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Conference Paper

Near Is My Shirt, But Nearer Is My Skin: Ideology or Self-Interest as Determinants of Public Opinion on Fiscal Policy Issues

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Near Is My Shirt, But Nearer Is My Skin: Ideology or Self-Interest as Determinants of Public Opinion on Fiscal Policy Issues

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Abstract

Several empirical studies derive that personal positions with respect to policy measures are dominated by ideology instead of narrow self-interest. In the present field study we carried out a telephone survey with 1.003 respondents all over Austria. Instead of only measuring self-interest indirectly, we requested respondents to assess directly whether they expect to be affected by policy measures. Our results indicate that such a subjectively measured narrow self-interest explains attitudes towards economic policies at least as good as ideological conviction. In some cases, however, ideology appears to determine whether people feel affected by a proposed policy measure.

Key words: public opinion, sociotropic voting, ideology, self-interest, telephone surveys

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1 Introduction

Which factors determine public opinion on economic policy issues? How do people derive their personal positions with respect to policy measures? Although these questions are at the heart of an understanding of voting behavior and, probably, for the making of economic policies in democratic societies (*Page and Shapiro, 1983*), Public Choice theory still lacks a unique conception about the process of individual preference formation and voter motivation. Somewhat simplifying, two broad lines of reasoning to explain opinion formation can be separated, an egocentric (self-interest) approach and a sociotropic approach.

Simple rational choice theory claims that individual attitudes towards economic policies are determined by narrow self-interest. Individuals know what is in their own interest and make choices accordingly. Based on perceptions of the individual costs and benefits people develop expectations about the net effects of policies on their personal well-being. If the expected effect of a certain policy measure is positive, the respective citizen-voters are in favor of it. All that is required for an accurate determination of individual attitudes towards some specific policy measure is an assessment of the economic consequences on personal well-being. Hence, from this point of view individual opinion is exclusively shaped by egocentric motivation.

This view is often criticized. First, it is argued that an average person does not have the capability to calculate the individual costs and benefits of most policy measures. She/he usually lacks the technical knowledge and the information to gauge the personal consequences of certain policy measures on her/his personal well-being. Second, rational citizen-voters usually do not have an incentive to become informed about economic policy issues. As the cost of acquiring information are positive and the individual impact of an informed vote on final election outcomes is negligible, citizen-voters should remain rationally ignorant with respect to the effects of most policy issues.

Attitudes towards economic policies are then often driven by ideological convictions (*Downs, 1957*). Party ideologies serve as a substitute for the individual cost of acquiring political and economic information. Yet such ideologically shaped opinions might still be consistent with self-interested behavior. Rational individuals 'choose' a certain ideology as an information short-cut, and their choice depends on which ideological party affiliation is expected to suit best to selfish motives. In many cases ideological and self-interested opinion formation are therefore not easily separable.

A somewhat different thinking dominates the sociotropic approach. According to this view, when forming opinions about economic policies, people have a normative view of the world in mind, i.e. a notion how it 'should' be (*Denzau and North, 1994*). Ideas and ideologies matter in particular in collective choices, as people do not have an incentive to collect information. According to the theory of low-cost decisions and expressive voting (see e.g. *Kirchgässner and Pommerehne, 1993; Brennan and Lomansky, 1993*) supporting or opposing a specific economic policy has no direct consequences for personal well-being, as individual action does not have an effect on the overall outcome. In such a situation it is almost without personal costs to express ideological convictions that are not necessarily in accordance with narrow self-interest. On the contrary, in the market sphere decisions which are only based on ideological judgments are associated with high costs as the consequences of a decision are borne by the decider. Hence, due to the low cost character of expressing preferences in the political sphere, ideology and a personal conception of "the common good" are stronger motives in

individual voting behaviour and may thus explain opinion formation much better than pure self-interest.

Empirical investigations of individual and collective opinion formation so far often support the latter view. Studies from the fields of economics, sociology and political science show an increasing interest in the topic of self-interest and opinions on economic policy issues and address the question of the empirical relevance of former assumptions (see *Citrin and Green, 1990; Sears and Funk, 1990; MacKuen et al., 1992; Mutz, 1993; Holbrook and Garand, 1996; Krause, 1997; Fuchs et al. 1998; Boeri and Tabellini, 2005*). In general, these studies find (often based on the 1996 “*Survey of Americans and Economists on the Economy*”) that attitudes towards economic policy issues deviate with a systematic bias from self-interest, i.e. the opinion whether a specific economic policy should be carried out is often not systematically related to egoistic motivations. Empirical studies for the U.S. (*Walstad, 1997; Caplan, 2001, 2002, 2006*) and for Germany (*Heinemann et al., 2007*) conclude that knowledge and ideology are of special relevance in explaining the bias, or are even the main determinants of opinion formation.

In a widely recognized recent paper, *Blinder and Krueger (2004)* use a specially designed telephone survey to address the problem of opinion formation on economic policy issues in the U.S. A main result of their study is that public opinion on the quality and adequacy of economic policies is mainly driven by ideological factors. With respect to policy issues like taxes, budget deficits, minimum wages, social security, and health insurance, ideology is the most consistently important determinant of individual preferences and policy acceptance, whereas objective measures of self-interest are the least important. These findings seem consistent with the idea that people use ideology as a short cut for deciding which position to take, especially when informing oneself is costly. *Blinder and Krueger (2004)* report that in many cases respondents in the telephone survey seem to have answered against their narrow self-interest, which is proxied by 'objective' variables, most notably household income.

Yet it is somewhat questionable whether narrow self-interest can be measured objectively. What matters eventually is what people *believe* to be in their self-interest. *Blinder and Krueger* have in mind a specific economic model on how certain individuals are affected by particular economic policies. In general there is no guarantee that the *Blinder-Krueger* economic view of the world is identical to what respondents think about the working properties of an economy. Most probably, this is not the case, as laymen usually have a different view of the economic world (*Caplan, 2001*). If we want to know whether people systematically neglect their own self-interest in the process of opinion formation on economic policies in favor of an ideologically defined common good, we should have a better, i.e. a *subjective measure of self-interest*. Put differently, in order to find out if narrow self-interest is really dominated by ideological convictions and ideas of 'the public good', it is important to know which policies people perceive to be in their self-interest or not. As ideology should serve as a simple rule-of-thumb in case of a lack of knowledge, people might express ideological preferences that appear to be against their self-interest from the view of economists. However, in their own view respondents might express opinions on policy issues which they believe to be in their narrow interest. The main purpose of the present paper is to examine whether the often found dominance of ideological convictions survives if we measure self-interest more subjectively and directly.

The methodology of the present study closely follows *Blinder and Krueger (2004)*. In autumn 2008 we carried out a telephone survey with 1.003 respondents all over Austria. The survey consisted of a

series of questions about personal opinions on a variety of fiscal policy issues. In contrast to *Blinder-Krueger* we not only asked for certain 'objective' measures that appear to be related to egocentric opinion formation. We additionally requested respondents directly to assess whether they expect to benefit from certain economic and fiscal policy measures. Hence, we need not speculate about a respondent's economic view of the world and whether he/she deviates from narrow self-interest; we simply asked them. All in all, our results show that – in contrast to *Blinder and Krueger (2004)* and several other investigations –subjectively measured narrow self-interest explains attitudes towards economic policies at least as good as ideological conviction.

A usual and often heard objection is that in interviews individuals can easily express opinions for an economic policy although they know that this policy will reduce their own well-being or income. Hence, doubts have been raised about whether the questions commonly asked in opinion polls show true preferences. This is certainly correct, but it does not invalidate our results. Taking part in a public opinion survey is comparable to the act of voting. In either case, individual action does not have individual consequences. Hence, both are certainly situations in which it is not individually costly to express socially desired or ideological preferences.

The paper proceeds as follows. In section 2 we present a very short overview on the political and methodological background of the study and the telephone survey. Section 3 reports some descriptive statistics. In section 4 we present the main results of our logit-regressions and discuss the results in the light of the two different approaches to opinion formation. Section 5 concludes.

2 Political and methodological background

In September 2008 we launched a telephone survey in Austria in order to replicate and verify the results of *Blinder and Krueger (2004)* that “*ideology seems to play a stronger role in shaping opinion on economic policy issues than either self-interest or knowledge*“ for the case of Austria. Of course we adapted the methodology; in particular we focus on ideology and self-interest only, leaving out knowledge as a possible determinant in the present study. 1.003 eligible Austrian voters were interviewed over the telephone. Fieldwork covered the last days of the campaign in federal elections for the Austrian National Council in 2008 and some of the first days after the elections.

One of the main topics discussed during the election campaign was whether and in which way a reform of the income tax should be put into practice.¹ The two parties which formed a grand coalition before as well as after the elections in principle agreed on the need for an income tax reform and that the reduction should amount to approximately € 3 bn, i.e. about 1% of GDP (*Statistik Austria, 2009*). Although it was obvious that at least parts of the income tax reductions had to be financed by raising other taxes and/or by cutting expenditures in the federal budget, politicians' statements on financing the income tax reform were at best very ambiguous. Against this background we asked the participants of our survey which of the following ten policy measures would be appropriate for financing a reduction of the income tax²:

- Raising the VAT
- Raising the petroleum tax

¹ Note that in September 2008 there was still no open public debate about the possible consequences of the U.S. housing market and financial crisis on the Austrian economy.

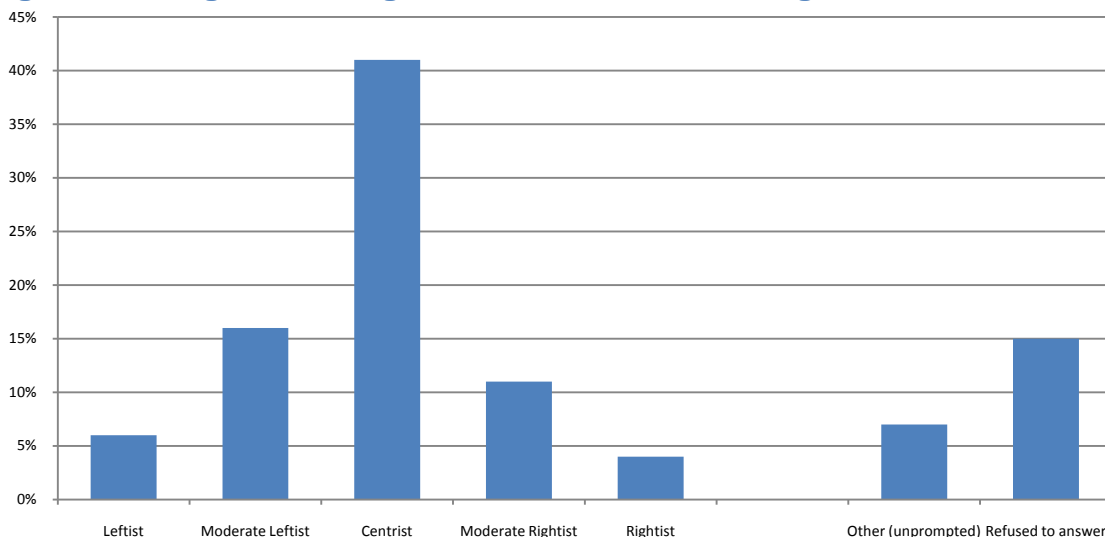
² To prevent order biases the sequence of categories was randomized.

