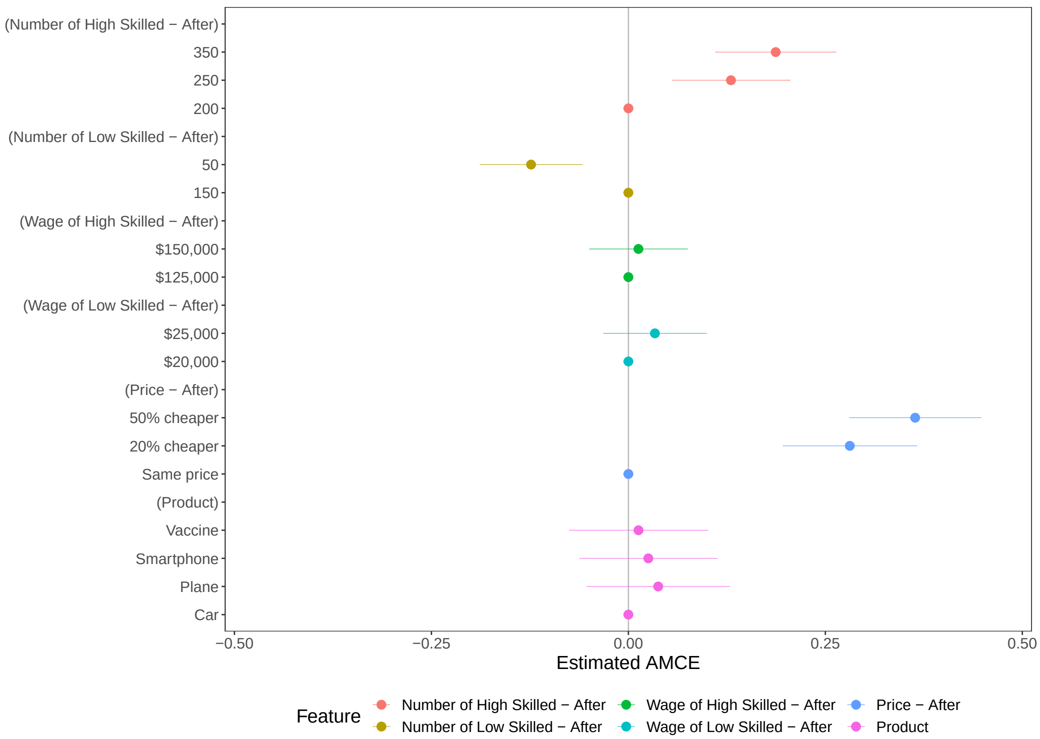

Figure A25: Average marginal component effects for fairness DV: Canada

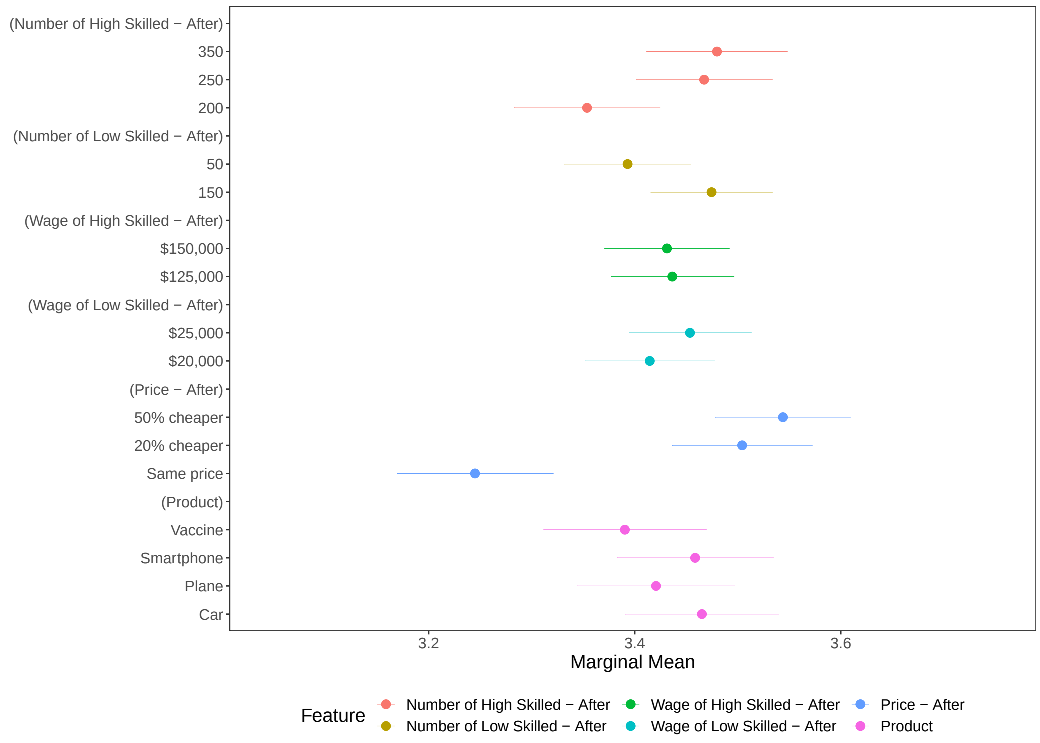

Figure A26: Marginal means for CEO DV: Canada

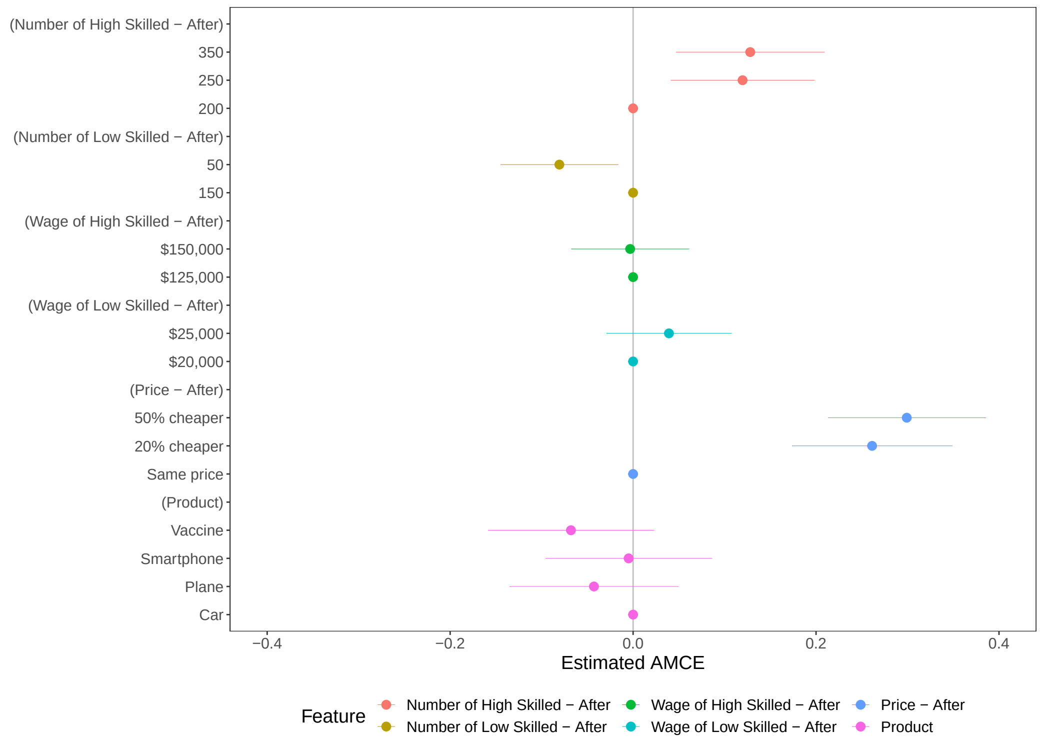

Figure A27: Average marginal component effects for CEO DV: Canada

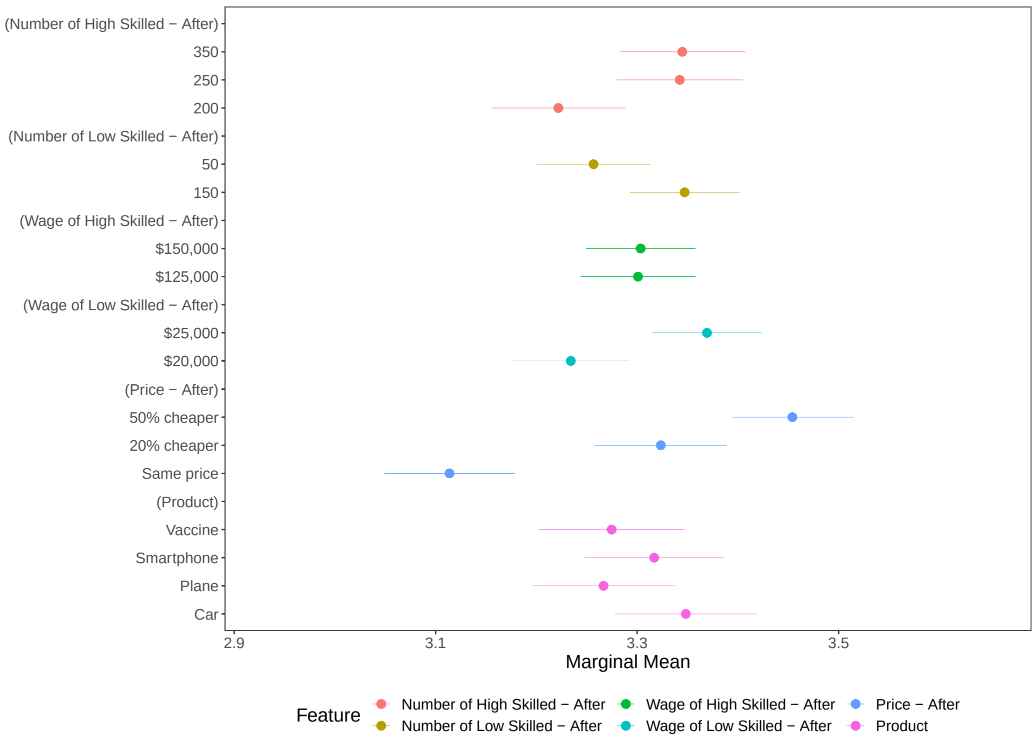

Figure A28: Marginal means for fairness DV: UK

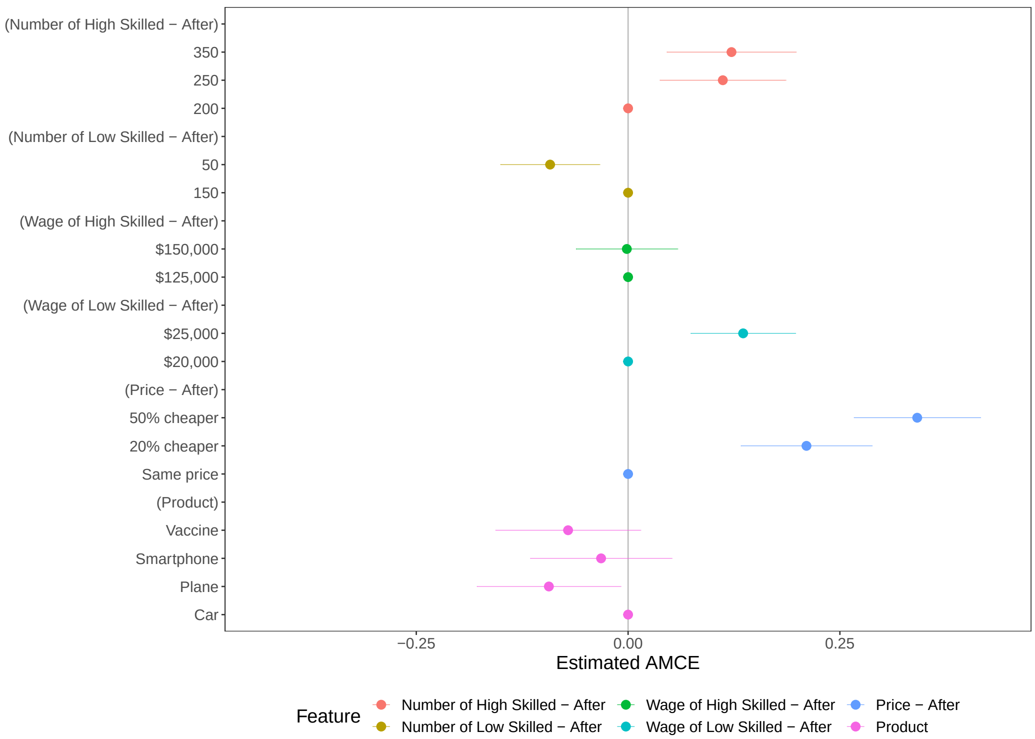

Figure A29: Average marginal component effects for fairness DV: UK

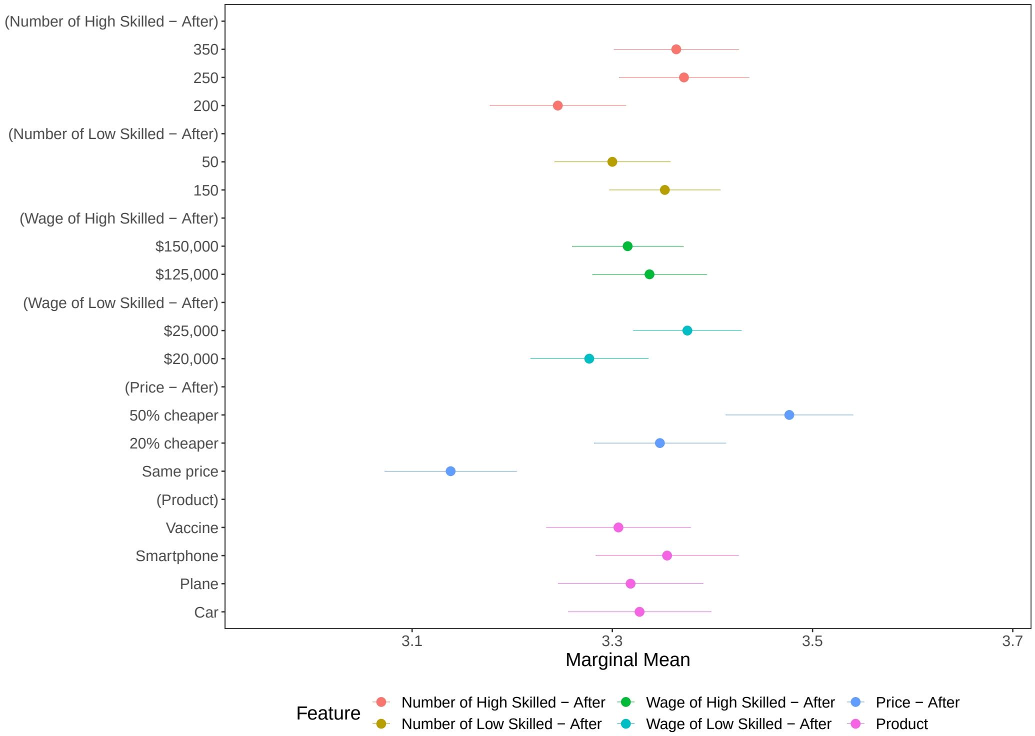

Figure A30: Marginal means for CEO DV: UK

