***Supplementary Material:* Left to Right: Labor Market Policy, Labor Market Status, and Political Affinities**

**Appendix A: Descriptive Statistics and Codings**

**Table A.1: Descriptive Statistics**

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**Table A.2: Country-years in Union Regressions**

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**Table A.3: Country-years in Party-Manifestos Regressions**

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**Coding Outsiders**

The EVS and WVS both contain a question regarding the respondent's employment status in each wave. The possible responses are:

1. Full-time
2. Part-time
3. Self-employed
4. Retired
5. Housewife
6. Student
7. Unemployed
8. Other

The 2008 wave of the EVS and the 2009 wave of the WVS also ask a question about the employment status of the respondent's partner. The categories are the same except for including additional categories for whether the partner is in military service and for whether the partner is disabled. Previous waves of the EVS and WVS ask two questions, which are less ideal than asking about the partner's employment status, but still allow a richer view of employment status in the family than just asking about the respondent's employment status: whether the respondent is the chief wage earner in the household and whether the chief wage earner is unemployed. I code the respondent as an outsider if he/she meets *any* of the following conditions:

* The chief wage earner is unemployed and the respondent is either part-time employed, self-employed, a housewife, a student, or unemployed.
* The respondent is the chief wage earner and is either part-time employed or unemployed.
* The respondent is not the chief wage earner, is employed part-time, self-employed, a housewife, a student, or unemployed and the family income is in one of the bottom two income deciles.
* The respondent is part-time employed and the partner is either part-time employed, in military service, a housewife, a student, unemployed, or disabled.
* The respondent is a housewife and the partner is either part-time employed, in military service, a housewife, a student, unemployed, or disabled.
* The respondent is a student and the partner is either part-time employed, in military service, a housewife, unemployed, or disabled.
* The respondent is unemployed and the partner is either part-time employed, in military service, a housewife, a student, unemployed, or disabled.

Additionally, I drop respondents who we can reasonably assume are not searching for jobs.[[1]](#footnote-1) I drop respondents for whom both members of the household are retired or one is retired and the other works a part-time job. I assume that these individuals are not seeking regular employment. If the respondent is retired and his/her partner is employed full-time, I code this respondent as an insider. I drop respondents who list their occupation as 'other,' unless they list their partner as being full-time employed, in which case I classify this respondent as an insider. I also drop respondents who list their occupation as student, and for whom the partner's occupation is either 'student' or 'other.' Finally, I recoded any individuals coded as outsiders according to the above scheme as insiders if their family income fell within the top 4 deciles, on the assumption that these respondents likely have substantial assets, which reduce the importance of employment status.

**Coding Populist Radical Right Parties**

My theory holds that outsiders should be more susceptible to anti-immigration, anti-globalization, anti-elite appeals when labor market rigidity is high. This set of positions is clearly associated with populist radical right parties, such as the Front National in France and UKIP in the United Kingdom. But there are two issues with relying on lists of these parties: 1) it is not clear for all of the countries and years in my dataset which parties should be included; 2) mainstream parties may shift in this direction due to a shift in issue salience or due to competition from populist radical right parties. In this case, the list-based coding would not pick up these shifts, but individuals may be supporting more mainstream right parties because they shifted to the right on these issues.

To give a few examples (not included in my dataset) of why it is important to use an issue-based coding, consider the Republican Party in the United States under Donald Trump and the Conservative Party in the United Kingdom under Theresa May. Neither of these parties would be included on a list of populist radical right parties, but we might want to include a preference for them (especially the former) under these two leaders as a preference for populist radical right politics. Both are strongly anti-immigration and have expressed anti-globalization, economic populist sentiments.

**Issue-Based Coding**

For the issue-based coding, I merged data from the Comparative Manifestos Project of the Wissenschaftzentrum Berlin, which contains codings of more than 3,000 election manifestos for more than 650 parties in over 50 countries into the combined EVS/WVS data (Volkens et al 2013). The manifestos are broken up into text units called 'quasi-sentences,' which are recognized as expressing a positive or negative position on one of 56 mutually exclusive policy categories.[[2]](#footnote-2) Issue 'scores' are generated by adding up the number of positive and negative mentions and dividing by the total number of sentences in the manifesto.