- Raising profit taxes on public/private limited companies
- Raising environmental taxes on companies
- Impose a property or inheritance tax
- Raising the tax on capital returns
- Increasing public debt
- Cutting social security benefits
- Cutting subsidies for companies
- Cutting jobs in public administration

In stark contrast to *Blinder and Krueger* and other similar studies we did not only ask the respondents for socio-demographic characteristics, i.e. sex, age, occupation, personal income and education to assess whether they might be adversely affected by a certain policy measure, but also whether they believe this measure would have an adverse impact on them. This survey design enables us to find out how the *perceived adverse impact of a policy* measure influences its acceptance among the public.

To assess the effects of ideology on the acceptance of our policy measures we asked our interviewees to assign their political position on a five point Left-to-Right-Scale (LRS). Alternately the respondents could also choose “other” if they did not think the proposed scale matched their ideological position, or “refuse to answer” (the two latter categories were asked unprompted). Figure 1 shows the distribution of respondents' answers along the Left-to-Right-Scale. It is definitely clear that the by far largest group of people classifies itself as centrists, while the share of (moderate) leftists is slightly larger than the share of (moderate) rightists.

Figure 1: Ideological self-assignment based on the Left-to-Right-Scale



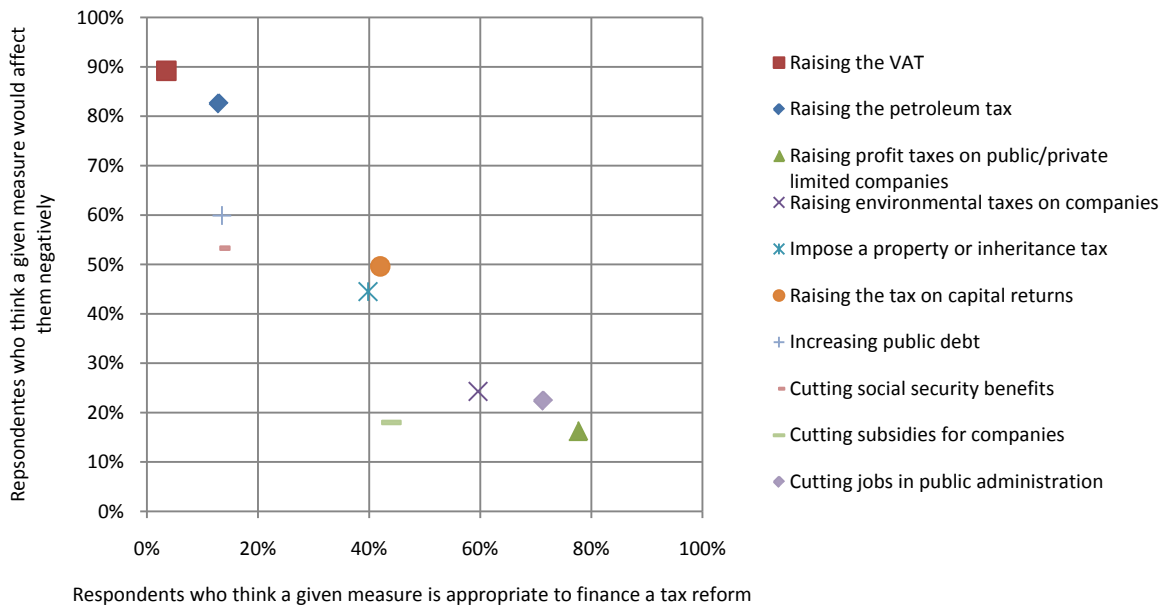
3 Descriptive Statistics

3.1 Acceptance of measures and subjective ('perceived') self-interest

Descriptive analyses reveal a clear adverse correlation between the share of respondents who suppose a given policy measure is appropriate for financing a tax reform (acceptance) and the share of respondents who think this specific measure would have an adverse impact on them (Pearson's Correlation Coefficient = -0.89). In other words: the more people expect to be adversely affected by a

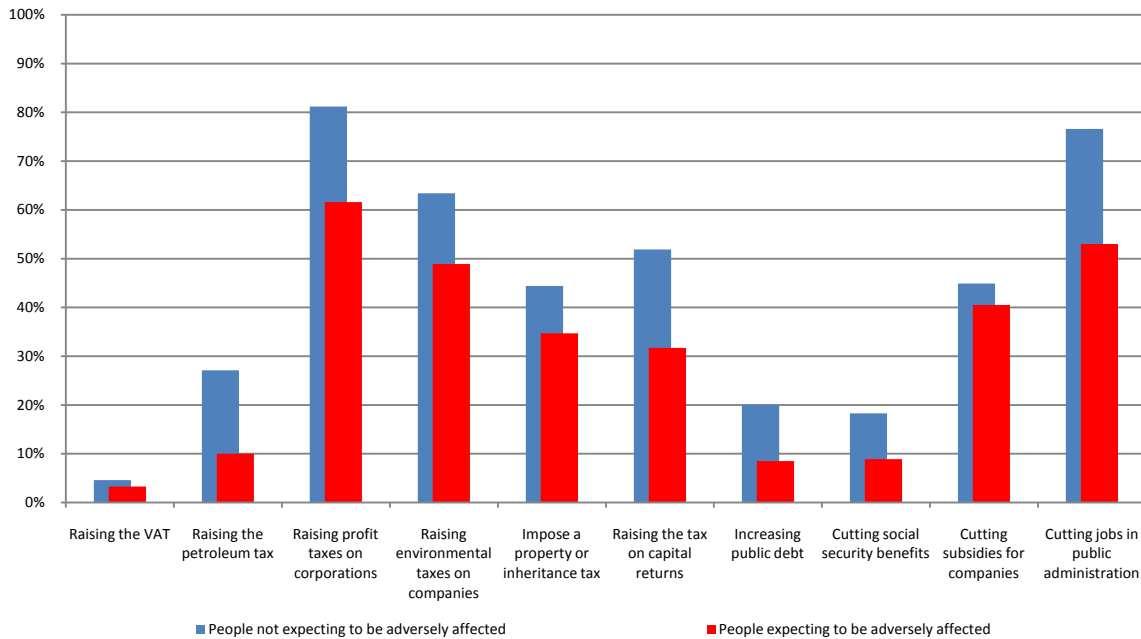
certain measure, the fewer people tend to accept this measure (see Figure 2). The least popular measure is a VAT increase, followed by an increase of the petroleum tax. Almost 80 % of the respondents think that raising profit taxes is an appropriate way to finance a personal income tax reduction, and about 70% think that savings by reducing jobs in public administration is an appropriate measure.

Figure 2: Acceptance of policy measures and average perceived personal impact



Remarkably this strong correlation does not simply imply that people who fear an adverse impact on themselves oppose a certain measure while people who do not feel affected are in favor of it. Figure 3 clearly shows that the rates of acceptance show a similar pattern for both groups (Pearson's Correlation Coefficient = 0.97), i.e. if many people feel negatively affected only few support a given measure, even among those who do not expect an adverse impact on themselves, and vice versa. However, in all cases adversely affected persons are less likely to accept a certain measure than people who do not expect a negative impact. In eight out of ten cases the difference is significant ($p < 0.05$). Only "cutting subsidies for companies" and "raising the VAT" do not show significant differences. In the latter case this is probably due to the fact that hardly anybody supports a higher VAT (4%), while a vast majority (89%) feels adversely affected by VAT increases so that there is hardly any room for a big differential among the groups.

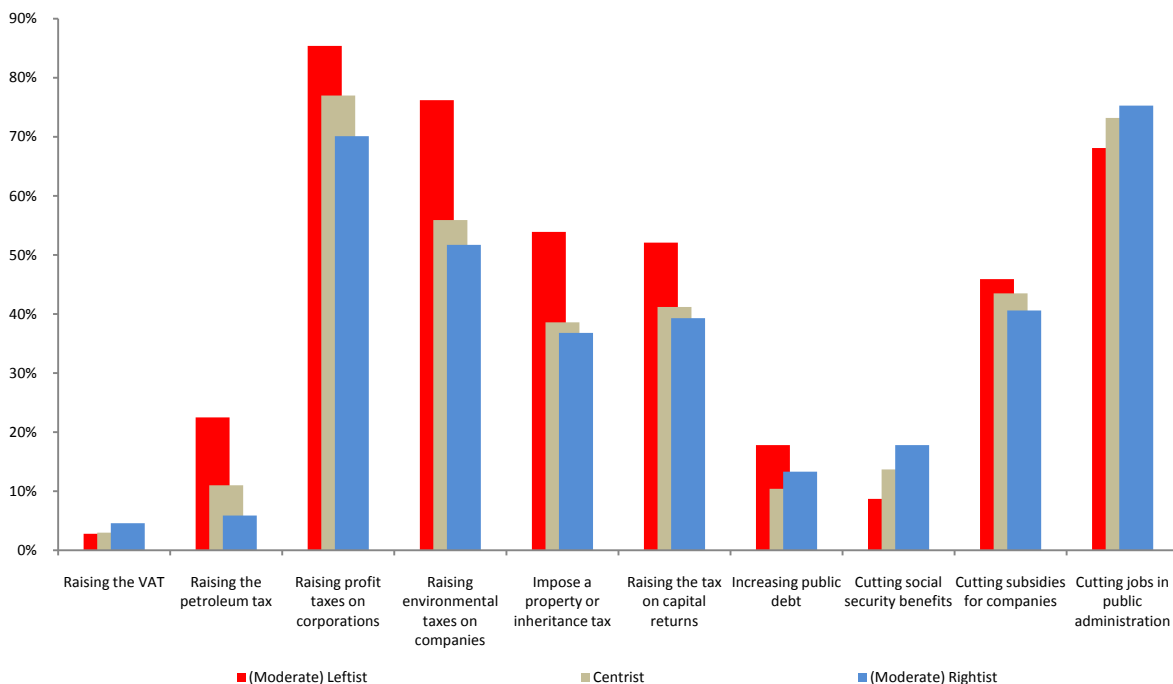
Figure 3: Acceptance of policy measures by subjective ('perceived') impact



3.3 Acceptance of measures and ideological orientation

Looking at the rates of acceptance according to ideological orientation based on the Left-to-Right-Scale³ we find a similar pattern. The rates of acceptance are highly correlated for all displayed groups (see Figure 6), while the differences between the ideological groups are significant for the same eight policy measures as above. However, while people who assign themselves to the political centre or the right agree on average with 3.5 measures and 3.4 measures respectively, leftists agree with 4.2 political measures (which are significantly more).

Figure 6: Acceptance of policy measures by political self-assignment



³ For clarity the groups "left" and "moderately left" as well as "right" and "moderately right" were merged into the groups "(moderate) leftist" and "(moderate) rightist" respectively.

Figure 5 also shows that people who declare themselves as standing 'left' in general seem to prefer tax increases (except for VAT) compared to people with a centrist or rightist ideological orientation. With respect to spending cuts differences between the ideological groups seem to disappear. Moreover, center and right ideology appear to be very closely related, while leftist ideology is much more distinct.