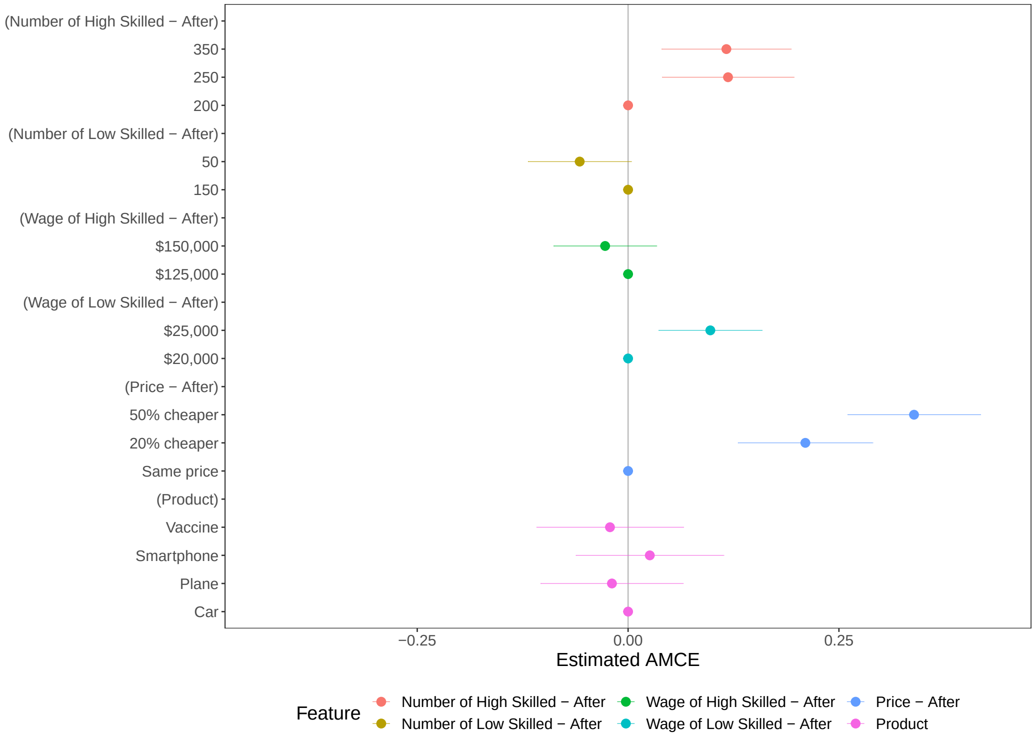

Figure A31: Average marginal component effects for CEO DV: UK

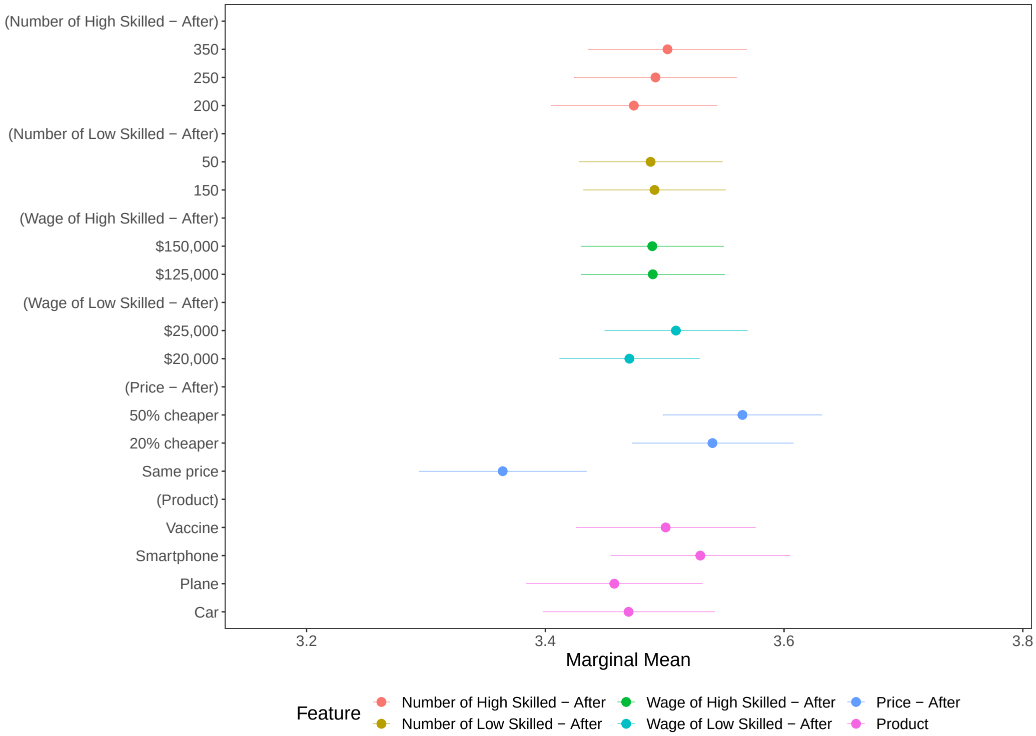

Figure A32: Marginal means for fairness DV: US

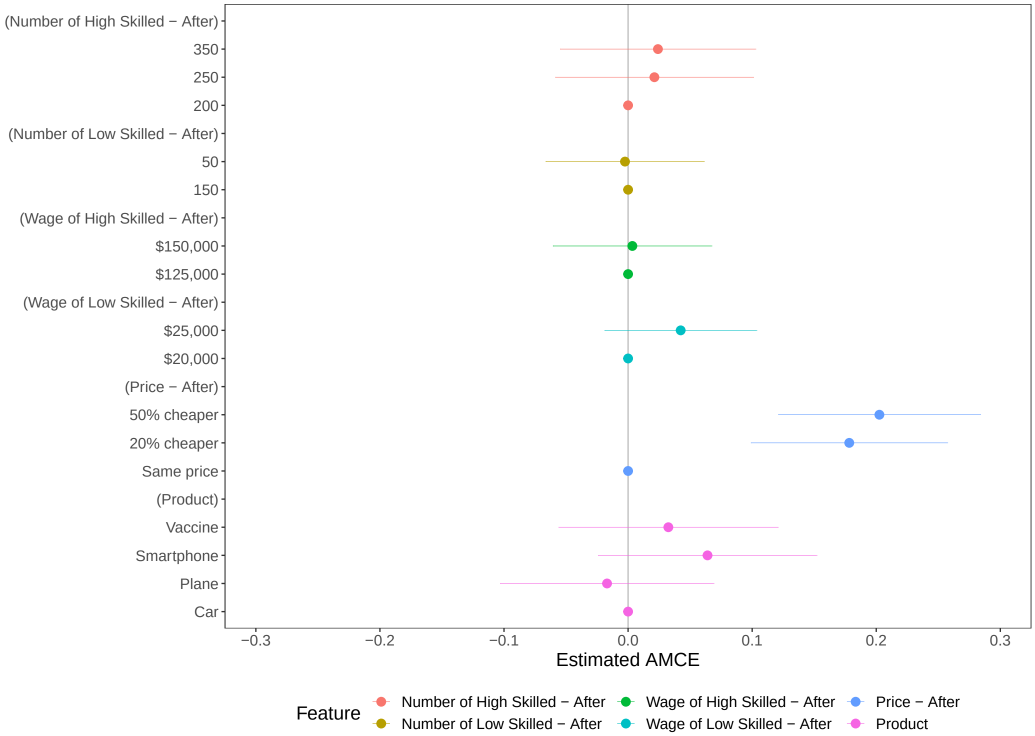

Figure A33: Average marginal component effects for fairness DV: US

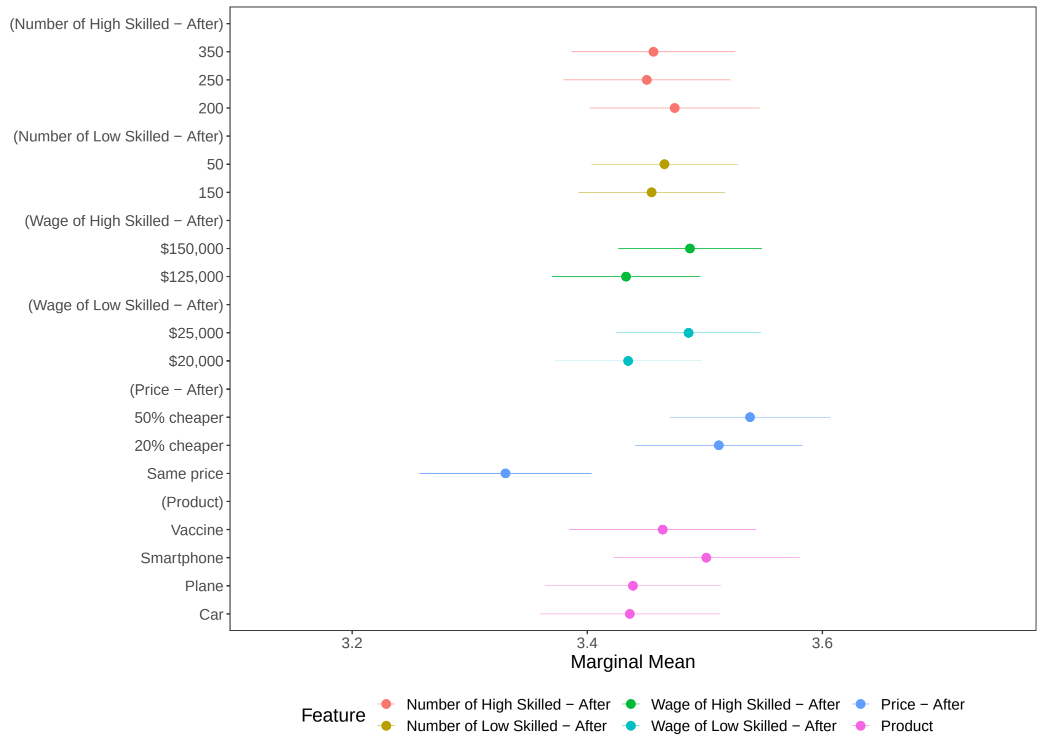

Figure A34: Marginal means for CEO DV: US

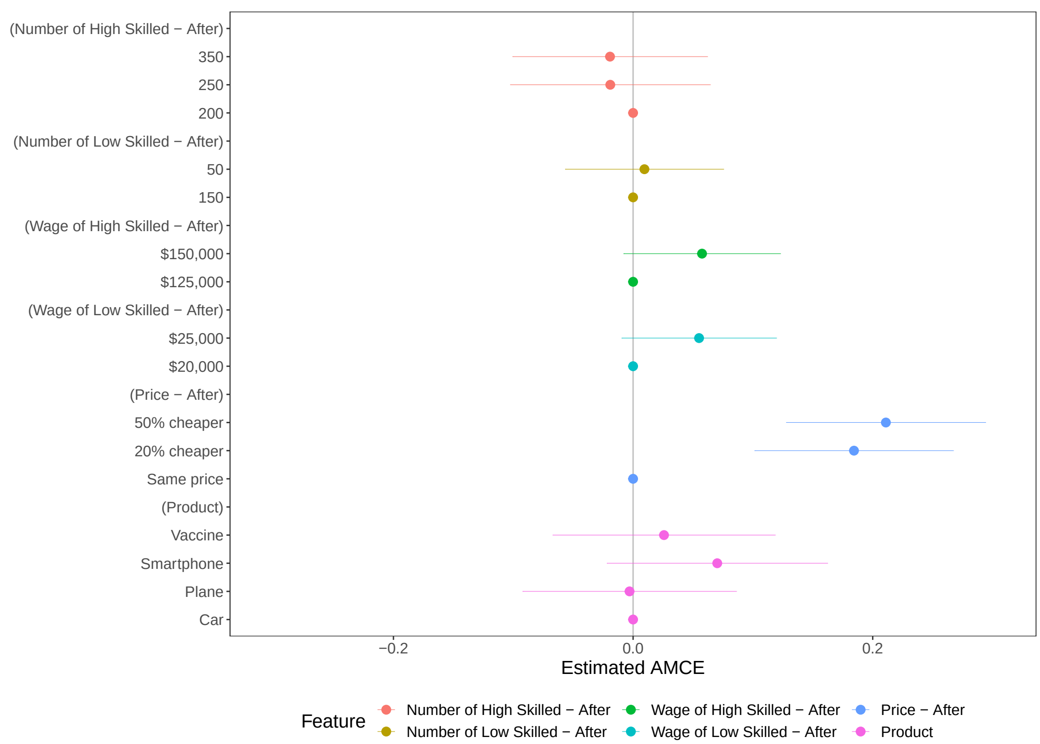

Figure A35: Average marginal component effects for CEO DV: US

Table A14: Regression analyses of treatment group on policy support for Australia. Standard errors in parentheses.