In order to generate a coding of far-right parties, I rely on a recommended coding of 'Social Liberal-Conservative,' one of the two fundamental axes of political competition (the other being economic left-right) as suggested by Lowe et al (2011). This measure was conceived by Benoit and Laver (2007) and is generated from 13 items in the Manifestos data. For left positions: *103 Anti-Imperialism: Anti-Colonialism, 105 Military: Negative, 106 Peace: Positive, 107 Internationalism: Positive, 202 Democracy: Positive*; For right positions: *104 Military: Positive, 201 Freedom and Human Rights: Positive, 203 Constitutionalism: Positive, 305 Political Authority: Positive, 601 National Way of Life: Positive, 603 Traditional Morality: Positive, 605 Law and Order: Positive, 606 Social Harmony: Positive*. I also use the logit coding scale of Lowe et al (2011), which is meant to capture the relative balance of sentences accorded R or L, not just their absolute quantity (as was the case in previous scalings). For multi-category indices, such as the one I am using, the logit scale is defined as:

where *j* are the individual right positions and *k* are the individual left positions. I code parties in the top 10% of scores as being far-right parties because where these parties have been present through the late 2000s, they have tended to receive between 5 and 15% of the vote.[[3]](#footnote-3)

**List-Based Coding**

For the list-based coding, I relied largely on Halikiopoulou and Vlandas' (2016) and Immerzeel et al's (2016) list of populist radical right parties in Europe. I included a few additional parties as populist radical right parties which these authors do not. For Hungary, I included the MIEP Life and Justice Party (Mudde 2007) as well as Fidesz under Victor Orban for the 2009 round of the survey. The justification for the latter is that while Fidesz started as a relatively liberal party, it has recently become much more anti-immigration, anti-EU, and economic populist, in part to compete with the right-wing nativist Jobbik party.

There are additional parties which could be considered Populist Radical Right, like the Republikaner in Germany, the Sweden Democrats, or the British National Party, but for which no respondent in any of the survey country-years expressed a preference and therefore are not included. Mudde (2007) also includes several additional parties not on the lists of either Halikiopoulou and Vlandas or Immerzeel et al, but none of these are represented in my data, so I have not included them in the table.

**Table A.4:** **Populist Radical Right Parties: List-Based Coding**



**Note:** Parties marked with a \* are listed by Halikiopoulou and Vlandas as populist radical right parties, but no respondent gave this as their preferred party.

**Appendix B: Additional Analyses**

**Full Regressions with Controls**

All data on individual-level survey responses come from the EVS-WVS. *Ideology* is the respondent’s self-placement on a left-to-right ideological scale, coded 1-10. *Union Member*  is an indicator variable coded 1 if the respondent is a union member and 0 if not. *Age* is a six-category variable, with age groups 15-24, 25-34,..., 65+. *Female* is an indicator variable, coded 1 if the respondent is a female and 0 if not. *Income* is a 10-category variable, with higher categories indicating higher self-reported income. *Education* is an 8-category variable, with categories ranging from "inadequately completed elementary education" to "university with degree/higher education." *Immigration* is a four-category variable, increasing with preference for immigration restrictions.[[4]](#footnote-4)

I also include several country-level variables that we might expect to influence respondents' attitudes toward trade unions and populist right parties. Data on union density (*Union Density*) used in the union attitudes models comes from Visser (2011). This variable captures union members as a percentage of the overall workforce. *GINI*  is the GINI Index, a measure of economic inequality. *logGDP* and *GDP Growth* are the log of GDP and GDP growth respectively. For populist radical right parties, I include two additional variables: *Imm. Rate* is the immigration rate, immigration as a percentage of the total population in a given survey year. *ENPP* is the effective number of political parties from Gallagher (2012), which Golder (2003) finds to be associated with a higher populist right vote share.

Table B.1 presents the same regressions as the main results in table 1, but showing the results for the controls as well. The individual-level control results for union attitudes are as we would expect. Those who identify with right-wing political ideology, higher income individuals, and more educated individuals are less likely to have favorable attitudes toward trade unions. Somewhat less intuitively, there is a negative and consistently significant correlation between age and having a positive view of unions. Union members are much more likely to have positive attitudes toward unions, as are females.