4 Results of logit regressions

4.1 Basic results

To analyze more deeply the impact of perceived adverse impacts and ideological orientation we ran a set of logit regressions to reveal the main drivers of acceptance of policy measures as a dependent variable. We included the following possible determinants of acceptance into our models:

1. "Subjective" self-interest
 - Expected adverse impact of the policy measure (dummy)
2. "Objective" self-interest
 - Occupation (set of dummies: employee in the private sector, employee in the public sector, self-employed, retired; reference group: others)
 - Personal net income (ordinal)
 - Living in a big city (100,000 inhabitants and more, dummy)
3. Ideology
 - (Moderately) leftist (dummy)⁴
4. Control variables
 - Sex (dummy)
 - Age (ordinal)
 - Educational level (ordinal)

Of course several of these variables are correlated. E.g., our survey shows that the higher the degree of education, the higher is the probability of adhering to a more left-wing ideology. However, tests of collinearity did not give any reason for concern. Interaction terms were not implemented given the methodological problems that their use causes in logit-models (see *Ai and Norton, 2003*). Seven of the ten models tested are properly specified, while for three models the chosen predictors are not meaningful, i.e. these three models fail in explaining the differences in the acceptance of the respective policy measures. The remaining seven models yield Pseudo-R² ranging from 0.16 – which we suppose to be acceptable – to rather limited 0.03.

Summing up results of our estimates we find that perceived adverse personal consequences of a policy measure have a significant impact on the acceptance of this measure in all seven properly specified models (at the 95%-level, see Table 1). The signs of the coefficients are – as expected – negative in all those cases, i.e. the acceptance of a policy measure is systematically lower among persons who expect to be adversely affected personally. This means that (perceived) self-interest clearly plays

⁴ As the descriptive results showed clear differences between (moderate) leftists on the one hand and centrists and (moderate) rightists on the other hand, the ordinary left-to-right-scale has been recoded into a dummy variable indicating whether a respondent declared herself as (moderately) left or not. Respondents who did not assign themselves to the left-to-right-scale (i.e. refused to answer or answered that the categories appropriate for them) were omitted from further analyses.

a remarkable if not dominant role – compared to ideology - in forming personal opinions on policy measures.

Personal net income, which is regularly used as a variable to proxy self-interest in many empirical investigations, is insignificant in all models. From an egoistic model of opinion formation, we would at least have expected that a higher net income is also associated with an increasing probability of acceptance of cuts in social benefits and a reduced acceptance of property tax increases in order to finance income tax reductions. With respect to occupation/profession as a determinant of objective self-interest, we find that public sector employees support profit tax and inheritance tax increases to a higher degree than other groups of persons. Somewhat surprisingly they do not oppose job cuts in the public sector significantly more often than other vocational groups. Interestingly people living in big cities (> 100.000 inhabitants) have a lower probability of accepting job cuts in the public sector than people from less urban areas. We suppose that this results from the large number of public sector employees living in the big cities where most of the workplaces in public administrations are located.

Remarkably, the share of opponents of higher petroleum taxes rises with the respondents' age. This is counterintuitive as older people (above 65) are less likely to have access to cars (*Herry and Sammer, 1998*) and therefore are less prone to increased petroleum taxes. Consistently they also feel adversely affected by higher petroleum taxes to a lesser extent than younger peer groups. We guess this contradiction between the low rate of adverse consequences and the high rate of refuse reflects differences in the valuation of private transport among different peer groups and might therefore indicate that ideological positions beyond political attribution might play a significant role in the opinion formation.

Political ideology plays a significant role in five of the seven proper models. Ideological left-wingers are systematically likelier to accept tax rises as policy measures than self-declared right-wingers and centrists, even when we control for objective and subjective self-interest as well as a number of further socio-economic variables. Somewhat surprisingly left-wingers are not significantly more dismissive towards cutting social security benefits than centrists and rightists.

Table 1: Acceptance of policy measures by several determinants (logit models, full specification)

	Pseudo R ²	Sub- jec- tive self- inter- est Expected adverse consequences of measure	Objective self-interest						Ide- ology (Moderate) Leftist	Control variables		
			Employee in the private sector	Employee in the public sector	Self-employed	Retired	Personal monthly net income	Living in a big city		Sex	Age	Educational level
Increasing VAT	0.14								↑		↑	
Increasing the petroleum tax	0.16	↓						↑		↓	↑	
Raising profit taxes on public/private limited companies	0.07	↓		↑				↑			↓	
Raising environmental taxes on companies	0.08	↓					↑	↑		↓		
Impose a property or inheritance tax	0.03	↓		↑				↑			↑	
Raising the tax on capital returns	0.06	↓						↑				
Increasing public debt	0.05	↓										
Cutting social security benefits	0.07	↓										
Cutting subsidies for companies	0.01											
Cutting jobs in public administration	0.08	↓								↑		

Expected adverse consequences of measure: 0 = No, 1 = Yes

Occupation (Employee in the private sector/Employee in the public sector/Self-employed/Retired): 0 = No, 1 = Yes, Other = Reference group

Living in a big city: 0 = No, 1 = Yes

Personal monthly net income: 1 = none, 2 = Up to 1000 €, 3 = 1001 to 1500 €, 4 = 1501 to 2000 €, 5 = 2001 to 2500 €, 6 = 2501 to 3000 €, 7 = More than 3000 €

(Moderate) Leftist: 0 = Rightist, moderate rightist, centrist, 1 = Moderate leftist, leftist

Sex: 0 = Female, 1 = Male

Age: 1 = 16 to 25 years, 2 = 26 to 35 years, 3 = 36 to 45 years, 4 = 46 to 55 years, 5 = 56 to 65 years, 6 = 65 years and older

Educational level: 1 = Compulsory education attendance, 2 = Apprenticeship, 3 = Vocational school, 4 = Abitur (British A-Level), 5 = University (of applied sciences)

↑ ... Positive coefficient, significant at the 95%-level

↓ ... Negative coefficient, significant at the 95%-level

✘ ... Variable not included in the model

■ ... Model misspecified, set of chosen predictors not meaningful (linktest, hat: $p > 0.05$)

■ ... Model misspecified, unobserved predictors or interactions probable (linktest, hatsq: $p < 0.05$)

4.2 Alternative specifications

To get a picture on how subjective and objective self-interest and ideology mutually impair each other we ran alternative specifications of the models introduced above. By omitting the subjective ('perceived') self-interest the indicators of objective self-interest become more important in explaining the acceptance of policy measures (Table 2). The number of significant cases of objective self-interest jumps from 4 to 10 out of 42 possible cases (6 variables x 7 valid models). Public sector employees, for example, now are less likely to accept job cuts in the public sector than other occupational groups, while self-employed are more in favor of lowering public security benefits than others. This shows that subjective ("perceived") self-interest corresponds to people's objective self-interest.

While in our basic model-setting ideology does not correspond significantly – and somewhat surprisingly – with the proposition of cutting social security benefits, by omitting the perceived self-interest from the model ideology becomes a significant predictor of people's attitudes towards this policy measure: leftists now are significantly less likely to acclaim to cutting social security benefits than centrists and rightists.

Table 2: Acceptance of policy measures by several determinants (logit models without 'subjective' – perceived - self-interest)

	Pseudo R ²	Sub-jective self-interest Expected adverse consequences of measure	Objective self-interest						Ide-ology (Moderate) Leftist	Control variables		
			Employee in the private sector	Employee in the public sector	Self-employed	Retired	Personal monthly net income	Living in a big city		Sex	Age	Educational level
Increasing VAT	0.13	✘							↑		↑	
Increasing the petroleum tax	0.12	✘					↑	↑		↓	↑	
Raising profit taxes on public/private limited companies	0.05	✘		↑				↑			↓	
Raising environmental taxes on companies	0.07	✘					↑	↑		↓		
Impose a property or inheritance tax	0.03	✘		↑				↑			↑	
Raising the tax on capital returns	0.03	✘	↑				↓	↑	↑			
Increasing public debt	0.02	✘						↑				
Cutting social security benefits	0.04	✘			↑			↓				
Cutting subsidies for companies	0.01	✘										
Cutting jobs in public administration	0.06	✘		↓				↓		↑		

Expected adverse consequences of measure: 0 = No, 1 = Yes

Occupation (Employee in the private sector/Employee in the public sector/Self-employed/Retired): 0 = No, 1 = Yes, Other = Reference group

Living in a big city: 0 = No, 1 = Yes

Personal monthly net income: 1 = none, 2 = Up to 1000 €, 3 = 1001 to 1500 €, 4 = 1501 to 2000 €, 5 = 2001 to 2500 €, 6 = 2501 to 3000 €, 7 = More than 3000 €

(Moderate) Leftist: 0 = Rightist, moderate rightist, centrist, 1 = Moderate leftist, leftist

Sex: 0 = Female, 1 = Male

Age: 1 = 16 to 25 years, 2 = 26 to 35 years, 3 = 36 to 45 years, 4 = 46 to 55 years, 5 = 56 to 65 years, 6 = 65 years and older

Educational level: 1 = Compulsory education attendance, 2 = Apprenticeship, 3 = Vocational school, 4 = Abitur (British A-Level), 5 = University (of applied sciences)

↑ ... Positive coefficient, significant at the 95%-level

↓ ... Negative coefficient, significant at the 95%-level

✘ ... Variable not included in the model

... Model misspecified, set of chosen predictors not meaningful (linktest, hat: $p > 0.05$)

... Model misspecified, unobserved predictors or interactions probable (linktest, hatsq: $p < 0.05$)

Omitting ideology as a predictor changes the set of properly specified models somewhat (Table 3). While this modification does not change the impact of perceived self-interest, it moderately raises the number of cases where objective measures of self-interest have a significant impact on the acceptance of policy measures from 4 out of 42 possible cases to 5 out of 48 (as now 8 models are properly specified). Three of these 5 cases occur in a specific model, i.e. apply to the acceptance of job cuts in the public sector. We therefore conclude that ideology and objective self-interest are only loosely related – at least as far as our set of objective measures is concerned.

Table 3: Acceptance of policy measures by several determinants (logit models without ideological orientation)

	Pseudo R ²	Sub- jec- tive self- inter- est Expected adverse consequences of measure	Objective self-interest						Ide- ology (Moderate) Leftist	Control variables		
			Employee in the private sector	Employee in the public sector	Self-employed	Retired	Personal net income	Living in a big city		Sex	Age	Educational level
Increasing VAT	0.10								✘	↑		↑
Increasing the petroleum tax	0.14	↓							✘	↑	↓	↑
Raising profit taxes on public/private limited companies	0.05	↓		↑					✘			↓
Raising environmental taxes on companies	0.06	↓					↑		✘		↓	
Impose a property or inheritance tax	0.02	↓							✘			↑
Raising the tax on capital returns	0.05	↓							✘			
Increasing public debt	0.05	↓							✘			
Cutting social security benefits	0.06	↓							✘	↑		
Cutting subsidies for companies	0.01								✘			
Cutting jobs in public administration	0.08	↓		↓	↑			↓	✘		↑	

Expected adverse consequences of measure: 0 = No, 1 = Yes

Occupation (Employee in the private sector/Employee in the public sector/Self-employed/Retired): 0 = No, 1 = Yes, Other = Reference group

Living in a big city: 0 = No, 1 = Yes

Personal monthly net income: 1 = none, 2 = Up to 1000 €, 3 = 1001 to 1500 €, 4 = 1501 to 2000 €, 5 = 2001 to 2500 €, 6 = 2501 to 3000 €, 7 = More than 3000 €

(Moderate) Leftist: 0 = Rightist, moderate rightist, centrist, 1 = Moderate leftist, leftist

Sex: 0 = Female, 1 = Male

Age: 1 = 16 to 25 years, 2 = 26 to 35 years, 3 = 36 to 45 years, 4 = 46 to 55 years, 5 = 56 to 65 years, 6 = 65 years and older

Educational level: 1 = Compulsory education attendance, 2 = Apprenticeship, 3 = Vocational school, 4 = Abitur (British A-Level), 5 = University (of applied sciences)

↑ ... Positive coefficient, significant at the 95%-level

↓ ... Negative coefficient, significant at the 95%-level

✘ ... Variable not included in the model

■ ... Model misspecified, set of chosen predictors not meaningful (linktest, hat: p > 0.05)

■ ... Model misspecified, unobserved predictors or interactions probable (linktest, hatsq: p < 0.05)

Removing the objective measures of self-interest from our basic models leaves the impact of perceived self-interest on the acceptance of policy measures unchanged (Table 4). The number of cases where ideology plays a significant role goes up from 5 to 6 out of 7 properly specified models. As the set of properly specified models differs from our basic specification a significant influence of ideology emerges for two policy measures which did not show a significant impact of ideology in the basic setting. Leftists oppose cutting social security benefits significantly more often than centrists and rightists when subjective self-interest is not included in the model specification.