	Dependent variable:							
	Social Spending	Basic Income	Job Guarantee	Unskilled	Skilled	Trade	Reskilling	Tax Automation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specific Information (ref. News)	0.117	−0.006	0.020	−0.116	−0.019	−0.042	0.062	0.017
	(0.063)	(0.075)	(0.070)	(0.076)	(0.079)	(0.074)	(0.060)	(0.076)
Generic Information	−0.006	−0.117	−0.065	−0.009	0.024	0.059	0.039	−0.129
	(0.078)	(0.094)	(0.087)	(0.095)	(0.099)	(0.092)	(0.075)	(0.094)
Constant	3.684***	3.593***	3.549***	3.658***	3.088***	3.313***	4.060***	3.558***
	(0.057)	(0.068)	(0.063)	(0.069)	(0.071)	(0.067)	(0.054)	(0.068)
Observations	1,852	1,867	1,865	1,868	1,873	1,821	1,884	1,856
Note:								* p<0.05; ** p<0.01; *** p<0.001

Table A15: Regression analyses of treatment group on policy support for Canada. Standard errors in parentheses.

	Dependent variable:							
	Social Spending	Basic Income	Job Guarantee	Unskilled	Skilled	Trade	Reskilling	Tax Automation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specific Information (ref. News)	0.051	−0.100	−0.029	−0.024	0.057	−0.116	−0.050	−0.134
	(0.064)	(0.077)	(0.071)	(0.077)	(0.079)	(0.071)	(0.060)	(0.077)
Generic Information	0.144	−0.053	0.029	0.080	0.017	−0.188*	0.061	−0.117
	(0.080)	(0.097)	(0.089)	(0.097)	(0.100)	(0.090)	(0.075)	(0.097)
Constant	3.611***	3.574***	3.457***	3.435***	2.804***	3.327***	4.061***	3.594***
	(0.057)	(0.068)	(0.063)	(0.068)	(0.071)	(0.063)	(0.053)	(0.069)
Observations	1,853	1,861	1,860	1,825	1,829	1,775	1,873	1,833

Note: * p<0.05; ** p<0.01; *** p<0.001

Table A16: Regression analyses of treatment group on policy support for the UK. Standard errors in parentheses.

	Dependent variable:							
	Social Spending	Basic Income	Job Guarantee	Unskilled	Skilled	Trade	Reskilling	Tax Automation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specific Information (ref. News)	−0.002	−0.034	0.022	0.044	0.038	0.111	0.003	0.048
	(0.059)	(0.070)	(0.067)	(0.074)	(0.075)	(0.070)	(0.056)	(0.073)
Generic Information	−0.071	−0.020	0.002	0.042	−0.098	0.012	0.006	0.053
	(0.073)	(0.087)	(0.083)	(0.092)	(0.094)	(0.088)	(0.070)	(0.091)
Constant	3.731***	3.674***	3.534***	3.579***	2.900***	3.083***	4.064***	3.515***
	(0.053)	(0.062)	(0.060)	(0.066)	(0.068)	(0.063)	(0.051)	(0.066)
Observations	1,928	1,939	1,939	1,942	1,938	1,858	1,960	1,920

Note: * p<0.05; ** p<0.01; *** p<0.001

Table A17: Regression analyses of treatment group on policy support for the US. Standard errors in parentheses.

	Dependent variable:							
	Social Spending	Basic Income	Job Guarantee	Unskilled	Skilled	Trade	Reskilling	Tax Automation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specific Information (ref. News)	-0.071	-0.044	-0.030	0.008	-0.066	0.031	-0.064	0.029
	(0.073)	(0.084)	(0.078)	(0.080)	(0.084)	(0.076)	(0.069)	(0.081)
Generic Information	-0.192^{*}	-0.106	-0.093	-0.027	-0.029	0.013	-0.131	0.047
	(0.093)	(0.107)	(0.100)	(0.103)	(0.108)	(0.097)	(0.088)	(0.104)
Constant	3.601^{***}	3.312^{***}	3.447^{***}	3.546^{***}	3.315^{***}	3.350^{***}	3.961^{***}	3.365^{***}
	(0.065)	(0.075)	(0.070)	(0.072)	(0.075)	(0.068)	(0.062)	(0.073)
Observations	1,828	1,846	1,850	1,835	1,834	1,797	1,854	1,827

Note: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

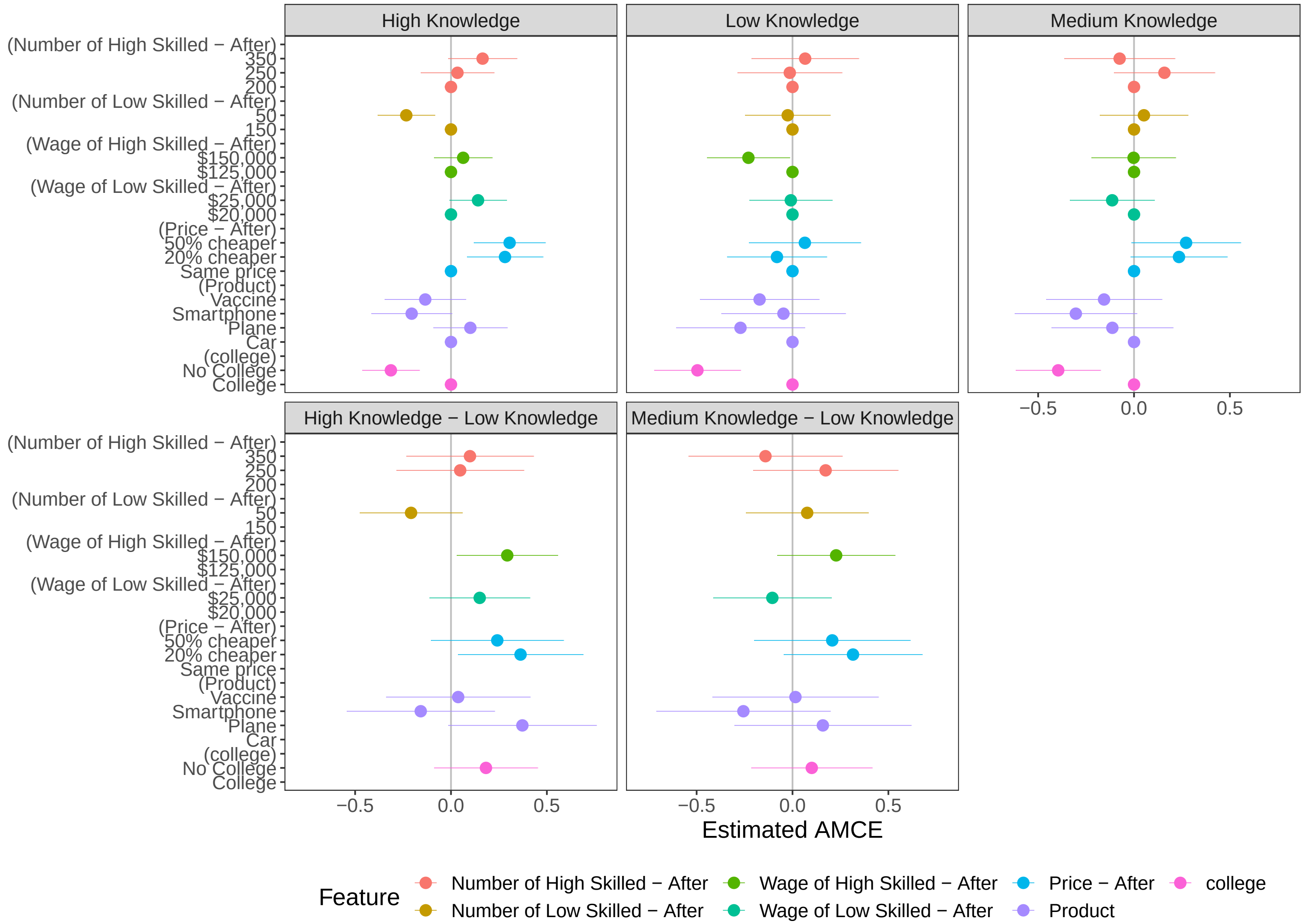

Figure A36: Average marginal component effects for fairness DV by objective knowledge: Australia

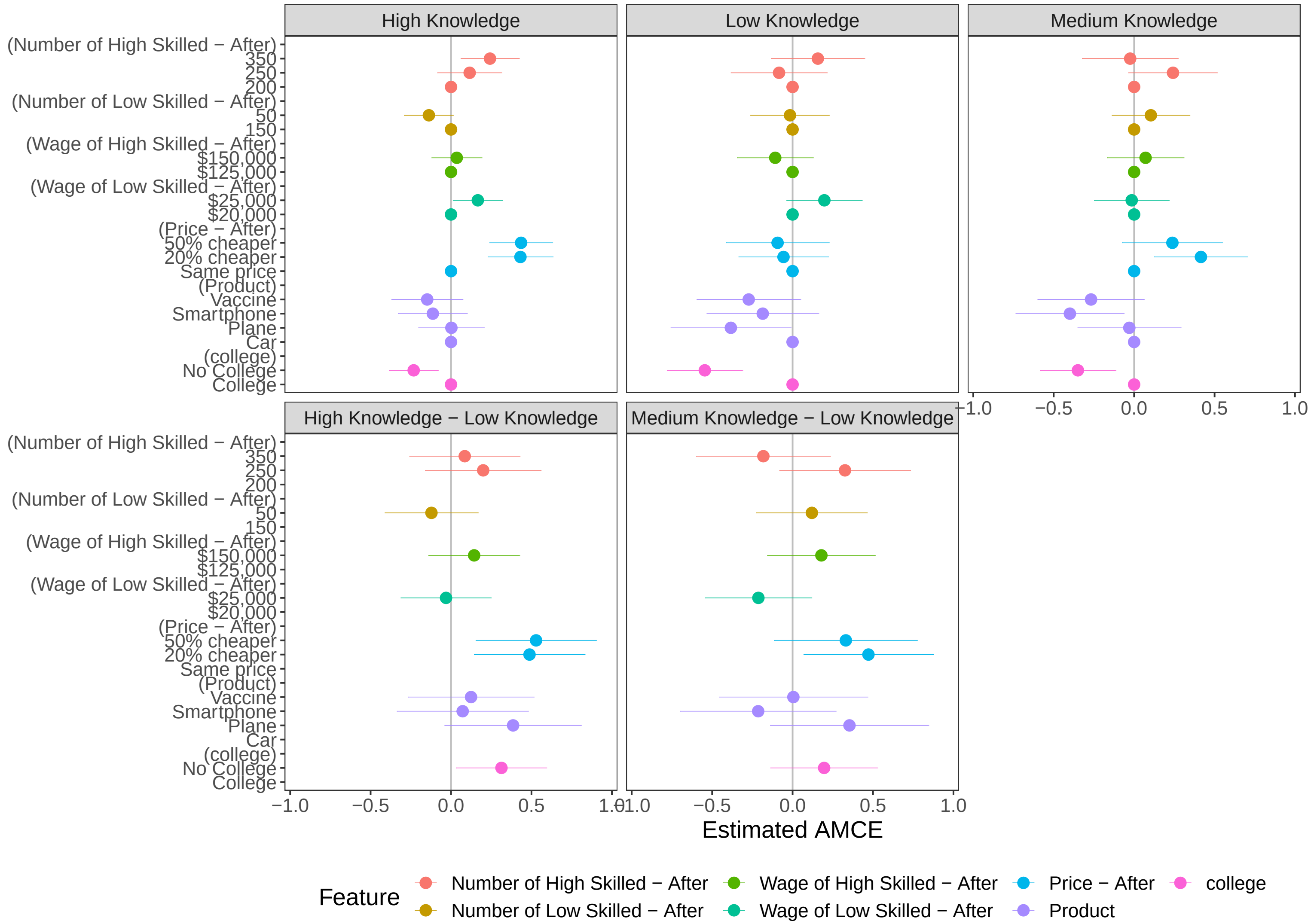

Figure A37: Average marginal component effects for CEO DV by objective knowledge: Australia