The results for the macro-level variables are dependent on the model choice. Higher levels of inequality are associated with less favorable attitudes toward unions, but only significantly so in the fixed effects regressions. We might expect to see the opposite, given that unions are typically seen as a counterweight to business and inequality is due in large part to top incomes rising. LogGDP and union density are negative and significant across all models.

Turning to populist radical right parties in columns 4-9, some of the individual-level results are fairly interesting. The finding that those of right-wing political ideology are more likely to support populist right parties is not surprising. The results for the other variables differ somewhat depending on whether we use the issue-based or list-based codings for populist radical right parties. The most consistent of these is the indicator for whether the respondent is a female. Females are always less likely to support populist radical right parties under both measures, although the results are much stronger for the list-based measure. While the coefficient for being a union member is always negative and of similar size across the two types of dependent variables, the standard errors are larger and it is not significant for the list-based regressions. The results for income and education also vary across the two dependent variable codings. The coefficients are consistently negative but not significant for education under the issue-based coding and they switch across specifications for income under this coding. The results for both income and education are more in line with expectations for the list-based coding. All coefficients for both are negative and significant, consistent with previous research. Finally, people who oppose immigration are more likely to support these parties.

The results for the macro-level variables are mostly insignificant, but a few deserve mention. EPL is associated with lower aggregate levels of support for populist right parties. GDP growth is a consistent, negative predictor of support for the list-based coding of populist radical right parties, which is sensible because we might think that when economies are performing well, individuals will generally have fewer grievances and be less willing to support grievance-based parties. The inconsistent results for the inward immigration rate conflict with previous work which finds that a higher percentage of foreign-born individuals is associated with increased support for populist radical right parties (Golder 2003) or that the inward immigration rate is associated with greater support (Arzheimer 2009). While all but one specification has the predicted positive sign, only one is significant.