Table 4: Acceptance of policy measures by several determinants (logit models without 'objective' self-interest)

	Pseudo R ²	Sub- jec- tive self- inter- est Expected adverse consequences of measure	Objective self-interest							Ide- ology (Moderate) Leftist	Control variables		
			Occupation								Sex	Age	Educational level
			Employee in the private sector	Employee in the public sector	Self-employed	Retired	Personal monthly net income	Living in a big city					
Increasing VAT	0.09		✘	✘	✘	✘	✘	✘		↑	↓		
Increasing the petroleum tax	0.14	↓	✘	✘	✘	✘	✘	✘	↑		↓	↑	
Raising profit taxes on public/private limited companies	0.05	↓	✘	✘	✘	✘	✘	✘	↑				
Raising environmental taxes on companies	0.07	↓	✘	✘	✘	✘	✘	✘	↑		↓		
Impose a property or inheritance tax	0.03	↓	✘	✘	✘	✘	✘	✘	↑			↑	
Raising the tax on capital returns	0.04	↓	✘	✘	✘	✘	✘	✘	↑				
Increasing public debt	0.05	↓	✘	✘	✘	✘	✘	✘					
Cutting social security benefits	0.06	↓	✘	✘	✘	✘	✘	✘	↓		↓		
Cutting subsidies for companies	0.01		✘	✘	✘	✘	✘	✘					
Cutting jobs in public administration	0.06	↓	✘	✘	✘	✘	✘	✘		↑	↑	↑	

Expected adverse consequences of measure: 0 = No, 1 = Yes

Occupation (Employee in the private sector/Employee in the public sector/Self-employed/Retired): 0 = No, 1 = Yes, Other = Reference group

Living in a big city: 0 = No, 1 = Yes

Personal monthly net income: 1 = none, 2 = Up to 1000 €, 3 = 1001 to 1500 €, 4 = 1501 to 2000 €, 5 = 2001 to 2500 €, 6 = 2501 to 3000 €, 7 = More than 3000 €

(Moderate) Leftist: 0 = Rightist, moderate rightist, centrist, 1 = Moderate leftist, leftist

Sex: 0 = Female, 1 = Male

Age: 1 = 16 to 25 years, 2 = 26 to 35 years, 3 = 36 to 45 years, 4 = 46 to 55 years, 5 = 56 to 65 years, 6 = 65 years and older

Educational level: 1 = Compulsory education attendance, 2 = Apprenticeship, 3 = Vocational school, 4 = Abitur (British A-Level), 5 = University (of applied sciences)

↑ ... Positive coefficient, significant at the 95%-level

↓ ... Negative coefficient, significant at the 95%-level

✘ ... Variable not included in the model

... Model misspecified, set of chosen predictors not meaningful (linktest, hat: p > 0.05)

... Model misspecified, unobserved predictors or interactions probable (linktest, hatsq: p < 0.05)

Summarizing, people who expect adverse effects of a certain policy measure on themselves are less likely to assent to this specific measure. Subjective (perceived) self-interest therefore turns out to be a valid and robust indicator of the acceptance of policy measures – given that large proportions of the observed variance remain unexplained. The same holds true for ideology – given raising taxes is the topic. Leftists are clearly in favor of tax increases compared to centrists and rightists. Attitudes towards cutting public expenses seem to be unaffected by ideological orientation when subjective and/or objective measures of self-interest are taken into account. Only after removing variables representing self-interest from the models the impression of an ideological bias emerges, i.e. that leftists are more reluctant to cuts in public spending than centrists and rightists.

4.2 Ideology and perceived adverse affection

To complete the picture and to find out whether ideology has an impact on the expectations of adverse impacts stemming from policy measures we ran similar logit regressions as above on the acceptance of policy measures: the model specification stays in principle the same while – of course – the expected adverse impact is now the dependent variable.

In principle, we should not expect ideological convictions to have a significant impact on people's perception of the consequences of specific policy measures: whether an action affects a person ad-

versely is not a question of ideology or political belief. Nevertheless, the results presented above indicate some interaction of ideology and (perceived) self-interest. All in all our models do not cope very well with this task. Only four out of ten models are properly specified (Table 5). This might be interpreted as an indication that in these cases ideology – on the one hand – does not contribute much in explaining perceived self interest, as the chosen set of predictors turns out to be not meaningful and/or unobserved predictors (including unobserved interaction effects) are indicated. In these cases the same is true for our objective measures of self-interest, suggesting that the concept of subjective self-interest covers objective interests beyond the scope of our dataset and/or only imagined interests.

Focusing on the four properly specified models we find that objective self-interest determines subject self-interest in all four cases. Most times the coefficients' signs are headed in the expected direction. Still, it is astonishing that the self-employed feel less affected by increasing the capital return tax than other groups and, moreover, that the pensioners suppose to be less prone to cuts of social security benefits than other occupational groups as their (main) income, i.e. pensions are a social security benefit. Yet, we cannot exclude that the pensioners do not identify received pension payments as a social transfer. Ideology is a significant predictor in two of the four properly specified models. This suggests that the political orientation might at least in some cases influence the perception of political measures. However, we cannot reject the possibility that ideology only proxies objective interests not operationalized in our models.

Table 5: Determinants of subjective ('perceived') adverse consequences of policy measures (logit-models)

	Pseudo R ²	Objective self-interest						Ideology (Moderate) Leftist	Control variables		
		Employee in the private sector	Employee in the public sector	Self-employed	Retired	Personal monthly net income	Living in a big city		Sex	Age	Educational level
Increasing VAT	0.06										↑
Increasing the petroleum tax	0.11					↑	↓	↓			
Raising profit taxes on public/private limited companies	0.03		↓			↑	↓	↓			
Raising environmental taxes on companies	0.03		↓	↑			↓				
Impose a property or inheritance tax	0.02							↓			↑
Raising the tax on capital returns	0.03			↓		↑					
Increasing public debt	0.01				↓						
Cutting social security benefits	0.04		↓	↓	↓						
Cutting subsidies for companies	0.08		↓				↓				
Cutting jobs in public administration	0.05		↑								

Occupation (Employee in the private sector/Employee in the public sector/Self-employed/Retired): 0 = No, 1 = Yes, Other = Reference group

Living in a big city: 0 = No, 1 = Yes

Personal monthly net income: 1 = none, 2 = Up to 1000 €, 3 = 1001 to 1500 €, 4 = 1501 to 2000 €, 5 = 2001 to 2500 €, 6 = 2501 to 3000 €, 7 = More than 3000 €

(Moderate) Leftist: 0 = Rightist, moderate rightist, centrist, 1 = Moderate leftist, leftist

Sex: 0 = Female, 1 = Male

Age: 1 = 16 to 25 years, 2 = 26 to 35 years, 3 = 36 to 45 years, 4 = 46 to 55 years, 5 = 56 to 65 years, 6 = 65 years and older

Educational level: 1 = Compulsory education attendance, 2 = Apprenticeship, 3 = Vocational school, 4 = Abitur (British A-Level), 5 = University (of applied sciences)

↑ ... Positive coefficient, significant at the 95%-level

↓ ... Negative coefficient, significant at the 95%-level

✘ ... Variable not included in the model

■ ... Model misspecified, set of chosen predictors not meaningful (linktest, hat: p > 0.05)

■ ... Model misspecified, unobserved predictors or interactions probable (linktest, hatsq: p < 0.05)

5 Conclusions

Following *Blinder and Krueger (2004)* we conducted a survey among 1.003 eligible Austrian voters in order to test whether their findings and those of several others - namely that ideology is a more powerful predictor of attitudes towards policy measures than self-interest – hold. Nevertheless we modified the methodology by introducing the concept of “subjective (perceived) self-interest”: we asked people if they think a specific measure will affect them adversely.

We find that subjective self-interest – in this specific case the expectation of personally adverse consequences of a policy measure – is the most important, if not dominant, identified determinant of the acceptance of policy measures. People who expect to personally face adverse consequences of a policy measure are less likely to find this measure appropriate.

Our results therefore do not suggest that “*ideology seems to play a stronger role in shaping opinion on economic policy issues than either self-interest or knowledge*” (*Blinder and Krueger, 2004*) – given that our operationalizations of both – self-interest and ideology – differ from the operationalizations chosen by Blinder and Krueger and that we do not account for knowledge in our models. On the contrary, our results indicate that *(subjective, perceived) self-interest* is the stable factor in opinion formation while the influence of ideology is vastly dependent on the nature of the tested policy measure (tax raises vs. spending cuts).

Ideology too appears to play a part in the process of opinion forming, but only in certain contexts. In particular (moderate) leftists are more likely to accept tax raises as adequate policy measures than centrists and (moderate) rightists. Concerning cuts in public expenditures the political orientation is a significant predictor only after measures of objective and/or subjective self-interest are omitted from the analyses.

Some results related to the attitudes towards raising the petroleum tax among different age groups suggest that ideological concepts apart from political ideology might play a role in shaping opinions on policy measures, for example peer group related concepts of private transport.

However, we find that objective self-interest and ideology are only loosely related. Moreover, subjective (perceived) self-interest and ideology contribute to the acceptance of policy measures in parallel; therefore not substituting each other at least as far as tax increases are concerned. This addresses the question whether (political) ideology is the laymen’s shortcut to political opinion formation, not because of some normative view of the world how it “should be”, but because ideology shapes the positive view of how the economy works.

Subjective and objective self-interest as well as ideology only explain a small fraction of the variation inherent in the formation of public opinions. For example 80% of those not feeling adversely affected think that raising profit taxes on corporations is an appropriate measure for financing a reform of the income tax, while still 60% among those who feel adversely affected agree with this measure. This of course raises the question on what determines the opinion formation of those 60% and how the relevant determinants can be measured.