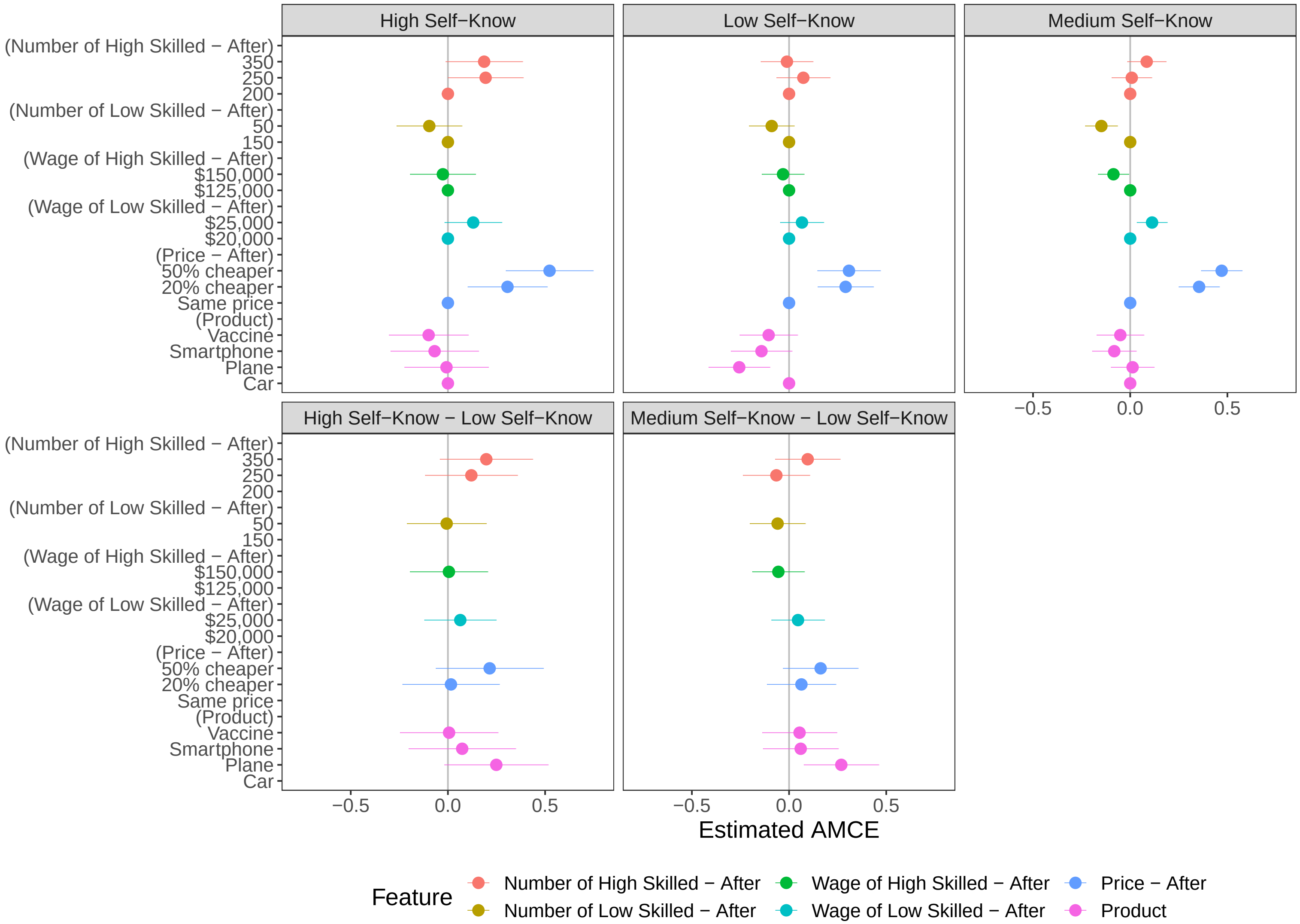

Figure A38: Average marginal component effects for fairness DV by self-reported subjective knowledge: Australia

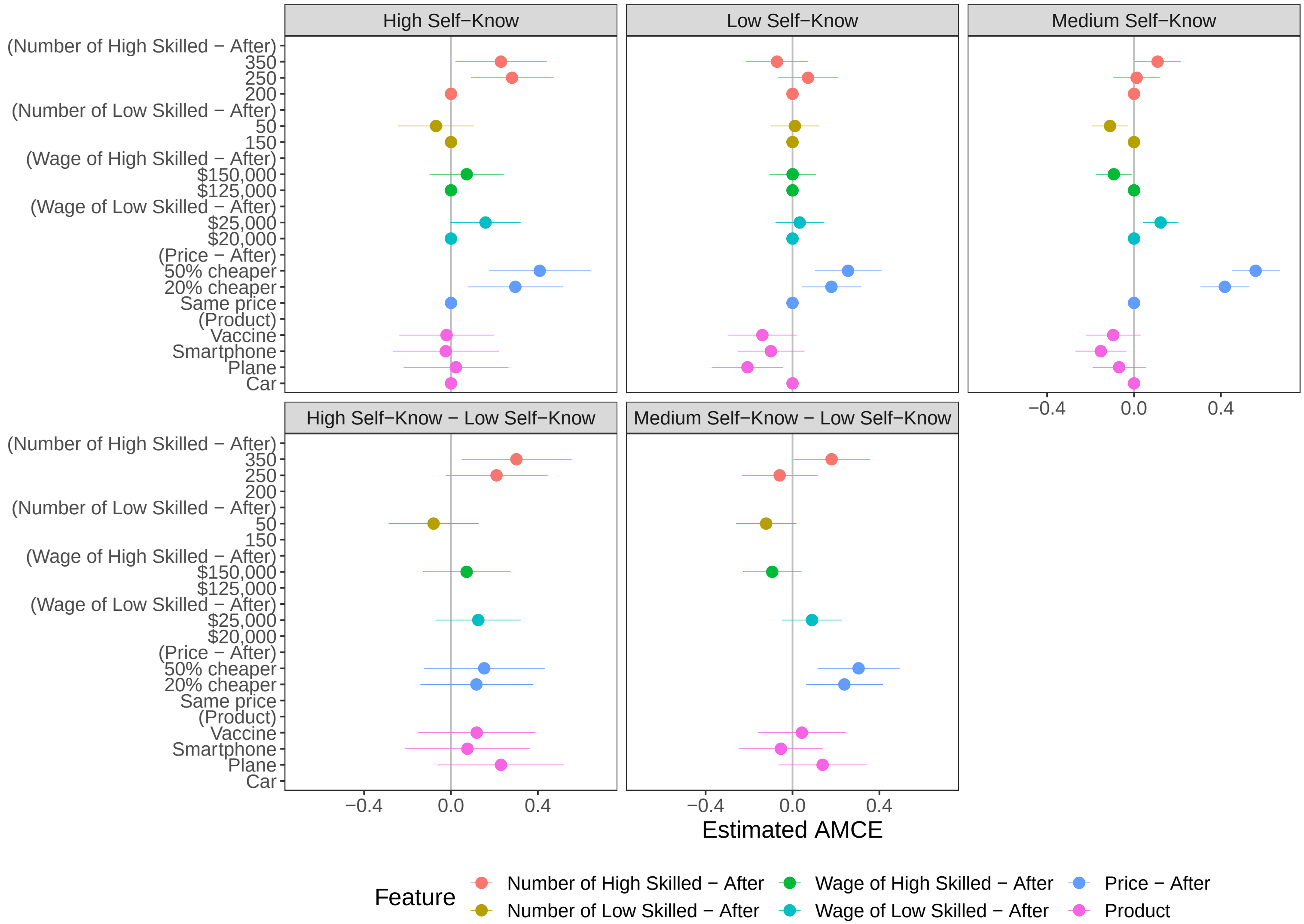

Figure A39: Average marginal component effects for CEO DV by self-reported subjective knowledge: Australia

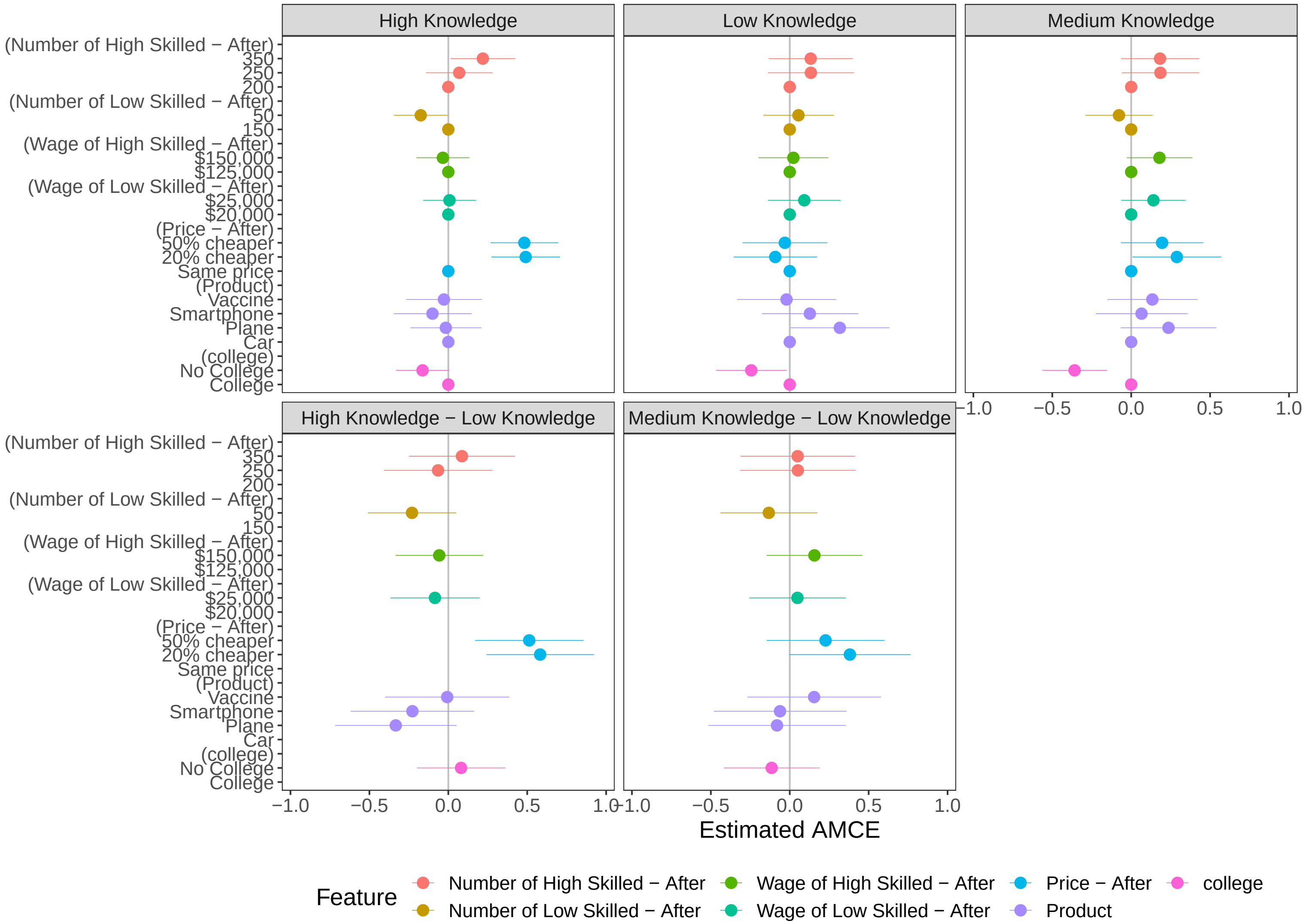

Figure A40: Average marginal component effects for fairness DV by objective knowledge: Canada