**Table B.1: Main Regression with Controls**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | (1) | (2) | (3) | | (4) | | (5) | | (6) | | (7) | | (8) | | (9) | |
| Outsider | .06  (.05) | .04  (.05) | .03  (.05) | | .20\*\*  (.10) | | .27\*\*  (.11) | | .32\*\*  (.14) | | .08  (.22) | | .03  (.25) | | .13  (.26) | |
| Outsider X LMRI |  | -.11\*\*  (.05) |  |  | | .42\*\*\*  (.12) | |  | |  | | .82\*\*\*  (.30) | |  | |
| Outsider X EPL | -.07\*  (.04) |  | -.11\*\*  (.05) | | .40\*\*  (.18) | |  | | .53\*\*  (.24) | | 1.70\*\*\*  (.54) | |  | | 1.83  (.52)\*\*\* | |
| Outsider X ALMP |  |  | .12\*  (.06) | |  | |  | | -.27\*\*\*  (.10) | |  | |  | | .54  (.49) | |
| Outsider X PLMP |  | -.04  (.05) | -.04  (.07) | |  | | .38\*\*\*  (.15) | | .17  (.14) | |  | | .92\*\*  (.40) | | -.51  (.53) | |
| Ideology | -.14\*\*\*  (.02) | .14\*\*\*  (.02) | -.14\*\*\*  (.02) | | .25\*\*\*  (.06) | | .24\*\*\*  (.06) | | .25\*\*\*  (.06) | | .30\*\*\*  (.05) | | .29\*\*\*  (.04) | | .30\*\*\*  (.05) | |
| Union Member | .95\*\*\*  (.03) | .95\*\*\*  (.03) | .95\*\*\*  (.03) | | -.18\*\*  (.09) | | -.22\*\*\*  (.07) | | -.21\*\*\*  (.07) | | -.10  (.12) | | -.13  (.13) | | -.09  (.12) | |
| Age | -.12\*\*\*  (.01) | -.16\*\*\*  (.01) | -.12\*\*\*  (.02) | | -.00  (.03) | | -.00  (.03) | | .00  (.02) | | -.10\*\*  (.04) | | -.10\*\*  (.04) | | -09\*\*  (.04) | |
| Female | .15\*\*\*  (.02) | .15\*\*\*  (.02) | .15\*\*\*  (.02) | | -.09  (.06) | | -.10\*  (.05) | | -.10\*  (.06) | | -.19\*\*  (.08) | | -.20\*\*  (.08) | | -.20\*\*  (.08) | |
| Income | -.02\*\*  (.01) | -.01\*\*  (.01) | -.02\*\*  (.01) | | .02  (.02) | | .01  (.03) | | .02  (.03) | | -.10\*\*\*  (.03) | | -.13\*\*\*  (.04) | | -.08\*\*  (.04) | |
| Education | -.02\*\*\*  (.01) | -.02\*\*\*  (.01) | -.02\*\*\*  (.01) | | -.00  (.03) | | .00  (.03) | | -.00  (.03) | | -.13\*\*\*  (.04) | | -.11\*\*\*  (.04) | | -.14\*\*\*  (.04) | |
| Immigration |  |  |  | | .12\*  (.06) | | .15\*\*  (.08) | | .12\*  (.06) | | .51\*\*\*  (.08) | | .52\*\*\*  (.08) | | .50\*\*\*  (.08) | |
| LMRI |  | .07  (.05) |  | |  | | -.39  (.36) | |  | |  | | -.56  (.49) | |  | |
| EPL | .19\*\*\*  (.07) |  | .22\*\*\*  (.08) | | -2.16\*\*  (1.00) | |  | | -2.15  (.90)\*\* | | -2.93\*\*\*  (1.11) | |  | | -3.03  (1.03)\*\*\* | |
| ALMP |  |  | -.05  (.06) | |  | |  | | .15  (.40) | |  | |  | | -.59  (.89) | |
| PLMP |  | .02  (.08) | .01  (.07) | |  | | .20  (.73) | | .31  (.77) | |  | | -.44  (.74) | | .99  (1.22) | |
| GINI | -12.00\*\*\*  (2.30) | -12.49\*\*\*  (2.67) | -12.15\*\*\*  (2.62) | | -31.47\*\*  (15.27) | | -22.83  (16.58) | | -27.64\*  (16.71) | | 8.96  (16.70) | | -2.77  (14.16) | | 15.29  (16.10) | |
| logGDP | -2.02\*\*\*  (.38) | -1.94  (.41)\*\*\* | -2.08  (.39)\*\*\* | | -3.56  (2.69) | | -5.76\*\*  (2.38) | | -3.22  (2.37) | | 2.27  (4.57) | | -4.23  (3.28) | | 2.03  (4.21) | |
| GDP Growth | -.01  (.01) | -.01  (.01) | -.01  (.01) | | .02  (.15) | | -.00  (.14) | | .04  (.15) | | -.39\*\*  (.15) | | -.51\*\*  (.21) | | -.38\*\*  (.`16) | |
| Unemp. | -.01  (.01) | -.00  (.01) | -.01  (.01) | | .23  (.19) | | .00  (.15) | | .18  (.21) | | .23  (.16) | | .05  (.15) | | .15  (.21) | |
| Union  Density | -.03\*\*\*  (.01) | -.03\*\*\*  (.01) | -.03\*\*\*  (.01) | |  | |  | |  | |  | |  | |  | |
| Imm. Rate |  |  |  | | .64  (.70) | | 1.30\*  (.78) | | .71  (.72) | | -.93  (1.07) | | .91  (.75) | | -.81  (.89) | |
| ENPP |  |  |  | | -.32  (.60) | | .04  (.66) | | -.44  (.76) | | -.56  (.58) | | .31  (.41) | | -.64  (.59) | |
| DV | Unions | Unions | Unions | | Parties-Issues | | Parties-Issues | | Parties-Issues | | Parties-List | | Parties-List | | Parties-List | |
| R2 | .06 | .06 | .06 | | .20 | | .18 | | .21 | | .39 | | .36 | | .39 | |
| N | 49597 | 49597 | 49597 | | 30230 | | 30230 | | 30230 | | 24077 | | 24077 | | 24077 | |
| Level 2 N | 70 | 70 | 70 | | 60 | | 60 | | 60 | | 50 | | 50 | | 50 | |
|  |  |  |  | |  | |  | |  | |  | |  | |  | |