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Annex 1 - List of Variables

Acceptance of policy measures (0 = No, 1 = Yes)

- f10_1x ... Increasing VAT
- f10_2x ... Increasing the petroleum tax
- f10_3x ... Raising profit taxes on public/private limited companies
- f10_4x ... Raising environmental taxes on companies
- f10_5x ... Impose a property or inheritance tax
- f10_6x ... Raising the tax on capital returns
- f10_7x ... Increasing public debt
- f10_8x ... Cutting social security benefits
- f10_9x ... Cutting subsidies for companies
- f10_10x ... Cutting jobs in public administration

Expected adverse consequences of measure (0 = No, 1 = Yes)

- f11_1x ... Increasing VAT
- f11_2x ... Increasing the petroleum tax
- f11_3x ... Raising profit taxes on public/private limited companies
- f11_4x ... Raising environmental taxes on companies
- f11_5x ... Impose a property or inheritance tax
- f11_6x ... Raising the tax on capital returns
- f11_7x ... Increasing public debt
- f11_8x ... Cutting social security benefits
- f11_9x ... Cutting subsidies for companies
- f11_10x ... Cutting jobs in public administration

Occupation (0 = No, 1 = Yes , Other = Reference group)

- s3_1x ... Employee in the private sector
- s3_2x ... Employee in the public sector
- s3_3x ... Self-employed
- s3_4x ... Retired

s4x ... Personal monthly net income (1 = None, 2 = Up to 1000 €, 3 = 1001 to 1500 €, 4 = 1501 to 2000 €, 5 = 2001 to 2500 €, 6 = 2501 to 3000 €, 7 = More than 3000 €)

GrStadt ... Living in a big city (0 = No, 1 = Yes)

leftist ... (Moderate) Leftist (0 = Rightist, moderate rightist, centrist, 1 = Moderate leftist, leftist)

s1x ... Sex (0 = Female, 1 = Male)

s2x ... Age (1 = 16 to 25 years, 2 = 26 to 35 years, 3 = 36 to 45 years, 4 = 46 to 55 years, 5 = 56 to 65 years, 6 = 65 years and older)

s7x ... Educational level (1 = Compulsory education attendance, 2 = Apprenticeship, 3 = Vocational school, 4 = Abitur (British A-Level), 5 = University (of applied sciences))

Annex 2 – Acceptance of policy measures by several determinants (logit models, full specification)

Collinearity Diagnostics

Variable	VIF	SQRT		R-Squared
		VIF	Tolerance	
f11_1x	1.04	1.02	0.9607	0.0393
s3_1x	2.38	1.54	0.4196	0.5804
s3_2x	1.76	1.33	0.5694	0.4306
s3_3x	1.74	1.32	0.5749	0.4251
s3_4x	4.02	2.01	0.2487	0.7513
s4x	1.70	1.30	0.5896	0.4104
GrStadt	1.11	1.05	0.9045	0.0955
leftist	1.06	1.03	0.9463	0.0537
s1x	1.24	1.11	0.8056	0.1944
s2x	2.55	1.60	0.3915	0.6085
s7x	1.27	1.13	0.7852	0.2148

Mean VIF 1.81

	Eigenval	Cond Index
1	6.6078	1.0000
2	1.1353	2.4125
3	1.0189	2.5466
4	1.0041	2.5652
5	0.7732	2.9234
6	0.5768	3.3846
7	0.4243	3.9465
8	0.1855	5.9685
9	0.1240	7.3007
10	0.0640	10.1625
11	0.0604	10.4619
12	0.0258	15.9941

Condition Number 15.9941

Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)

Det(correlation matrix) 0.0816

Iteration 0: log likelihood = -108.88629
Iteration 1: log likelihood = -100.20432
Iteration 2: log likelihood = -94.379397
Iteration 3: log likelihood = -94.124386
Iteration 4: log likelihood = -94.122586
Iteration 5: log likelihood = -94.122585

Logistic regression Number of obs = 729
 LR chi2(11) = 29.53
 Prob > chi2 = 0.0019
Log likelihood = -94.122585 Pseudo R2 = 0.1356

f10_1x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_1x	-.7908343	.5486105	-1.44	0.149	-1.866091 .2844225
s3_1x	-.5523875	.6826995	-0.81	0.418	-1.890454 .785679
s3_2x	-.5168884	.9427688	-0.55	0.584	-2.364681 1.330904
s3_3x	-.5492724	.9475763	-0.58	0.562	-2.406488 1.307943
s3_4x	.8530472	1.060614	0.80	0.421	-1.225718 2.931812
s4x	-.2544873	.2294624	-1.11	0.267	-.7042252 .1952507
GrStadt	.3662238	.4539218	0.81	0.420	-.5234466 1.255894
leftist	-.5472242	.5102837	-1.07	0.284	-1.547362 .4529135
s1x	1.723561	.5476459	3.15	0.002	.6501945 2.796927
s2x	-.4019306	.2272795	-1.77	0.077	-.8473903 .043529
s7x	.3744895	.1831893	2.04	0.041	.015445 .7335339
_cons	-2.809879	1.037068	-2.71	0.007	-4.842495 -.7772629

Iteration 0: log likelihood = -108.88629
Iteration 1: log likelihood = -96.753467
Iteration 2: log likelihood = -94.495369
Iteration 3: log likelihood = -94.114269
Iteration 4: log likelihood = -94.092761
Iteration 5: log likelihood = -94.092673
Iteration 6: log likelihood = -94.092673

Logistic regression Number of obs = 729
 LR chi2(2) = 29.59
 Prob > chi2 = 0.0000
Log likelihood = -94.092673 Pseudo R2 = 0.1359

f10_1x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.209533	.8709117	1.39	0.165	-.4974224 2.916489
_hatsq	.0353261	.1425574	0.25	0.804	-.2440812 .3147334
_cons	.2683865	1.23363	0.22	0.828	-2.149484 2.686257

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_3x	1.03	1.01	0.9709	0.0291
s3_1x	2.43	1.56	0.4120	0.5880
s3_2x	1.80	1.34	0.5568	0.4432
s3_3x	1.75	1.32	0.5710	0.4290
s3_4x	4.01	2.00	0.2495	0.7505
s4x	1.72	1.31	0.5828	0.4172
GrStadT	1.09	1.05	0.9140	0.0860
leftist	1.07	1.03	0.9383	0.0617
s1x	1.23	1.11	0.8107	0.1893
s2x	2.54	1.59	0.3936	0.6064
s7x	1.25	1.12	0.7980	0.2020
Mean VIF	1.81			

	Eigenval	Cond Index
1	5.9407	1.0000
2	1.1425	2.2803
3	1.0471	2.3819
4	1.0037	2.4329
5	0.8483	2.6463
6	0.7116	2.8893
7	0.5669	3.2371
8	0.3994	3.8566
9	0.1664	5.9756
10	0.0788	8.6820
11	0.0617	9.8141
12	0.0329	13.4462

Condition Number 13.4462
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.0820

Iteration 0: log likelihood = -356.99586
 Iteration 1: log likelihood = -333.35226
 Iteration 2: log likelihood = -331.77852
 Iteration 3: log likelihood = -331.74639
 Iteration 4: log likelihood = -331.74632

Logistic regression Number of obs = 683
 LR chi2(11) = 50.50
 Prob > chi2 = 0.0000
 Log likelihood = -331.74632 Pseudo R2 = 0.0707

f10_3x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_3x	-.9879703	.2336066	-4.23	0.000	-1.445831 - .5301097
s3_1x	.1011876	.3062727	0.33	0.741	-.4990958 .7014711
s3_2x	1.542693	.5409684	2.85	0.004	.4824142 2.602971
s3_3x	-.4391373	.3988181	-1.10	0.271	-1.220806 .3425318
s3_4x	-.0317585	.4053246	-0.08	0.938	-.8261801 .7626631
s4x	.0746167	.0975634	0.76	0.444	-.116604 .2658373
GrStadT	.0029887	.224228	0.01	0.989	-.4364901 .4424674
leftist	.644791	.2394007	2.69	0.007	.1755743 1.114008
s1x	.028512	.2134862	0.13	0.894	-.3899133 .4469373
s2x	.0688365	.089909	0.77	0.444	-.1073818 .2450549
s7x	-.1912686	.0822071	-2.33	0.020	-.3523916 -.0301456
_cons	1.30792	.4133036	3.16	0.002	.4978595 2.11798

Iteration 0: log likelihood = -356.99586
 Iteration 1: log likelihood = -332.76805
 Iteration 2: log likelihood = -331.14356
 Iteration 3: log likelihood = -331.1271
 Iteration 4: log likelihood = -331.12709

Logistic regression Number of obs = 683
 LR chi2(2) = 51.74
 Prob > chi2 = 0.0000
 Log likelihood = -331.12709 Pseudo R2 = 0.0725

f10_3x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.361018	.3556096	3.83	0.000	.6640359 2.058
_hatsq	-.1483315	.1285798	-1.15	0.249	-.4003433 .1036804
_cons	-.1564586	.247352	-0.63	0.527	-.6412596 .3283424

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_7x	1.02	1.01	0.9814	0.0186
s3_1x	2.38	1.54	0.4204	0.5796
s3_2x	1.77	1.33	0.5657	0.4343
s3_3x	1.74	1.32	0.5751	0.4249
s3_4x	3.91	1.98	0.2559	0.7441
s4x	1.69	1.30	0.5910	0.4090
GrStadt	1.10	1.05	0.9111	0.0889
leftist	1.06	1.03	0.9475	0.0525
s1x	1.23	1.11	0.8163	0.1837
s2x	2.47	1.57	0.4041	0.5959
s7x	1.26	1.12	0.7968	0.2032

Mean VIF 1.78

	Eigenval	Cond Index
1	6.3674	1.0000
2	1.1330	2.3706
3	1.0164	2.5029
4	1.0043	2.5179
5	0.7725	2.8710
6	0.5773	3.3211
7	0.4475	3.7719
8	0.3426	4.3111
9	0.1649	6.2137
10	0.0776	9.0571
11	0.0631	10.0417
12	0.0333	13.8382

Condition Number 13.8382
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.0879

Iteration 0: log likelihood = -268.01122
Iteration 1: log likelihood = -255.02355
Iteration 2: log likelihood = -254.33376
Iteration 3: log likelihood = -254.3324
Iteration 4: log likelihood = -254.3324

Logistic regression
Log likelihood = -254.3324
Number of obs = 696
LR chi2(11) = 27.36
Prob > chi2 = 0.0041
Pseudo R2 = 0.0510

f10_7x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_7x	-.9360231	.2350137	-3.98	0.000	-1.396641 - .4754048
s3_1x	.1809622	.3694938	0.49	0.624	-.5432323 .9051567
s3_2x	-.3814285	.5296132	-0.72	0.471	-1.419451 .6565942
s3_3x	-.4394001	.5587307	-0.79	0.432	-1.534492 .655692
s3_4x	-.0657797	.5080991	-0.13	0.897	-1.061636 .9300762
s4x	-.0183433	.1186364	-0.15	0.877	-.2508663 .2141798
GrStadt	.1075649	.261337	0.41	0.681	-.4046462 .619776
leftist	.4196343	.2503452	1.68	0.094	-.0710333 .910302
s1x	-.0775409	.2546968	-0.30	0.761	-.5767374 .4216556
s2x	-.1067965	.1099775	-0.97	0.332	-.3223485 .1087554
s7x	.0383986	.0974302	0.39	0.693	-.1525611 .2293584
_cons	-1.189522	.4933384	-2.41	0.016	-2.156447 -.2225964

Iteration 0: log likelihood = -268.01122
Iteration 1: log likelihood = -256.16372
Iteration 2: log likelihood = -253.84873
Iteration 3: log likelihood = -253.84697
Iteration 4: log likelihood = -253.84697

Logistic regression
Log likelihood = -253.84697
Number of obs = 696
LR chi2(2) = 28.33
Prob > chi2 = 0.0000
Pseudo R2 = 0.0528

f10_7x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	2.007756	1.032922	1.94	0.052	-.0167335 4.032245
_hatsq	.2797592	.2807236	1.00	0.319	-.270449 .8299673
_cons	.8059711	.8880234	0.91	0.364	-.9345228 2.546465

Annex 3 – Acceptance of policy measures by several determinants (logit models without ‘subjective’ – perceived - self-interest)