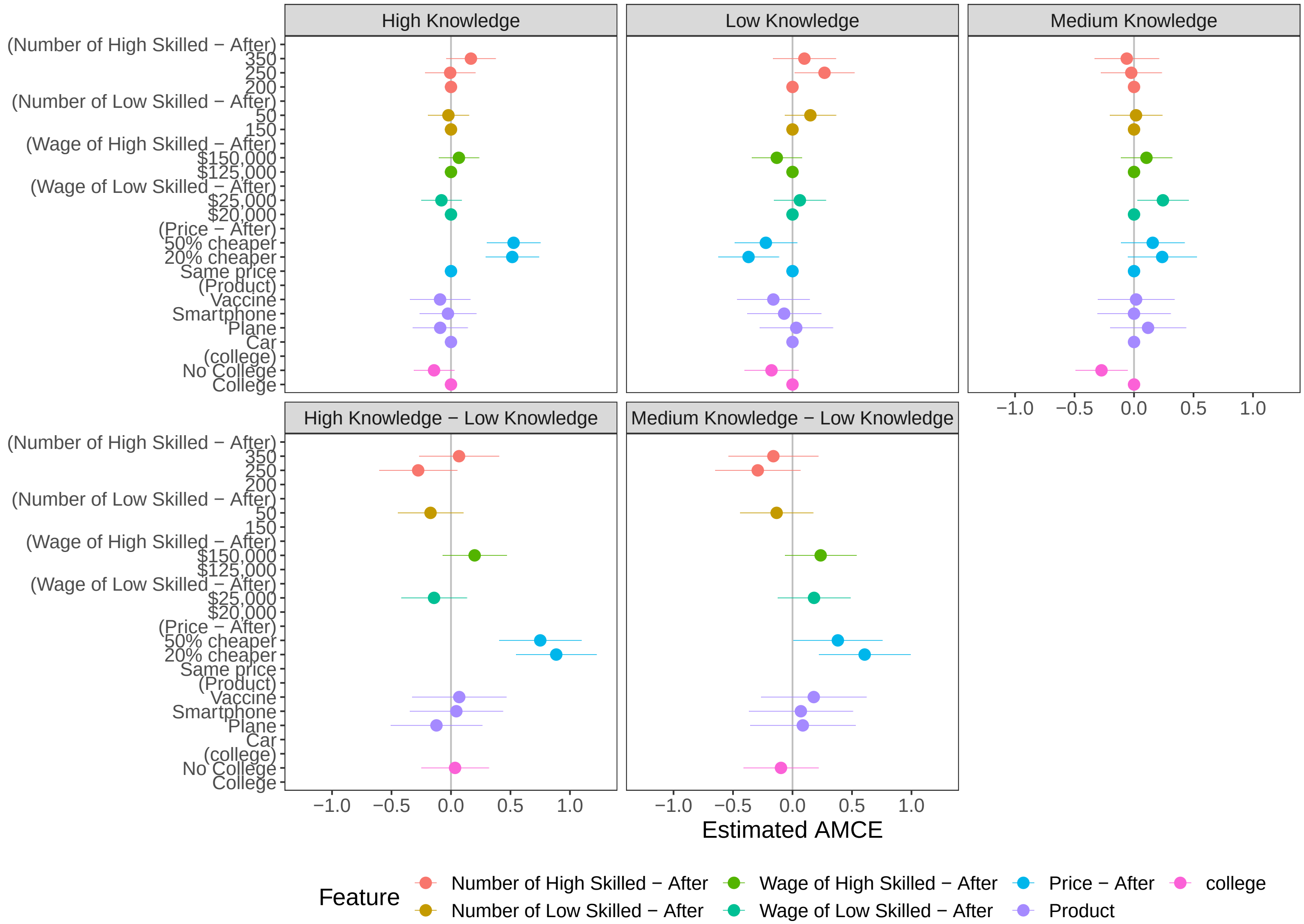

Figure A41: Average marginal component effects for CEO DV by objective knowledge: Canada

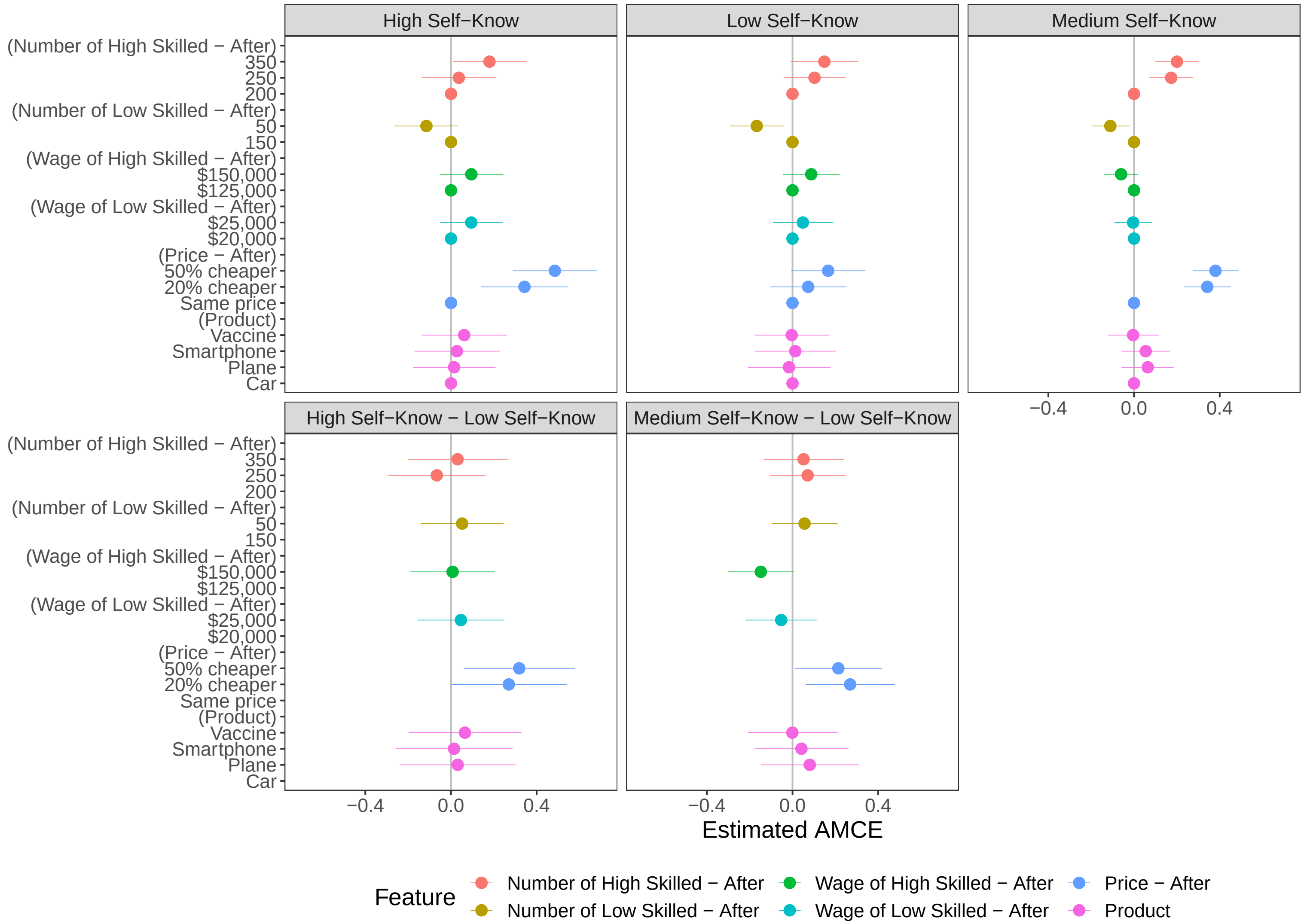

Figure A42: Average marginal component effects for fairness DV by self-reported subjective knowledge: Canada

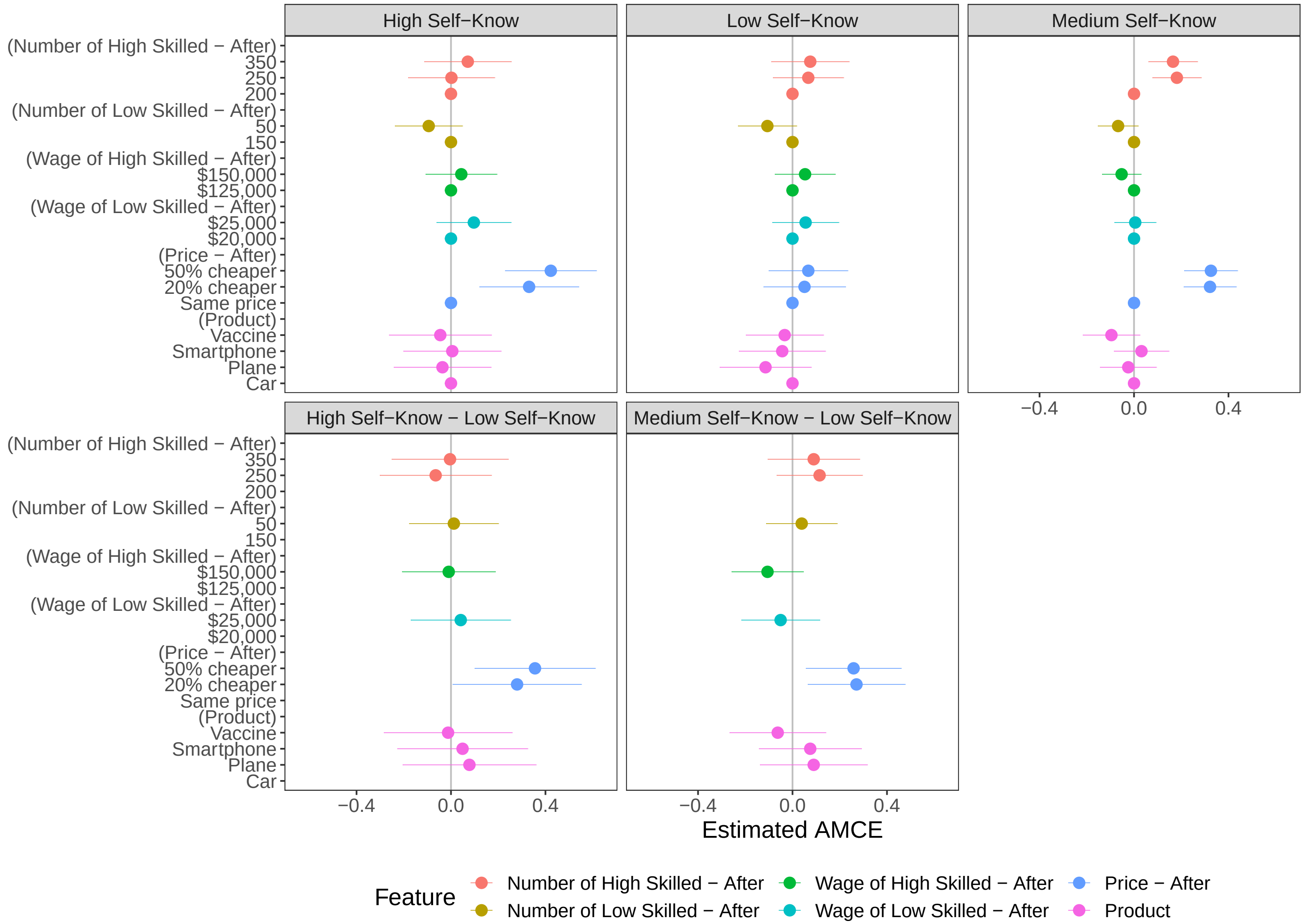

Figure A43: Average marginal component effects for CEO DV by self-reported subjective knowledge: Canada

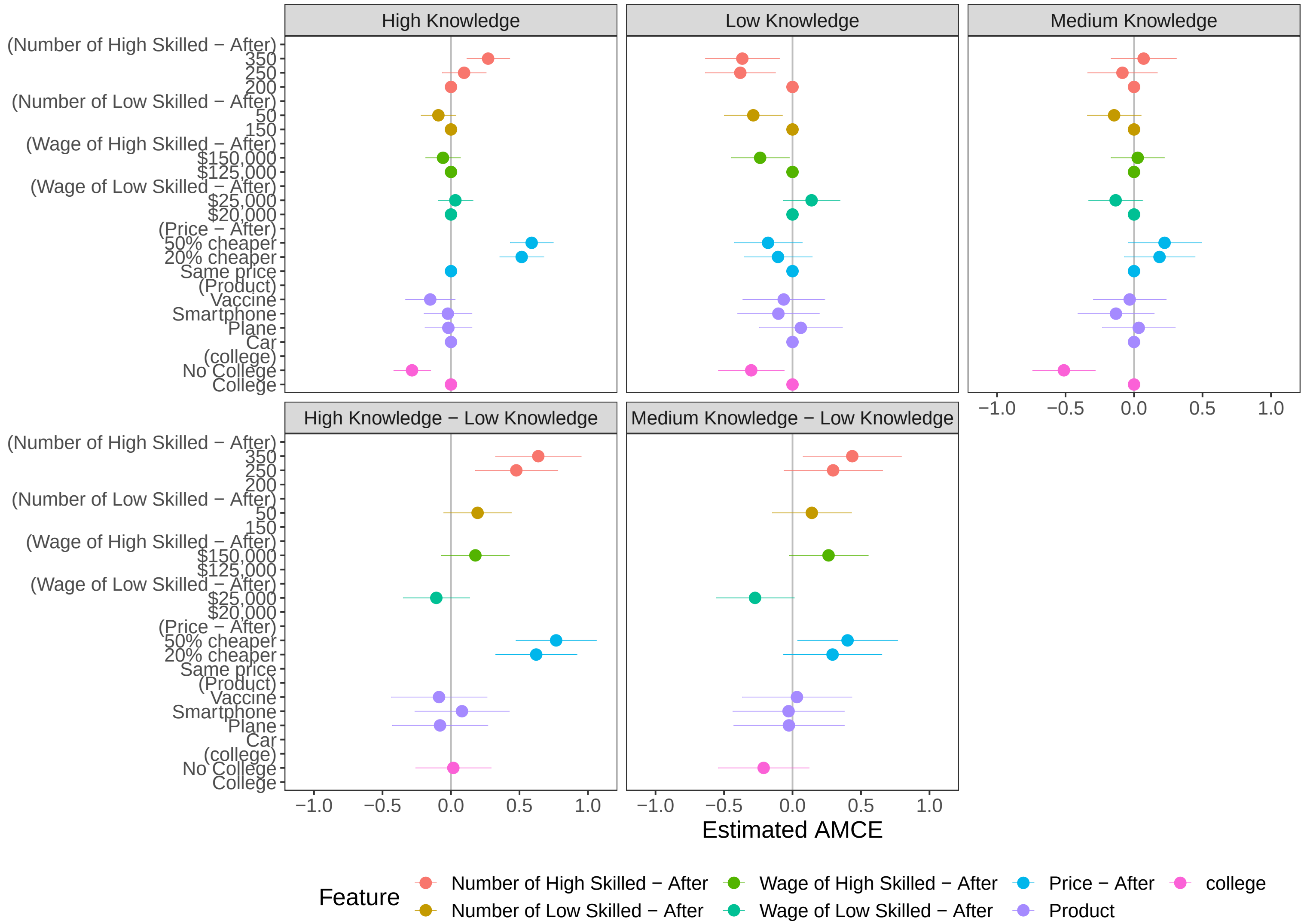

Figure A44: Average marginal component effects for fairness DV by objective knowledge: UK