***Note:*** Standard errors clustered by country-year. \* p<.1, \*\* p<.05, \*\*\* p<.01.

**Different Codings of Outsiders**

In this section, I provide a variety of robustness checks for the main results, including using different codings of outsiders, different types of specifications, and jackknife tests where I run the main specifications repeatedly dropping individual countries and years. Table B.2 presents fixed effects regressions for the main specification (Outsider X LMRI) with three different codings of outsider: (1) considering all part-time and unemployed workers as outsiders, but not accounting for the employment status of others in the household and not dropping individuals who are likely not searching for work (columns 1-3); (2) coding just unemployed workers as outsiders, again, not accounting for household employment status or dropping those not in the labor market (columns 4-6); (3) counting just part-time workers as outsiders, not accounting for household employment status or dropping those not in the labor market, and dropping the unemployed (columns 7-9).

As we can see in columns 1-3, the simpler, respondent employment status-based coding of outsider produces similar results to the more complicated coding in the paper, which also accounts for employment status of others in the household. The regressions for the narrower definitions of outsider in columns 4-9 all have the same signs as the main result and the part-time/unemployed coding, but the results are mostly non-significant. These results could be due to smaller sample sizes—the effect magnitudes are similar across the different outsider codings but the standard errors are a bit larger for the unemployed and part-time codings. Another possible explanation is that in the unemployment codings I am now counting part-timers as insiders and for the part-time codings, I am dropping the unemployed, who should be considered outsiders. Both should create downward bias in the results. I would interpret the lack of results for these separate codings as evidence that the theory only holds when both are considered outsiders.

**Table B.2: Different Codings of Outsiders**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Outsider | .01  (.02) | .04  (.07) | .16\*  (.10) | -.12  (.04)\*\*\* | -.06  (.12) | .17  (.14) | .09\*\*\*  (.03) | .09  (.12) | .12  (.16) |
| Outsider X LMRI | -.06\*\*  (.03) | .12\*\*  (.06) | .20\*\*\*  (.07) |  |  |  |  |  |  |
| Unemployed X LMRI |  |  |  | -.07  (.05) | .08  (.09) | .34\*  (.19) |  |  |  |
| Part-Time X LMRI |  |  |  |  |  |  | -.04  (.02) | .14\*  (.08) | .13  (.12) |
| DV | Unions | Parties-Issues | Parties-List | Unions | Parties-Issues | Parties-List | Unions | Parties-Issues | Parties-List |
| R2 | .05 | .18 | .34 | .05 | .18 | .34 | .06 | .18 | .34 |
| N | 64136 | 40413 | 32773 | 64136 | 40413 | 32773 | 60663 | 38432 | 31254 |
| Level 2 N | 68 | 59 | 50 | 68 | 59 | 50 | 68 | 59 | 50 |

***Note:*** Regressions contain all of the same controls as in table 1. All regressions include fixed effects for country and year. Standard errors clustered by country-year. \* p<.1, \*\* p<.05, \*\*\* p<.01.

**Multi-Level Models, OLS Fixed Effects Regressions**

Table B.3 contains two types of additional robustness checks: (1) Outsider X LMRI in random effects multi-level models (columns 2, 5, and 9); (2) Outsider X LMRI and the specifications which split EPL and ALMP with OLS plus country and year fixed effects.

As we can see in columns 1, 4, and 7, the random effects multi-level model are substantively very similar to those in the fixed effects regressions in table 1 of the main text. The OLS fixed effects results are mostly similar to the ordered logit and logit results in table 1, although some of the results for parties are a bit weaker. The main specification for the list-based coding of parties still has a positive coefficient, but this is no longer significant. Outsider X EPL remains positive and significant in the specification which split EPL and ALMP, but Outsider X ALMP is no longer significant (but has the correct sign) for the issue-based coding of parties and remains insignificant for the list-based coding. While not every result is robust to using OLS with fixed effects, most of the main results are.