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
s3_1x	2.37	1.54	0.4216	0.5784
s3_2x	1.75	1.32	0.5713	0.4287
s3_3x	1.73	1.32	0.5772	0.4228
s3_4x	3.96	1.99	0.2528	0.7472
s4x	1.71	1.31	0.5859	0.4141
GrStadt	1.10	1.05	0.9108	0.0892
leftist	1.06	1.03	0.9468	0.0532
s1x	1.24	1.11	0.8068	0.1932
s2x	2.53	1.59	0.3957	0.6043
s7x	1.27	1.13	0.7881	0.2119
Mean VIF	1.87			

	Eigenval	Cond Index
1	5.7542	1.0000
2	1.1342	2.2524
3	1.0181	2.3773
4	1.0037	2.3944
5	0.7640	2.7444
6	0.5764	3.1595
7	0.4028	3.7798
8	0.1710	5.8005
9	0.0802	8.4693
10	0.0624	9.6035
11	0.0330	13.2099

Condition Number 13.2099
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.0859

```

Iteration 0: log likelihood = -108.88629
Iteration 1: log likelihood = -100.23238
Iteration 2: log likelihood = -95.264905
Iteration 3: log likelihood = -95.050224
Iteration 4: log likelihood = -95.048816
Iteration 5: log likelihood = -95.048816

```

```

Logistic regression              Number of obs   =       729
                                LR chi2(10)      =       27.67
                                Prob > chi2         =       0.0020
Log likelihood = -95.048816     Pseudo R2      =       0.1271

```

f10_1x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
s3_1x	-.5680755	.6884022	-0.83	0.409	-1.917319 .7811681
s3_2x	-.5264414	.9377107	-0.56	0.575	-2.364321 1.311438
s3_3x	-.5565995	.9471815	-0.59	0.557	-2.413041 1.299842
s3_4x	.8851626	1.043714	0.85	0.396	-1.160479 2.930804
s4x	-.2521256	.2333465	-1.08	0.280	-.7094763 .2052252
GrStadt	.4051542	.4524816	0.90	0.371	-.4816934 1.292002
leftist	-.5273115	.5033358	-1.05	0.295	-1.513831 .4592085
s1x	1.78058	.5458372	3.26	0.001	.7107588 2.850401
s2x	-.3848149	.2244692	-1.71	0.086	-.8247664 .0551365
s7x	.3592026	.1828626	1.96	0.049	.0007985 .7176067
_cons	-3.55735	.9086245	-3.92	0.000	-5.338221 -1.776478

```

Iteration 0: log likelihood = -108.88629
Iteration 1: log likelihood = -97.596125
Iteration 2: log likelihood = -95.442133
Iteration 3: log likelihood = -95.059658
Iteration 4: log likelihood = -95.03825
Iteration 5: log likelihood = -95.038163
Iteration 6: log likelihood = -95.038163

```

```

Logistic regression              Number of obs   =       729
                                LR chi2(2)        =       27.70
                                Prob > chi2         =       0.0000
Log likelihood = -95.038163     Pseudo R2      =       0.1272

```

f10_1x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.129534	.9050492	1.25	0.212	-.6443296 2.903398
_hatsq	.0218086	.148243	0.15	0.883	-.2687424 .3123596
_cons	.1682096	1.296135	0.13	0.897	-2.372168 2.708587

```

Iteration 0: log likelihood = -286.3125
Iteration 1: log likelihood = -257.0175
Iteration 2: log likelihood = -253.34084
Iteration 3: log likelihood = -253.32138
Iteration 4: log likelihood = -253.32138

```

```

Logistic regression              Number of obs   =       732
                                LR chi2(10)      =       65.98
                                Prob > chi2         =       0.0000
Log likelihood = -253.32138     Pseudo R2      =       0.1152

```

f10_2x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
s3_1x	-.3599865	.3666473	-0.98	0.326	-1.078602 .3586291
s3_2x	.3042289	.4384899	0.69	0.488	-.5551955 1.163653
s3_3x	-.100799	.4821028	0.21	0.834	-.844105 1.045703
s3_4x	-.0081093	.523899	-0.02	0.988	-1.034932 1.018714
s4x	-.2068779	.1225336	-1.69	0.091	-.4470394 .0332836
GrStadt	.6828089	.2454939	2.78	0.005	.2016498 1.163968
leftist	.8063847	.238928	3.38	0.001	.3380945 1.274675
s1x	.3358355	.252586	1.33	0.184	-.1592239 .8308949
s2x	-.264673	.110831	-2.39	0.017	-.4818978 -.0474483
s7x	.2425665	.0975311	2.49	0.013	.0514091 .4337239
_cons	-1.746256	.4765749	-3.66	0.000	-2.680326 -.8121863

```

Iteration 0: log likelihood = -286.3125
Iteration 1: log likelihood = -262.00338
Iteration 2: log likelihood = -253.25777
Iteration 3: log likelihood = -252.97681
Iteration 4: log likelihood = -252.97679

```

```

Logistic regression              Number of obs   =       732
                                LR chi2(2)        =       66.67
                                Prob > chi2         =       0.0000
Log likelihood = -252.97679     Pseudo R2      =       0.1164

```

f10_2x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.343492	.4331273	3.10	0.002	.4945785 2.192406
_hatsq	.106141	.1267155	0.84	0.402	-.1422169 .3544988
_cons	.1910265	.3333545	0.57	0.567	-.4623363 .8443893

Iteration 0: log likelihood = -364.06809
 Iteration 1: log likelihood = -348.22308
 Iteration 2: log likelihood = -347.24916
 Iteration 3: log likelihood = -347.22475
 Iteration 4: log likelihood = -347.22471

```
Logistic regression
Number of obs   =      691
LR chi2(10)    =      33.69
Prob > chi2    =      0.0002
Pseudo R2     =      0.0463

Log likelihood = -347.22471
```

f10_3x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
s3_1x	.1958493	.2982926	0.66	0.511	-.3887935 .7804921
s3_2x	1.702324	.5370288	3.17	0.002	.6497673 2.754881
s3_3x	-.3934741	.3866977	-1.02	0.309	-1.151388 .3644394
s3_4x	.1676681	.391542	0.43	0.668	-.5997402 .9350763
s4x	.0345106	.0951809	0.36	0.717	-.1520406 .2210618
GrStadt	-.0202008	.2193554	-0.09	0.927	-.4501295 .4097279
leftist	.7184113	.2333886	3.08	0.002	.2609781 1.175845
s1x	.0002389	.2081508	0.00	0.999	-.4077293 .408207
s2x	.044689	.0870942	0.51	0.608	-.1260124 .2153905
s7x	-.1726222	.0801707	-2.15	0.031	-.3297539 -.0154905
_cons	1.145212	.4027332	2.84	0.004	.35587 1.934555

Iteration 0: log likelihood = -364.06809
 Iteration 1: log likelihood = -347.9481
 Iteration 2: log likelihood = -347.11725
 Iteration 3: log likelihood = -347.09173
 Iteration 4: log likelihood = -347.09167

```
Logistic regression
Number of obs   =      691
LR chi2(2)     =      33.95
Prob > chi2    =      0.0000
Pseudo R2     =      0.0466

Log likelihood = -347.09167
```

f10_3x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.317153	.6369272	2.07	0.039	.0687988 2.565508
_hatsq	-.1090696	.2070462	-0.53	0.598	-.5148727 .2967336
_cons	-.1949229	.4461293	-0.44	0.662	-1.06932 .6794744

Iteration 0: log likelihood = -471.03976
 Iteration 1: log likelihood = -437.45033
 Iteration 2: log likelihood = -436.9064
 Iteration 3: log likelihood = -436.90538
 Iteration 4: log likelihood = -436.90538

```
Logistic regression
Number of obs   =      705
LR chi2(10)    =      68.27
Prob > chi2    =      0.0000
Pseudo R2     =      0.0725

Log likelihood = -436.90538
```

f10_4x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
s3_1x	-.0936852	.2832717	-0.33	0.741	-.6488875 .4615172
s3_2x	.0431302	.3605978	0.12	0.905	-.6636284 .7498889
s3_3x	-.65691	.365887	-1.80	0.073	-1.374035 .0602154
s3_4x	.2485533	.343372	0.72	0.469	-.4244434 .9215501
s4x	-.0689992	.0838325	-0.82	0.410	-.2333078 .0953094
GrStadt	.4950018	.1930918	2.56	0.010	.1165488 .8734547
leftist	.8295875	.1966563	4.22	0.000	.4441482 1.215027
s1x	-.0781625	.181061	-0.43	0.666	-.4330356 .2767105
s2x	-.2979203	.0802392	-3.71	0.000	-.4551863 -.1406544
s7x	.0547376	.0691526	0.79	0.429	-.080799 .1902742
_cons	1.347101	.3706489	3.63	0.000	.6206425 2.07356

Iteration 0: log likelihood = -471.03976
 Iteration 1: log likelihood = -437.49472
 Iteration 2: log likelihood = -436.43123
 Iteration 3: log likelihood = -436.41361
 Iteration 4: log likelihood = -436.4136

```
Logistic regression
Number of obs   =      705
LR chi2(2)     =      69.25
Prob > chi2    =      0.0000
Pseudo R2     =      0.0735

Log likelihood = -436.4136
```

f10_4x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.8234626	.2190753	3.76	0.000	.3940829 1.252842
_hatsq	-.1667027	.1701867	0.98	0.327	-.1668571 .5002625
_cons	-.0200516	.097902	-0.20	0.838	-.211936 .1718328

Iteration 0: log likelihood = -492.37674
 Iteration 1: log likelihood = -479.4982
 Iteration 2: log likelihood = -479.48473
 Iteration 3: log likelihood = -479.48472

Logistic regression Number of obs = 721
 LR chi2(10) = 25.78
 Prob > chi2 = 0.0040
 Log likelihood = -479.48472 Pseudo R2 = 0.0262

f10_5x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
s3_1x	.3756738	.2596677	1.45	0.148	-.1332656 .8846132
s3_2x	.7314749	.3382257	2.16	0.031	.0685648 1.394385
s3_3x	.010335	.352629	0.03	0.977	-.6808052 .7014752
s3_4x	.3087107	.3302729	0.93	0.350	-.3386123 .9560337
s4x	-.0810073	.0811383	-1.00	0.318	-.2400354 .0780208
GrStadt	-.0449127	.1780253	-0.25	0.801	-.3938359 .3040105
leftist	.5416325	.1724153	3.14	0.002	.2037047 .8795603
s1x	.270952	.1705461	1.59	0.112	-.0633123 .6052163
s2x	-.0148073	.0741939	-0.20	0.842	-.1602246 .13061
s7x	.1276368	.0649233	1.97	0.049	.0003894 .2548841
_cons	-.9337031	.3401668	-2.74	0.006	-1.600418 -.2669883

Iteration 0: log likelihood = -492.37674
 Iteration 1: log likelihood = -479.49358
 Iteration 2: log likelihood = -479.4802
 Iteration 3: log likelihood = -479.4802

Logistic regression Number of obs = 721
 LR chi2(2) = 25.79
 Prob > chi2 = 0.0000
 Log likelihood = -479.4802 Pseudo R2 = 0.0262

f10_5x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.016295	.2645695	3.84	0.000	.4977481 1.534841
_hatsq	.0397756	.4183013	0.10	0.924	-.7800798 .8596311
_cons	-.0043384	.1056445	-0.04	0.967	-.2113978 .202721

Iteration 0: log likelihood = -485.98894
 Iteration 1: log likelihood = -473.71428
 Iteration 2: log likelihood = -473.69388
 Iteration 3: log likelihood = -473.69388