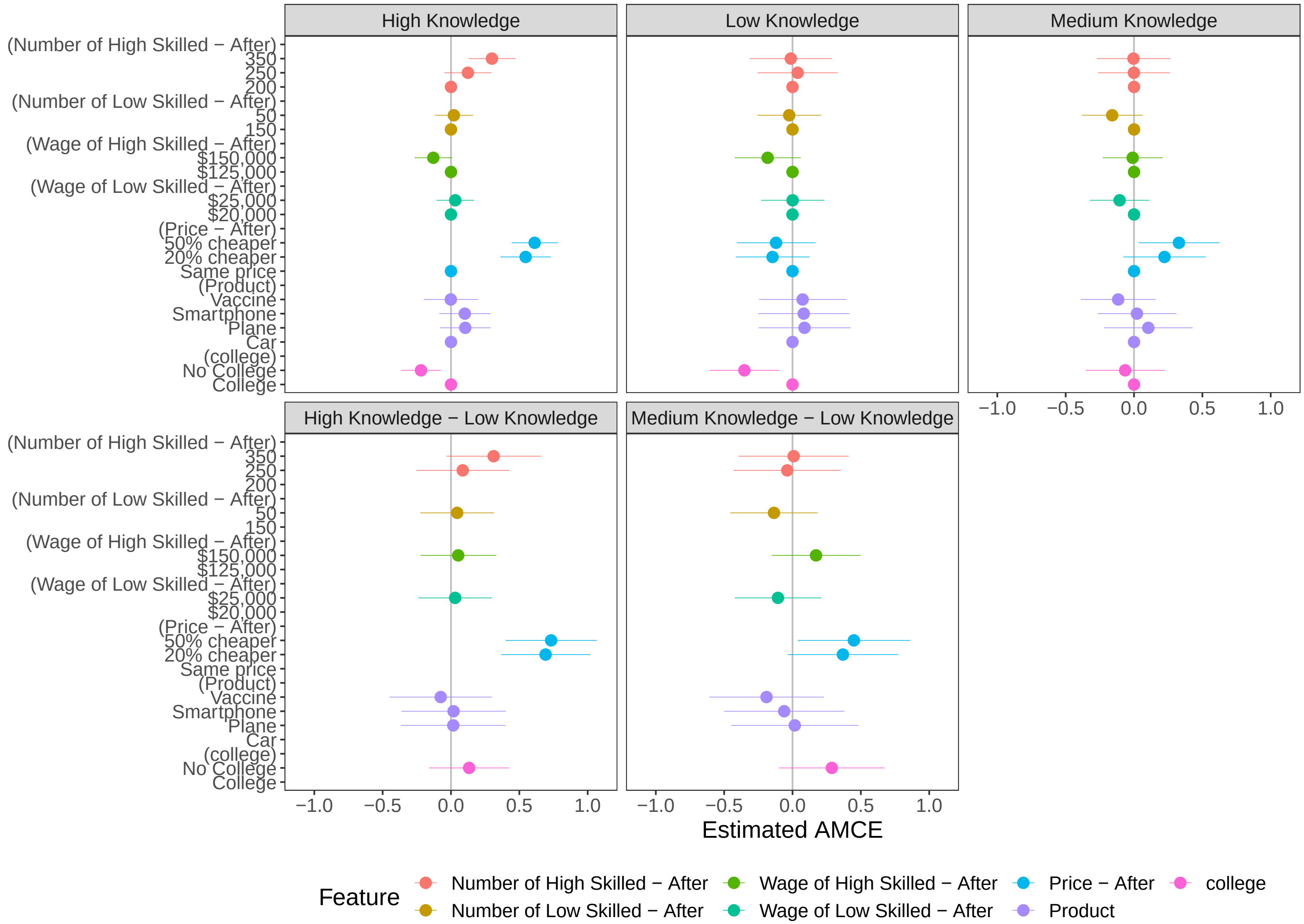

Figure A45: Average marginal component effects for CEO DV by objective knowledge: UK

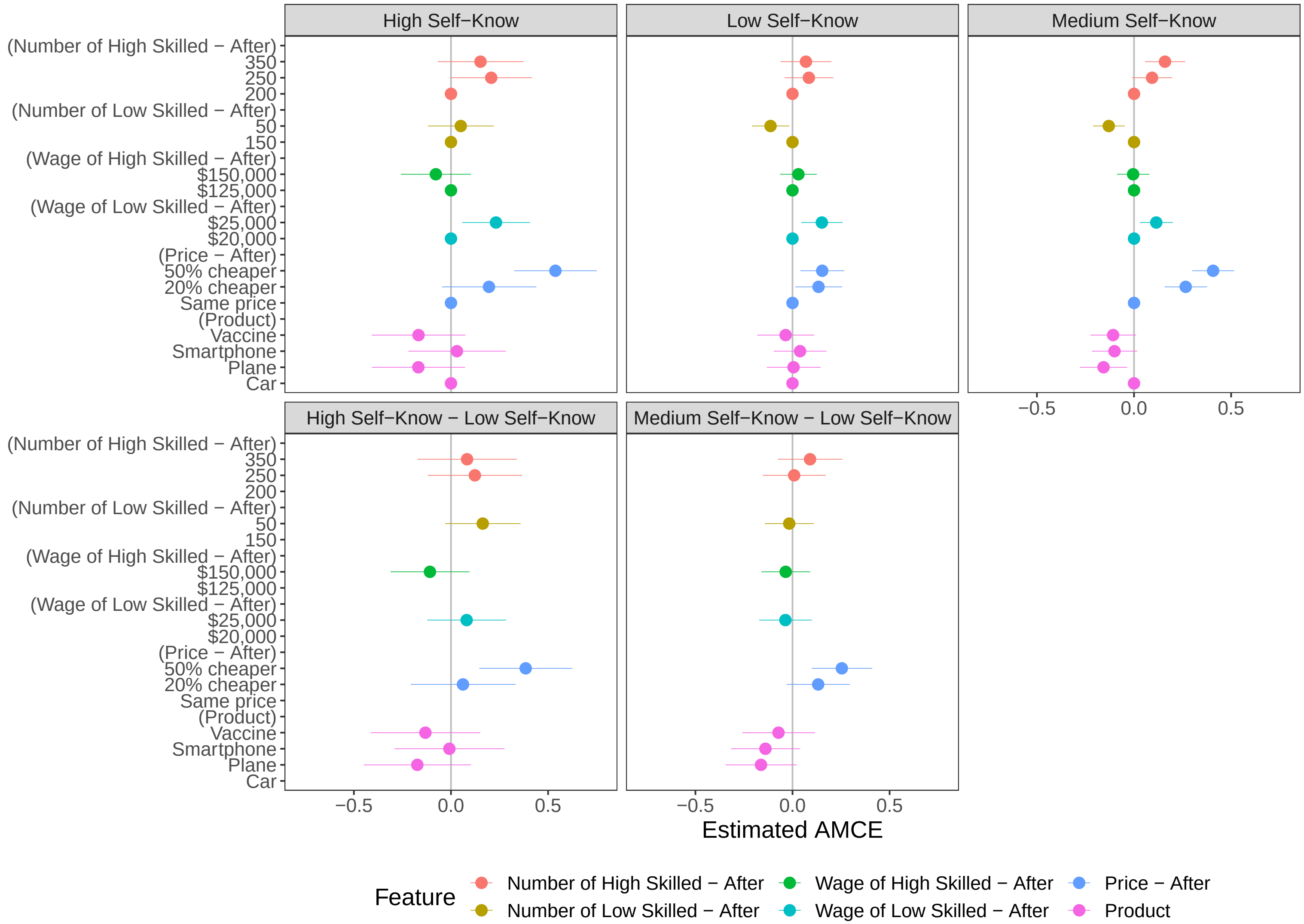

Figure A46: Average marginal component effects for fairness DV by self-reported subjective knowledge: UK

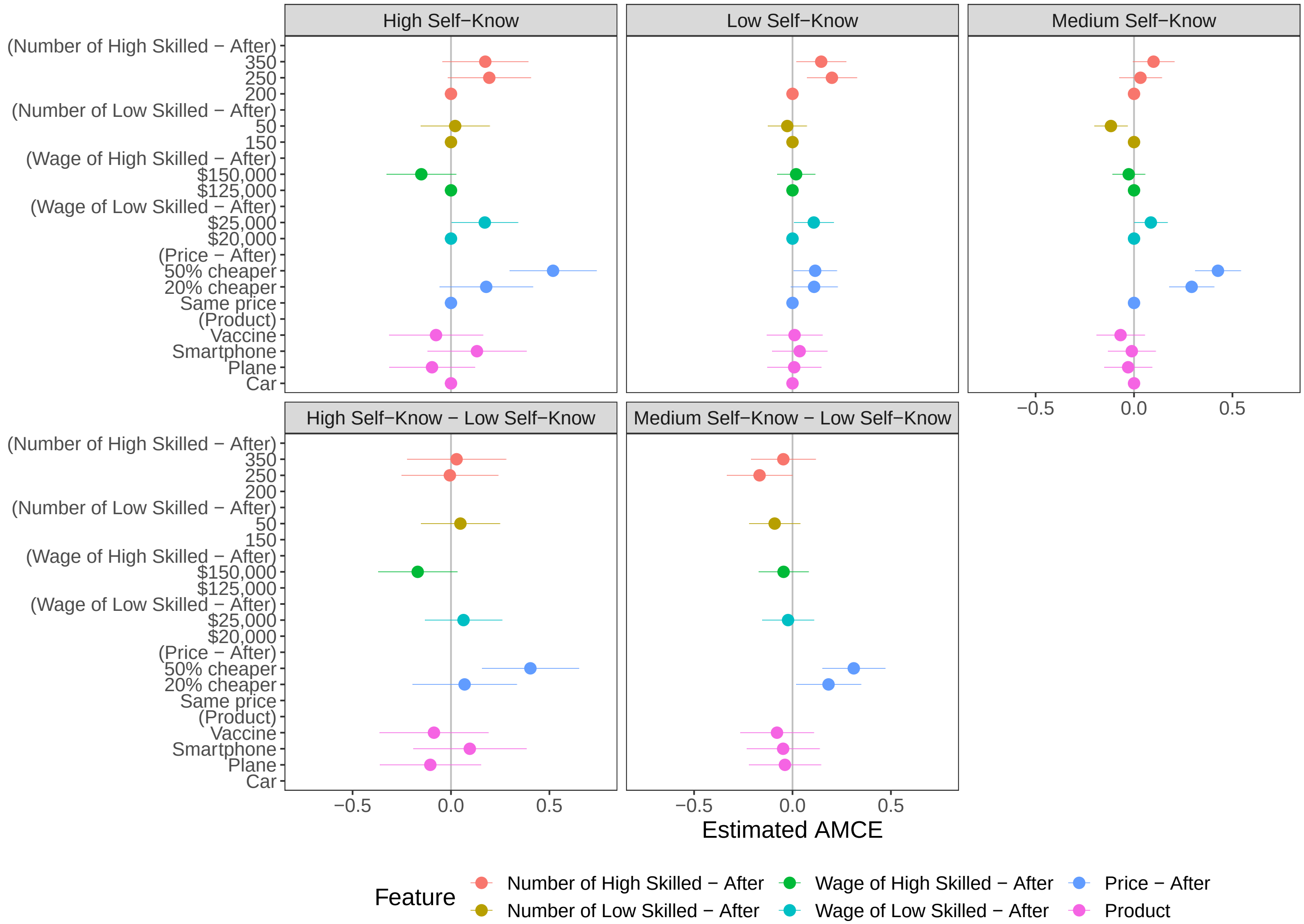

Figure A47: Average marginal component effects for CEO DV by self-reported subjective knowledge: UK