**Table B.3: Robustness Checks: Multi-Level Models, OLS with Fixed Effects.**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Outsider | .04  (.04) | .01  (.02) | .01  (.02) | .35\*\*\*  (.13) | .02\*\*  (.01) | .02\*\*  (.01) | -.01  (.21) | -.00  (.00) | .00  (.00) |
| Outsider X LMRI | -.09\*\*\*  (.03) | -.04\*\*  (.02) |  | .42\*\*\*  (.12) | .03\*\*\*  (.01) |  | .76\*\*\*  (.26) | .01  (.01) |  |
| Outsider X EPL |  |  | -.04\*\*  (.02) |  |  | .03\*\*  (.01) |  |  | .015\*\*  (.007) |
| Outsider X ALMP |  |  | .04\*  (.02) |  |  | -.02  (.01) |  |  | .00  (.00) |
| DV | Unions | Unions | Unions | Parties-Issues | Parties-Issues | Parties-Issues | Parties-List | Parties-List | Parties-List |
| R2 |  | .12 | .12 |  | .14 | .16 |  | .15 | .16 |
| N | 49597 | 49597 | 49597 | 30230 | 32253 | 32253 | 25015 | 31852 | 31852 |
| Level 2 N | 70 | 70 | 70 | 60 | 63 | 63 | 52 | 63 | 63 |
| Model Type | Multi-Level  Ordered  Logit | OLS-Fixed Effects | OLS-Fixed Effects | Multi-Level  Logit | OLS-Fixed Effects | OLS-Fixed Effects | Multi-Level  Logit | OLS-Fixed Effects | OLS-Fixed Effects |
|  |  |  |  |  |  |  |  |  |  |

***Note:*** Regressions contain all of the same controls as in table 1. OLS regressions include fixed effects for country and year. \*p<.1, \*\* p<.05, \*\*\* p<.01.

**Jackknife Tests**

I order to address concerns about the sensitivity of the results to individual countries and years, I perform a series of jackknife tests where I individually drop countries and years. For the union regressions, the results were robust to dropping each country, except Sweden. The sign on Outsider X LMRI when I dropped Sweden was still negative, but with p≈.16. This could perhaps be due to loss of observations because dropping it resulted in a loss of about 3,600 observations (from 49,597 to 45,931). The union results were also robust to dropping each wave except 1999, which has the correct negative sign, but with p≈.12. This is also likely due to a decline in sample size, in this case from 49,597 to 37,603.

For the manifestos-based coding of parties, the results are robust to dropping each country individually. The results are somewhat sensitive to dropping Sweden, but Outsider X LMRI still has the correct positive sign and p≈.06. The results are robust to dropping each year individually. The results for the list-based coding of parties are robust to dropping each country individually. They are robust to dropping each year individually except 1999, as in the union regressions. The loss of sample size here is more severe—the sample declines from 24,077 to 13,793. Nevertheless, Outsider X LMRI has the correct positive sign and is almost significant at a conventional level (p≈.14).

Overall, I would argue that the main results are robust to these jackknife tests. Of 110 regressions (27 countries X 3 variables + 13 years X 3 variables), the results are robust to all but 3. These three regressions have the correct sign and have p≈.16, p≈.12, and p≈.14 respectively.

1. See table B.2 columns 1-3 for robustness checks with a measure of outsider that does not drop these individuals. [↑](#footnote-ref-1)
2. Quasi-sentences are either a complete natural sentence or a fragment of one. There may be multiple quasi-sentences expressing positions on different policy categories within a single natural sentence. [↑](#footnote-ref-2)
3. Some have done substantially better than this, with the Swiss People's Party and the Austrian FPÖ reaching totals above 20% (Mudde 2013). [↑](#footnote-ref-3)
4. One variable which, unfortunately, is not consistently available in the EVS/WVS is the respondent's ethnic background. We might expect this in particular to affect support for populist radical right parties. If anything, however, this should downward-bias the results for populist radical right parties; ethnic minorities are more likely to be outsiders, but would be less likely than non-minorities to support populist radical right parties. The direction of bias for trade union support is less clear, but it is unlikely that minority outsiders would be more likely to support trade unions than other outsiders. [↑](#footnote-ref-4)