Logistic regression Number of obs = 708
 LR chi2(10) = 24.59
 Prob > chi2 = 0.0062
 Log likelihood = -473.69388 Pseudo R2 = 0.0253

f10_6x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
s3_1x	.5230366	.2624612	1.99	0.046	.0086221 1.037451
s3_2x	.4665406	.3381784	1.38	0.168	-.1962768 1.129358
s3_3x	-.0164927	.3506346	-0.05	0.962	-.7037238 .6707383
s3_4x	-.1135322	.3301791	-0.34	0.731	-.7606714 .5336069
s4x	-.1843409	.0831126	-2.22	0.027	-.3472385 -.0214432
GrStadt	.3856085	.1782415	2.16	0.031	.0362616 .7349553
leftist	.4258994	.1745458	2.44	0.015	.0837959 .7680029
s1x	.2815549	.1727089	1.63	0.103	-.0569483 .6200581
s2x	.0866907	.0745759	1.16	0.245	-.0594754 .2328569
s7x	-.0049805	.0650783	-0.08	0.939	-.1325316 .1225707
_cons	-.5281895	.3391548	-1.56	0.119	-1.192921 .1365417

Iteration 0: log likelihood = -485.98894
 Iteration 1: log likelihood = -473.65376
 Iteration 2: log likelihood = -473.63774
 Iteration 3: log likelihood = -473.63774

Logistic regression Number of obs = 708
 LR chi2(2) = 24.70
 Prob > chi2 = 0.0000
 Log likelihood = -473.63774 Pseudo R2 = 0.0254

f10_6x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.049366	.2553284	4.11	0.000	.548932 1.549801
_hatsq	.1247686	.3717894	0.34	0.737	-.6039253 .8534626
_cons	-.0124952	.0975855	-0.13	0.898	-.2037592 .1787688

Iteration 0: log likelihood = -281.13036
 Iteration 1: log likelihood = -274.51846
 Iteration 2: log likelihood = -274.3273
 Iteration 3: log likelihood = -274.32714

Logistic regression Number of obs = 722
 LR chi2(10) = 13.61
 Log likelihood = -274.32714 Prob > chi2 = 0.1917
 Pseudo R2 = 0.0242

f10_7x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
s3_1x	.3385971	.3608063	0.94	0.348	-.3685702 1.045764
s3_2x	-.2286306	.5028057	-0.45	0.649	-1.214112 .7568505
s3_3x	-.3241497	.5516205	-0.59	0.557	-1.405306 .7570067
s3_4x	.2000031	.4911313	0.41	0.684	-.7625966 1.162603
s4x	-.0065663	.1187813	-0.06	0.956	-.2393733 .2262408
GrStadt	.0851923	.2527334	0.34	0.736	-.4101561 .5805408
leftist	-.5197652	.2365813	-2.20	0.028	-.0560744 .9834561
s1x	-.2004049	.2469172	-0.81	0.417	-.6843538 .283544
s2x	-.1345566	.1088282	-1.24	0.216	-.347856 .0787427
s7x	.0118766	.0938441	0.13	0.899	-.1720544 .1958075
_cons	-1.632392	.4788948	-3.41	0.001	-2.571009 -.6937758

Iteration 0: log likelihood = -281.13036
 Iteration 1: log likelihood = -274.66602
 Iteration 2: log likelihood = -274.27437
 Iteration 3: log likelihood = -274.27312
 Iteration 4: log likelihood = -274.27312

Logistic regression Number of obs = 722
 LR chi2(2) = 13.71
 Log likelihood = -274.27312 Prob > chi2 = 0.0011
 Pseudo R2 = 0.0244

f10_7x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.329735	2.071035	0.16	0.874	-3.729419 4.388889
_hatsq	-.1864166	.5711166	-0.33	0.744	-1.305785 .9329513
_cons	-.5716014	1.825433	-0.31	0.754	-4.149385 3.006182

Iteration 0: log likelihood = -276.36333
 Iteration 1: log likelihood = -266.03795
 Iteration 2: log likelihood = -265.35992
 Iteration 3: log likelihood = -265.35773
 Iteration 4: log likelihood = -265.35773

Logistic regression Number of obs = 729
 LR chi2(10) = 22.01
 Log likelihood = -265.35773 Prob > chi2 = 0.0150
 Pseudo R2 = 0.0398

f10_8x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
s3_1x	.242549	.3761991	0.64	0.519	-.4947876 .9798856
s3_2x	-.2484771	.54983	-0.45	0.651	-1.326124 .8291699
s3_3x	.8996532	.4598787	1.96	0.050	-.0016924 1.800999
s3_4x	.2481632	.5107392	0.49	0.627	-.7528672 1.249194
s4x	-.1417068	.1207192	-1.17	0.240	-.3783121 .0948985
GrStadt	.0679913	.2654792	0.26	0.798	-.4523384 .5883211
leftist	-.5965709	.2887599	-2.07	0.039	-1.16253 -.0306119
s1x	.4693406	.2560559	1.83	0.067	-.0325197 .9712008
s2x	-.1515589	.1091757	-1.39	0.165	-.3655393 .0624216
s7x	-.00099	.0958896	-0.01	0.992	-.1889301 .1869501
_cons	-1.312198	.4829477	-2.72	0.007	-2.258758 -.3656378

Iteration 0: log likelihood = -276.36333
 Iteration 1: log likelihood = -266.49374
 Iteration 2: log likelihood = -264.5536
 Iteration 3: log likelihood = -264.55165
 Iteration 4: log likelihood = -264.55165

Logistic regression Number of obs = 729
 LR chi2(2) = 23.62
 Log likelihood = -264.55165 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0427

f10_8x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	2.3941	1.093294	2.19	0.029	.251283 4.536917
_hatsq	.3813864	.2912207	1.31	0.190	-.1893957 .9521686
_cons	1.16292	.9837907	1.18	0.237	-.7652744 3.091114

Iteration 0: log likelihood = -458.04246
Iteration 1: log likelihood = -453.02463
Iteration 2: log likelihood = -453.02225

Logistic regression Number of obs = 669
 LR chi2(10) = 10.04
 Prob > chi2 = 0.4370
Log likelihood = -453.02225 Pseudo R2 = 0.0110

f10_9x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
s3_1x	-.3260807	.2632399	-1.24	0.215	-.8420215 .1898601
s3_2x	-.5054093	.3447809	-1.47	0.143	-1.181168 .1703488
s3_3x	-.6688831	.3579875	-1.87	0.062	-1.370526 .0327595
s3_4x	-.5361216	.3387615	-1.58	0.114	-1.200082 .1278388
s4x	.1245927	.0820671	1.52	0.129	-.0362558 .2854412
GrStadt	-.0082001	.1813607	-0.05	0.964	-.3636605 .3472603
leftist	.1774838	.1765596	1.01	0.315	-.1685665 .5235342
s1x	.1725378	.1754773	0.98	0.325	-.1713915 .5164671
s2x	.1227652	.0769142	1.60	0.110	-.0279839 .2735143
s7x	-.0508847	.0672507	-0.76	0.449	-.1826937 .0809244
_cons	-.7086393	.3484193	-2.03	0.042	-1.391529 -.0257501

Iteration 0: log likelihood = -458.04246
Iteration 1: log likelihood = -452.45237
Iteration 2: log likelihood = -452.43413
Iteration 3: log likelihood = -452.43413

Logistic regression Number of obs = 669
 LR chi2(2) = 11.22
 Prob > chi2 = 0.0037
Log likelihood = -452.43413 Pseudo R2 = 0.0122

f10_9x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.5114024	.5508109	0.93	0.353	-.5681672 1.590972
_hatsq	-.9807602	.9106213	-1.08	0.281	-2.765545 .8040248
_cons	-.0018004	.1135637	-0.02	0.987	-.2243813 .2207804

Iteration 0: log likelihood = -429.76251
Iteration 1: log likelihood = -405.213
Iteration 2: log likelihood = -404.76707
Iteration 3: log likelihood = -404.7662

Logistic regression Number of obs = 719
 LR chi2(10) = 49.99
 Prob > chi2 = 0.0000
Log likelihood = -404.7662 Pseudo R2 = 0.0582

f10_10x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
s3_1x	.2976663	.2778219	1.07	0.284	-.2468547 .8421873
s3_2x	-.765463	.3519123	-2.18	0.030	-1.455198 -.0757277
s3_3x	.8350654	.4311159	1.94	0.053	-.0099062 1.680037
s3_4x	.0206825	.3680803	0.06	0.955	-.7007416 .7421066
s4x	.068569	.0932661	0.74	0.462	-.1142292 .2513671
GrStadt	-.5791879	.1920034	-3.02	0.003	-.9555076 -.2028681
leftist	-.1989463	.1907554	-1.04	0.297	-.5728201 .1749275
s1x	.358933	.1920503	1.87	0.062	-.0174787 .7353446
s2x	.213842	.0834384	2.56	0.010	-.0503057 .3773783
s7x	.1389475	.0723263	1.92	0.055	-.0028095 .2807044
_cons	-.4931833	.3619756	-1.36	0.173	-1.202642 .2162759

Iteration 0: log likelihood = -429.76251
Iteration 1: log likelihood = -405.31488
Iteration 2: log likelihood = -404.69975
Iteration 3: log likelihood = -404.69799
Iteration 4: log likelihood = -404.69799

Logistic regression Number of obs = 719
 LR chi2(2) = 50.13
 Prob > chi2 = 0.0000
Log likelihood = -404.69799 Pseudo R2 = 0.0583

f10_10x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.110256	.3338269	3.33	0.001	.455967 1.764544
_hatsq	-.0682075	.1840123	-0.37	0.711	-.428865 .29245
_cons	-.0213566	.1643118	-0.13	0.897	-.3434018 .3006886

Annex 4 – Acceptance of policy measures by several determinants (logit models without ideological orientation)

Collinearity Diagnostics

Variable	VIF	SQRT		R-Squared
		VIF	Tolerance	
f11_1x	1.04	1.02	0.9621	0.0379
s3_1x	2.41	1.55	0.4153	0.5847
s3_2x	1.80	1.34	0.5560	0.4440
s3_3x	1.67	1.29	0.5979	0.4021
s3_4x	3.94	1.99	0.2537	0.7463
s4x	1.69	1.30	0.5902	0.4098
GrStadt	1.09	1.04	0.9207	0.0793
s1x	1.21	1.10	0.8236	0.1764
s2x	2.51	1.58	0.3984	0.6016
s7x	1.28	1.13	0.7803	0.2197
Mean VIF	1.86			

	Eigenval	Cond Index
1	6.2531	1.0000
2	1.1349	2.3473
3	1.0114	2.4865
4	1.0028	2.4971
5	0.6832	3.0254
6	0.4473	3.7389
7	0.1921	5.7056
8	0.1245	7.0882
9	0.0632	9.9504
10	0.0614	10.0907
11	0.0263	15.4290

Condition Number 15.4290
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.0883

Iteration 0: log likelihood = -139.05462
 Iteration 1: log likelihood = -129.90606
 Iteration 2: log likelihood = -124.82493
 Iteration 3: log likelihood = -124.64751
 Iteration 4: log likelihood = -124.64687
 Iteration 5: log likelihood = -124.64687