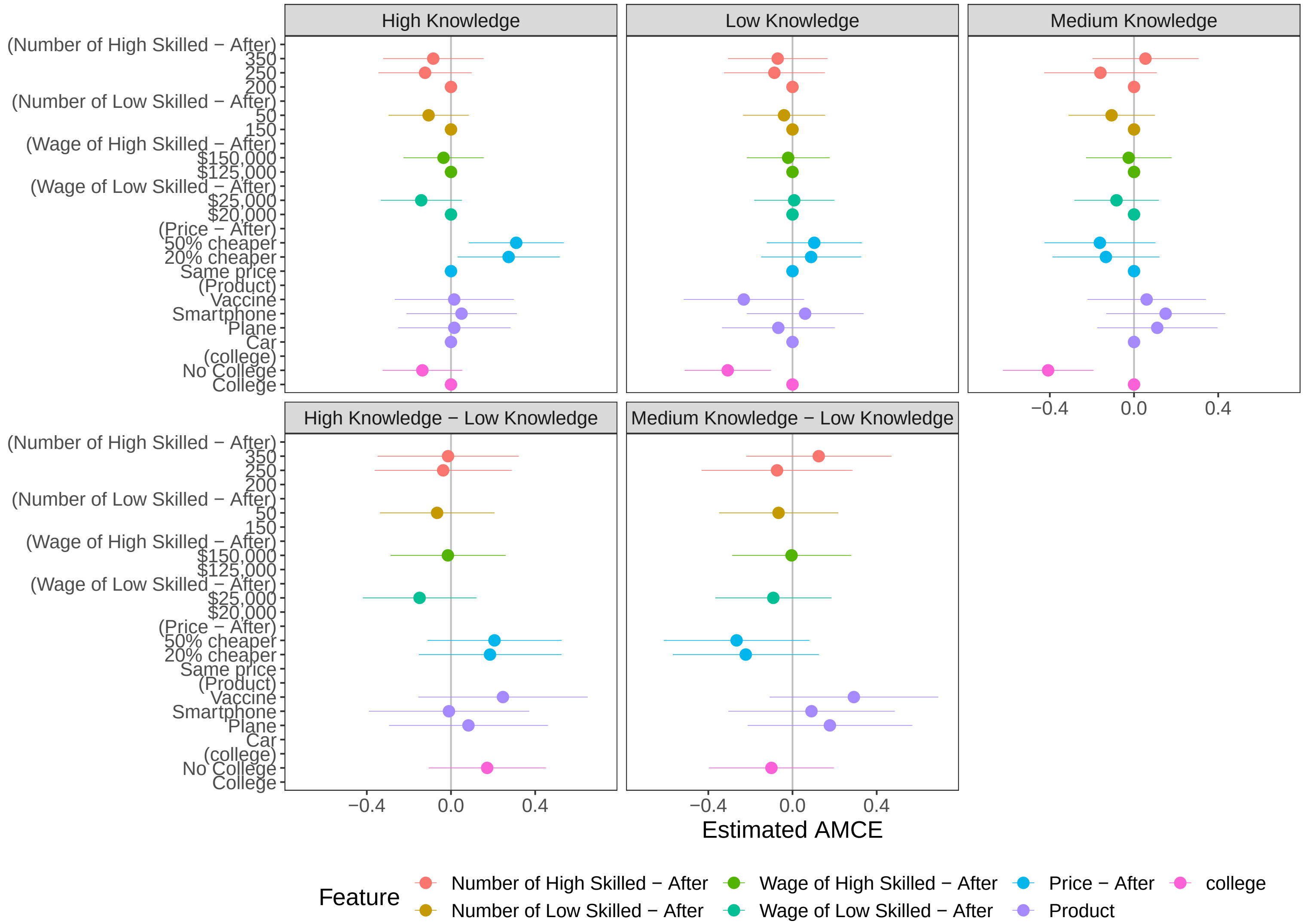

Figure A48: Average marginal component effects for fairness DV by objective knowledge: US

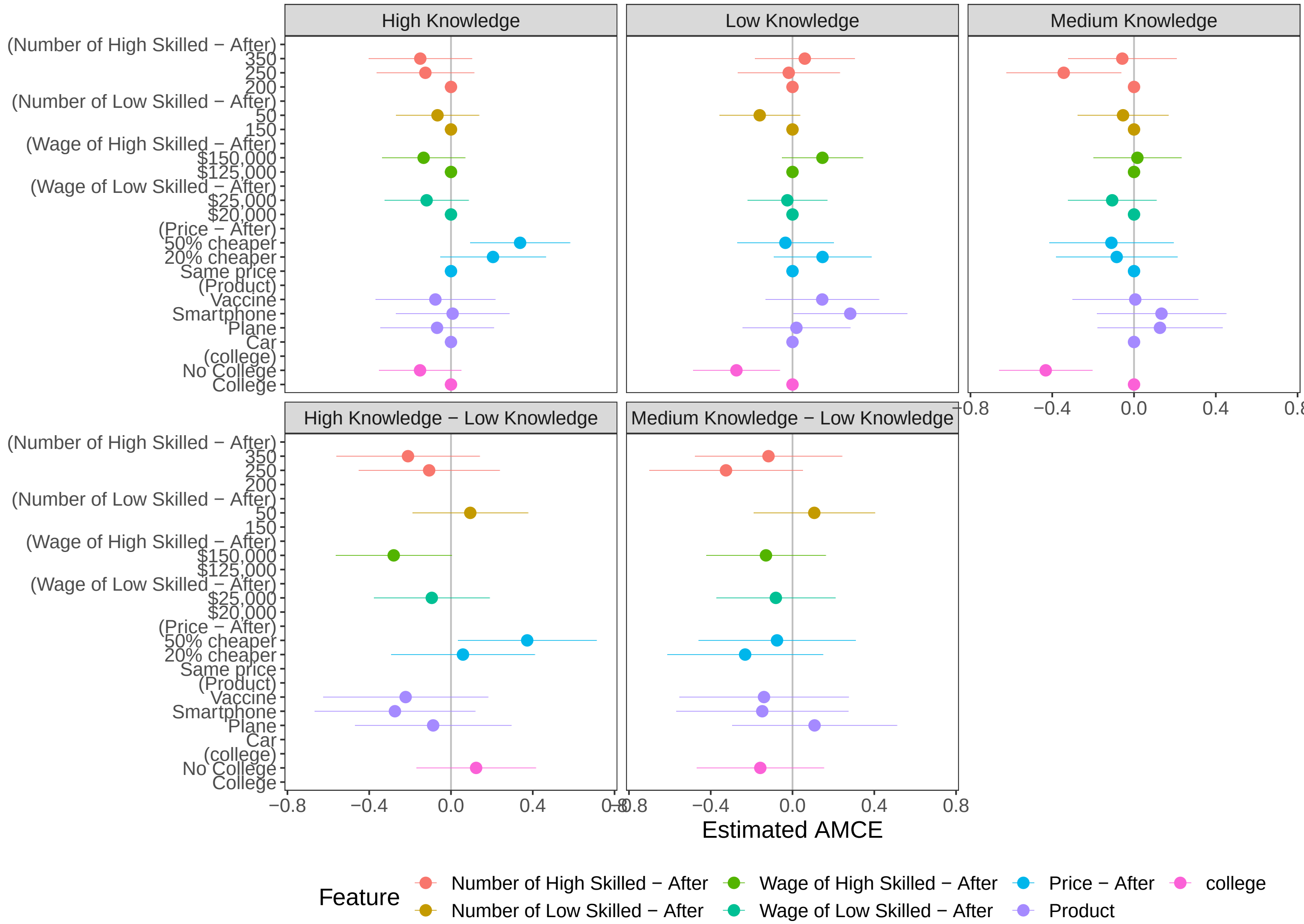

Figure A49: Average marginal component effects for CEO DV by objective knowledge: US

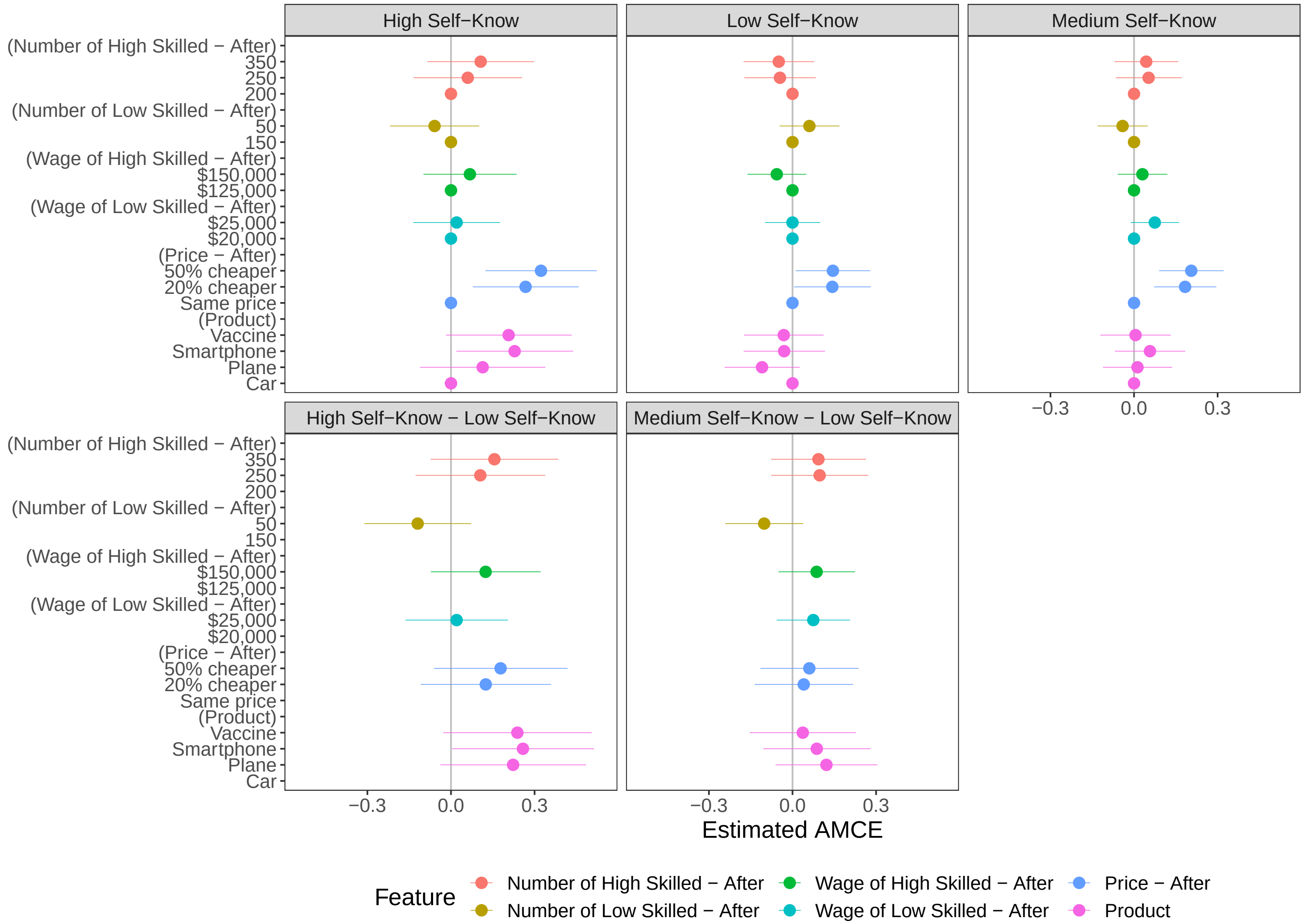

Figure A50: Average marginal component effects for fairness DV by self-reported subjective knowledge: US

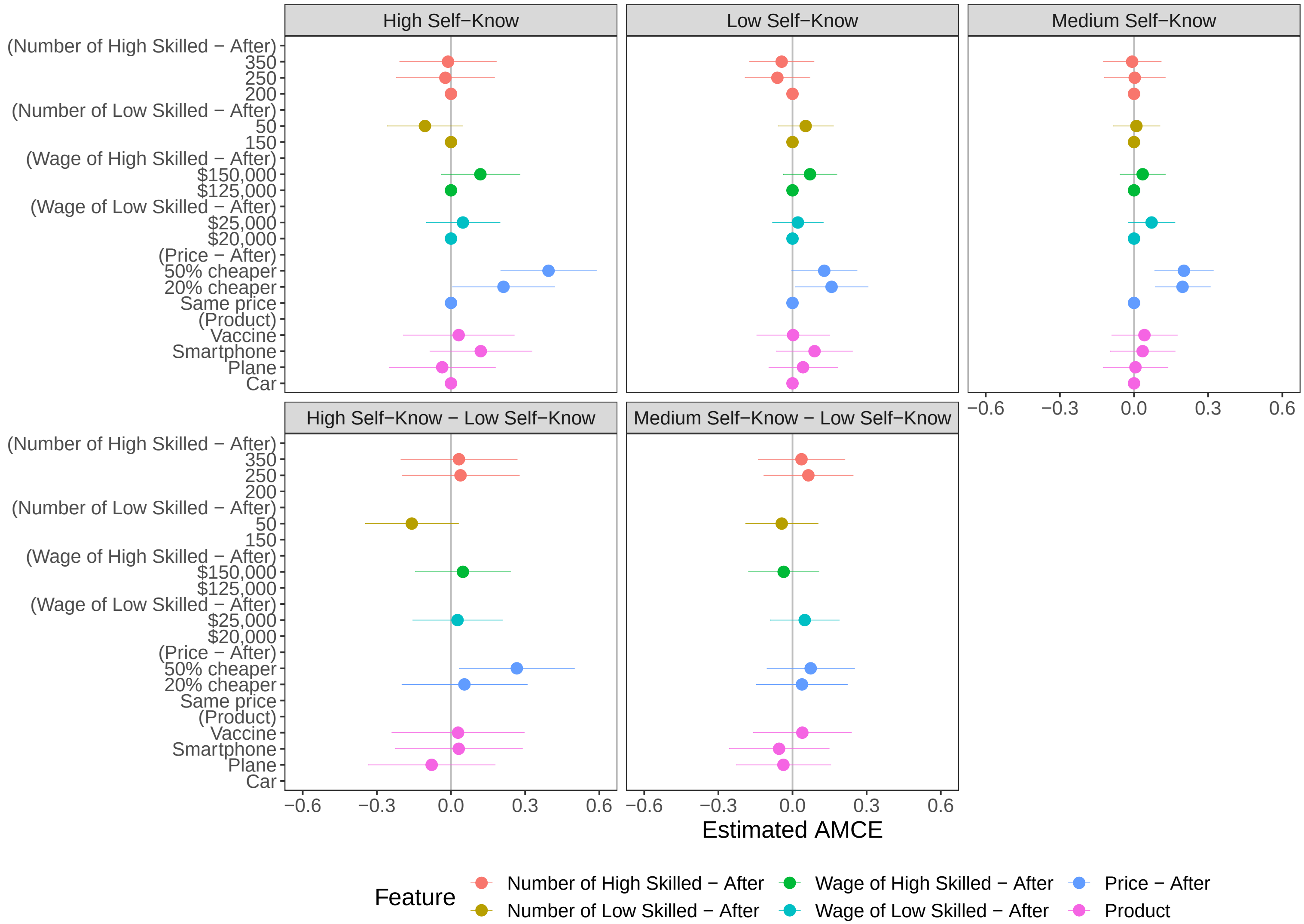

Figure A51: Average marginal component effects for CEO DV by self-reported subjective knowledge: US

Additional information on survey experiment and ethics

The section survey and the pre-analysis plan that we pre-registered on OSF contain a detailed description of our survey experiment, including how our survey sample provider Cint recruited respondents between March 11 and March 28, 2022. We recruited respondents over 18 years old (we undersampled older individuals over 65 since we wanted a sample reflective of working age individuals) and we applied quotas for age, gender, and region. All participants in our study provided explicit, informed, and voluntary consent. Respondents were compensated for their time through their respective panel provider, managed by sample provider Cint. Excluding respondents with questionable IP addresses, duplicate IDs, and very fast completion times (below the second percentile), a total of 8,033 respondents were surveyed: 1,955 in Australia, 1,972 in Canada, 2,031 in the UK and 1,966 in the US, with a median completion time of 15 minutes. The following text contains the consent form that each respondent saw before completing the survey, which also includes the IRB/research ethics board protocol number:

> "Thank you for agreeing to participate in our study. This study is being conducted by Peter Loewen (Professor of Political Science, University of Toronto, `peter.loewen@utoronto.ca`) and Bart Bonikowski (Associate Professor of Sociology, New York University, `bonikowski@nyu.edu`).
>
> The goal of this study is to better understand what people think about automation, artificial intelligence, and politics. In this survey you will be asked for your views on a variety of political issues. This survey will help researchers and policymakers better understand how to address future changes in the economy. The study should take between 12 and 15 minutes of your time.
>
> Your participation in this study is both voluntary and confidential. Information that could allow us to identify you will not be collected or shared; only anonymized data will be collected in this study. This data may be used by our team of researchers in academic publications, and other researchers may also be granted access to the anonymized data once published.
>
> You can end your participation at any time by simply closing your browser, and no data will be collected. If you wish to withdraw your data from the study, you may withdraw by sending an email to `peter.loewen@utoronto.ca` within one week of completing this survey.
>
> This study has been approved by the research ethics board, protocol 00040922.
>
> If you have any questions about your rights as a participant in this study you may contact the Research Oversight and Compliance Office - Human Research Ethics Program of the University of Toronto at `ethics.review@utoronto.ca`, +1-(416)-946-3273.
>
> The research study you are participating in may be reviewed for quality assurance to make sure that the required laws and guidelines are followed. If chosen, (a) representative(s) of the Human Research Ethics Program (HREP) may access study-related data and/or consent materials as part of the review. All information

accessed by the HREP will be upheld to the same level of confidentiality that has been stated by the research team."

Below is the French version for French-Canadian respondents:

> " Merci d'avoir accepté de participer à notre étude. Cette étude est menée par Peter Loewen (professeur de sciences politiques à l'Université de Toronto, `peter.loewen@utoronto.ca`) et Bart Bonikowski (professeur agrégé de sociologie à l'Université de New York, `bonikowski@nyu.edu`).
>
> Le but de cette étude est de mieux comprendre ce que pensent les gens de l'automatisation, de l'intelligence artificielle, et de la politique. Dans ce sondage, il vous sera demandé votre point de vue sur une variété de questions politiques. Ce sondage aidera les chercheurs et les décideurs à mieux comprendre comment aborder les changements futurs de l'économie. L'étude devrait prendre de 12 à 15 minutes de votre temps.
>
> Votre participation à cette étude est à la fois volontaire et confidentielle. Les informations qui pourraient nous permettre de vous identifier ne seront ni collectées ni partagées; seules des données rendues anonymes seront collectées dans le présent projet d'étude. Ces données pourraient être utilisées par notre équipe de chercheurs dans des publications universitaires, et d'autres chercheurs pourraient également accéder à ces données une fois publiées.
>
> Vous pouvez mettre fin à votre participation à tout moment simplement en fermant votre navigateur, et aucune donnée ne sera collectée. Si vous souhaitez retirer vos données de l'étude, vous pouvez vous rétracter en envoyant un courriel à `peter.loewen@utoronto.ca` dans la semaine suivant la fin de cette enquête.
>
> Cette étude a été approuvée par le comité d'éthique de la recherche, protocole no 00040922.
>
> Si vous avez des questions sur vos droits en tant que participant à cette étude, vous pouvez contacter le Bureau de surveillance, de recherche et de conformité — Programme d'éthique de la recherche humaine de l'Université de Toronto à `ethics.review@utoronto.ca`, +1-(416)-946-3273.
>
> L'étude à laquelle vous participez pourrait être examinée pour contrôler le respect des règles et lignes directrices requises. En cas de besoin, un ou plusieurs représentants du Programme d'éthique de la recherche humaine (HREP) peuvent accéder aux données relatives à l'étude et/ou aux documents de consentement dans le cadre de l'examen. Toutes les informations consultées par le HREP seront maintenues au même niveau de confidentialité que celui précisé par l'équipe de recherche."

Additional information: balance tests and quotas

Table A18: Balance tests: The table shows Ns (%) and p-values of Pearson's Chi-squared tests for categorical variables and mean (SD) and p-values of one-way analyses of means for numerical variables.

Characteristic	**News**	**Specific Information**	**Generic Information**	**p-value**
Gender				0.9
Female	646 (50%)	2,625 (50%)	658 (50%)	
Male	640 (50%)	2,646 (50%)	660 (50%)	
Education				0.6
High	473 (37%)	1,986 (38%)	510 (39%)	
Low	813 (63%)	3,285 (62%)	808 (61%)	
Employment Status				0.075
Employed	768 (60%)	3,358 (64%)	828 (63%)	
Other	154 (12%)	521 (9.9%)	144 (11%)	
Retired	192 (15%)	777 (15%)	191 (14%)	
Student	36 (2.8%)	175 (3.3%)	41 (3.1%)	
Unemployed	136 (11%)	440 (8.3%)	114 (8.6%)	
Age	45 (15)	44 (15)	44 (16)	0.11
Income	64,979 (110,504)	64,339 (89,320)	65,318 (96,903)	0.9

Table A19: Survey samples and programmed survey quotas by country based on national census data. We over-sampled working age individuals and hence adjusted the age group quotas accordingly.

	Australia		Canada		United Kingdom		United States	
	Quota	Sample	Quota	Sample	Quota	Sample	Quota	Sample
Female	50%	49.10%	50%	49.24%	50.99%	50.61%	50.99%	49.33%
Male	50%	50.38 %	50%	50.15 %	49.01%	48.89%	49.01%	49.79%
Age (18-24):	13.49%	13.19%	12.60%	12.06%	12.60%	11.42%	13.49%	11.85%
Age (25-34):	22.51%	23.47%	19.80%	19.06%	19.81%	19.69%	19.79%	19.27%
Age (35-44):	18.90%	19.89%	19.80%	20.74%	18.92%	19.44%	18.91%	20.04%
Age (45-54):	18.00%	14.88%	18.01%	16.48%	21.59%	22.15%	18.91%	20.04%
Age (55-64):	17.09%	18.00%	19.80%	21.04%	17.10%	16.98%	18.91%	19.02%
Age (65+):	10.01%	10.53%	9.99%	10.59%	9.89 %	10.29%	9.99 %	10.17%
Capital (Australia)	2%	1.12%						
NSW (Australia)	31.97%	33.19%						
Northern (Australia)	1.00%	0.20%						
Queensland (Australia)	20.01%	20.46%						
South (Australia)	7.00%	7.26%						
Tasmania (Australia)	2%	2.09%						
Victoria (Australia)	25.01%	26.03%						
Western (Australia)	11.01%	9.36%						
Atlantic (Canada)			5.71%	7.55%				
British Columbia (Canada)			10.62%	13.53%				
Ontario (Canada)			31.01%	39.75%				
Prairies (Canada)			14.68%	18.25%				
Quebec (Canada)			37.98%	20.84%				
East of England (UK)					8.99%	8.27%		
London (UK)					13.01%	12.70%		
Midlands (UK)					16.99%	17.03%		
N.E., Y. and H. (UK)					11.99%	12.16%		
North West (UK)					11.00%	11.07%		
Northern Ireland (UK)					3.00%	3.00%		
Scotland (UK)					8.01%	8.22%		
South East (UK)					14.00%	14.18%		
South West (UK)					8.01%	9.32%		
Wales (UK)					5.01%	5.02%		
Northeast (USA)							19.02%	19.02%
Midwest(USA)							22.99%	22.78%
South (USA)							35.98%	35.60%
West (USA)							22.01%	22.53 %

References

Borwein, Sophie et al. (2023). "Who Can Assert Ownership over Automation? Workplace Technological Change, Populist and Ethno-Nationalist Rhetoric, and Candidate Support". In: *Political Behavior*. Forthcoming.

Centre for the New Economy and Society (2018). *The Future of Jobs Report 2018 Insight*. Tech. rep. URL: http://www3.weforum.org/docs/WEF_Future_of_Jobs_2018.pdf.

De La Rica, Sara and Lucas Gortazar (2016). "Differences in Job De-Routinization in OECD Countries: Evidence from PIAAC". In: *IZA DP No. 9736*.

Di Tella, Rafael and Dani Rodrik (2020). "Labour Market Shocks and the Demand for Trade Protection: Evidence from Online Surveys". In: *The Economic Journal* 130.628, pp. 1008–1030. DOI: 10.1093/EJ/UEAA006.

Gallego, Aina, Alexander Kuo, and Dulce Manzano (2023). "Automation versus openness: Support for policies to address job threats". In: *Journal of Public Policy*.

Gallego, Aina, Alexander Kuo, Dulce Manzano, and José Fernández-Albertos (2021). "Technological Risk and Policy Preferences". In: *Comparative Political Studies* 55.1, pp. 60–92.

Ito, Aki (2015). *Six Things Technology Has Made Insanely Cheap*. Tech. rep. Bloomberg. URL: https://www.bloomberg.com/news/articles/2015-02-05/six-things-technology-has-made-insanely-cheap.

Ladreit, Colombe (2022). "Automation and Public Policy Preferences". In: *Working Paper*.

Loewen, Peter and Benjamin Allen Stevens (2019). *Automation, AI and Anxiety: Policy Preferred, Populism Possible*. Tech. rep. Public Policy Forum, pp. 1–28.

Menaldo, Victor (Forthcoming). *Twilight of the Third Industrial Revolution and Dawn of the Fourth*. Manuscript in Progress.

Ritchie, Hannah (2020). *The price of batteries has declined by 97% in the last three decades*. URL: https://ourworldindata.org/battery-price-decline.

Rodrik, Dani (2018). "Populism and the economics of globalization". In: *Journal of International Business Policy* 1, pp. 12–33.

Roser, Max (2020). *Why did renewables become so cheap so fast?* URL: https://ourworldindata.org/cheap-renewables-growth.

Rosoff, Matt (2015). *Why is Tech Getting Cheaper*. Tech. rep. World Economic Forum. URL: https://www.weforum.org/agenda/2015/10/why-is-tech-getting-cheaper/.

The Economist (2014). *The Rise of the Cheap Smartphone*. URL: https://www.economist.com/business/2014/04/05/the-rise-of-the-cheap-smartphone.

United Nations (2021). *Technology and Innovation Report*. Tech. rep. URL: https://unctad.org/system/files/official-document/tir2020_en.pdf.

Wu, Nicole (2022). "Restrict foreigners, not robots": Partisan responses to automation threat". In: *Economics & Politics*. URL: https://doi.org/10.1111/ecpo.12225.

Zhang, Baobao (2022). "No Rage Against the Machines: Threat of Automation Does Not Change Policy Preferences". In: *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society (AIES'22)*.

Zhang, John (2023). *Why are AI models getting cheaper as they improve?* URL: https://technode.com/2023/03/27/why-are-ai-models-getting-cheaper-as-they-improve/.