Logistic regression
 Number of obs = 924
 LR chi2(10) = 28.82
 Prob > chi2 = 0.0013
 Pseudo R2 = 0.1036
 Log likelihood = -124.64687

f10_1x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_1x	-.4746259	.5240467	-0.91	0.365	-1.501739 .5524868
s3_1x	-.9755235	.5961048	-1.64	0.102	-2.143868 .1928205
s3_2x	-.8363936	.7757693	-1.08	0.281	-2.356873 .6840862
s3_3x	-1.105469	.8753234	-1.26	0.207	-2.821071 .6101335
s3_4x	.2119853	.8514097	0.25	0.803	-1.456747 1.880718
s4x	-.0700955	.1905369	-0.37	0.713	-.4435411 .30335
GrStadt	.1715122	.4013359	0.43	0.669	-.6150916 .9581161
s1x	1.40822	.4464776	3.15	0.002	.5331396 2.283299
s2x	-.2596375	.1907051	-1.36	0.173	-.6334126 .1141376
s7x	.3460981	.1594046	2.17	0.030	.0336708 .6585255
_cons	-3.411415	.9180069	-3.72	0.000	-5.210675 -1.612155

Iteration 0: log likelihood = -139.05462
 Iteration 1: log likelihood = -126.36963
 Iteration 2: log likelihood = -124.46229
 Iteration 3: log likelihood = -124.28626
 Iteration 4: log likelihood = -124.28322
 Iteration 5: log likelihood = -124.28321

Logistic regression
 Number of obs = 924
 LR chi2(2) = 29.54
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.1062
 Log likelihood = -124.28321

f10_1x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.765106	.8962089	1.97	0.049	.0085692 3.521643
_hatsq	.128206	.1457282	0.88	0.379	-.1574161 .413828
_cons	1.013852	1.293131	0.78	0.433	-1.520637 3.548341

Collinearity Diagnostics

Variable	VIF	SQRT		R-Squared
		VIF	Tolerance	
f11_2x	1.09	1.04	0.9184	0.0816
s3_1x	2.41	1.55	0.4156	0.5844
s3_2x	1.80	1.34	0.5564	0.4436
s3_3x	1.67	1.29	0.5986	0.4014
s3_4x	3.92	1.98	0.2554	0.7446
s4x	1.71	1.31	0.5833	0.4167
GrStadt	1.11	1.05	0.8989	0.1011
s1x	1.21	1.10	0.8236	0.1764
s2x	2.50	1.58	0.4002	0.5998
s7x	1.27	1.13	0.7865	0.2135

Mean VIF 1.87

	Eigenval	Cond Index
1	6.1975	1.0000
2	1.1428	2.3287
3	1.0112	2.4757
4	1.0018	2.4873
5	0.6939	2.9885
6	0.4450	3.7318
7	0.1976	5.5999
8	0.1487	6.4549
9	0.0725	9.2468
10	0.0610	10.0786
11	0.0280	14.8774

Condition Number 14.8774
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.0846

Iteration 0: log likelihood = -355.02402
Iteration 1: log likelihood = -312.69592
Iteration 2: log likelihood = -305.60197
Iteration 3: log likelihood = -305.53608
Iteration 4: log likelihood = -305.53603

Logistic regression	Number of obs	=	925
	LR chi2(10)	=	98.98
	Prob > chi2	=	0.0000
Log likelihood = -305.53603	Pseudo R2	=	0.1394

f10_2x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_2x	-1.583581	.2536987	-6.24	0.000	-2.080821 -1.086341
s3_1x	-.5636687	.3366544	-1.67	0.094	-1.223499 .0961617
s3_2x	.0967693	.3931482	0.25	0.806	-.6737871 .8673257
s3_3x	-.1428504	.4443502	-0.32	0.748	-1.013761 .72806
s3_4x	-.3878565	.4743449	-0.82	0.414	-1.317555 .5418424
s4x	-.0627614	.108117	-0.58	0.562	-.2746668 .1491439
GrStadt	.3647034	.2327752	1.57	0.117	-.0915276 .8209344
s1x	.5097882	.2296693	2.22	0.026	.0596446 .9599319
s2x	-.3051157	.1014606	-3.01	0.003	-.5039749 -.1062566
s7x	.2603797	.0876504	2.97	0.003	.0885881 .4321712
_cons	-.3594961	.4711545	-0.76	0.445	-1.282942 .5639497

Iteration 0: log likelihood = -355.02402
Iteration 1: log likelihood = -319.69515
Iteration 2: log likelihood = -309.367
Iteration 3: log likelihood = -305.53441
Iteration 4: log likelihood = -305.53274
Iteration 5: log likelihood = -305.53274

Logistic regression	Number of obs	=	925
	LR chi2(2)	=	98.98
	Prob > chi2	=	0.0000
Log likelihood = -305.53274	Pseudo R2	=	0.1394

f10_2x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.019657	.2656996	3.84	0.000	.4988955 1.540419
_hatsq	.0065659	.0808924	0.08	0.935	-.1519804 .1651122
_cons	.0083471	.2318324	0.04	0.971	-.4460362 .4627303

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_3x	1.03	1.01	0.9731	0.0269
s3_1x	2.44	1.56	0.4097	0.5903
s3_2x	1.83	1.35	0.5468	0.4532
s3_3x	1.68	1.30	0.5941	0.4059
s3_4x	3.93	1.98	0.2542	0.7458
s4x	1.72	1.31	0.5824	0.4176
GrStadt	1.07	1.04	0.9331	0.0669
s1x	1.21	1.10	0.8253	0.1747
s2x	2.49	1.58	0.4014	0.5986
s7x	1.26	1.12	0.7953	0.2047

Mean VIF 1.87

	Eigenval	Cond Index
1	5.5992	1.0000
2	1.1445	2.2118
3	1.0220	2.3406
4	1.0010	2.3651
5	0.7861	2.6689
6	0.6748	2.8805
7	0.4247	3.6309
8	0.1739	5.6736
9	0.0801	8.3619
10	0.0610	9.5817
11	0.0326	13.1072

Condition Number 13.1072
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.0896

Iteration 0: log likelihood = -445.86032
Iteration 1: log likelihood = -425.03488
Iteration 2: log likelihood = -424.07714
Iteration 3: log likelihood = -424.07136
Iteration 4: log likelihood = -424.07135

Logistic regression
Log likelihood = -424.07135

Number of obs = 847
LR chi2(10) = 43.58
Prob > chi2 = 0.0000
Pseudo R2 = 0.0489

f10_3x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_3x	-.9699981	.2075768	-4.67	0.000	-1.376824 - .563138
s3_1x	.0004965	.2753082	0.00	0.999	-.5390976 .5400907
s3_2x	1.015674	.4290401	2.37	0.018	-.1747707 1.856577
s3_3x	-.6341687	.3544241	-1.79	0.074	-1.328827 .0604897
s3_4x	-.1772715	.3605068	-0.49	0.623	-.8838518 .5293087
s4x	.0713204	.0881772	0.81	0.419	-.1015038 .2441445
GrStadt	-.0087045	.1944271	-0.04	0.964	-.3897746 .3723656
s1x	.1036337	.1865056	0.56	0.578	-.2619105 .4691779
s2x	.0666749	.0810085	0.82	0.410	-.0920988 .2254485
s7x	-.1506376	.0725813	-2.08	0.038	-.2928943 -.008381
_cons	1.427926	.3719589	3.84	0.000	.6988999 2.156952

Iteration 0: log likelihood = -445.86032
Iteration 1: log likelihood = -424.46887
Iteration 2: log likelihood = -423.26375
Iteration 3: log likelihood = -423.26167

Logistic regression
Log likelihood = -423.26167

Number of obs = 847
LR chi2(2) = 45.20
Prob > chi2 = 0.0000
Pseudo R2 = 0.0507

f10_3x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.524637	.439697	3.47	0.001	.6628465 2.386427
_hatsq	-.2281285	.1753145	-1.30	0.193	-.5717387 .1154816
_cons	-.2312822	.27622	-0.84	0.402	-.7726634 .310099

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_4x	1.03	1.01	0.9746	0.0254
s3_1x	2.42	1.56	0.4126	0.5874
s3_2x	1.80	1.34	0.5548	0.4452
s3_3x	1.69	1.30	0.5921	0.4079
s3_4x	3.90	1.98	0.2561	0.7439
s4x	1.70	1.30	0.5888	0.4112
GrStadt	1.08	1.04	0.9277	0.0723
s1x	1.20	1.10	0.8326	0.1674
s2x	2.47	1.57	0.4042	0.5958
s7x	1.26	1.12	0.7936	0.2064

Mean VIF 1.86

	Eigenval	Cond Index
1	5.6603	1.0000
2	1.1303	2.2378
3	1.0546	2.3167
4	1.0021	2.3766
5	0.7324	2.7801
6	0.6433	2.9662
7	0.4268	3.6416
8	0.1769	5.6569
9	0.0787	8.4831
10	0.0618	9.5727
11	0.0328	13.1380

Condition Number 13.1380
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.0913

Iteration 0: log likelihood = -579.39838
Iteration 1: log likelihood = -545.14665
Iteration 2: log likelihood = -544.79142
Iteration 3: log likelihood = -544.79112

Logistic regression Number of obs = 862
LR chi2(10) = 69.21
Prob > chi2 = 0.0000
Log likelihood = -544.79112 Pseudo R2 = 0.0597

f10_4x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_4x	-.5949641	.1689332	-3.52	0.000	-.9260671 - .263861
s3_1x	-.182352	.2538342	-0.72	0.473	-.6798579 .3151539
s3_2x	-.1168218	.3244564	0.36	0.719	-.5191012 .7527447
s3_3x	-.3621152	.3352985	-1.08	0.280	-1.019288 .2950579
s3_4x	.2443964	.3072911	0.80	0.426	-.357883 .8466758
s4x	-.0720567	.0772025	-0.93	0.351	-.2233708 .0792574
GrStadt	.5983563	.1730874	3.46	0.001	.2591112 .9376014
s1x	-.0979215	.1595453	-0.61	0.539	-.4106245 .2147816
s2x	-.3052079	.072053	-4.24	0.000	-.4464291 -.1639868
s7x	.1083354	.0621328	1.74	0.081	-.0134426 .2301134
_cons	1.52982	.3340545	4.58	0.000	.8750851 2.184555

Iteration 0: log likelihood = -579.39838
Iteration 1: log likelihood = -545.14096
Iteration 2: log likelihood = -544.47975
Iteration 3: log likelihood = -544.47568
Iteration 4: log likelihood = -544.47568

Logistic regression Number of obs = 862
LR chi2(2) = 69.85
Prob > chi2 = 0.0000
Log likelihood = -544.47568 Pseudo R2 = 0.0603

f10_4x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.8709307	.2053518	4.24	0.000	.4684486 1.273413
_hatsq	.1391982	.1763267	0.79	0.430	-.2063959 .4847923
_cons	-.015834	.0887419	-0.18	0.858	-.189765 .158097

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
f11_5x	1.03	1.01	0.9746	0.0254
s3_1x	2.40	1.55	0.4159	0.5841
s3_2x	1.81	1.35	0.5512	0.4488
s3_3x	1.69	1.30	0.5929	0.4071
s3_4x	3.91	1.98	0.2555	0.7445
s4x	1.70	1.30	0.5889	0.4111
GrStadt	1.08	1.04	0.9288	0.0712
s1x	1.21	1.10	0.8239	0.1761
s2x	2.50	1.58	0.4001	0.5999
s7x	1.28	1.13	0.7828	0.2172

Mean VIF 1.86

	Eigenval	Cond Index
1	5.8640	1.0000
2	1.1362	2.2718
3	1.0116	2.4076
4	1.0010	2.4203
5	0.6843	2.9273
6	0.5735	3.1976
7	0.3836	3.9096
8	0.1717	5.8437
9	0.0801	8.5553
10	0.0619	9.7346
11	0.0320	13.5471

Condition Number 13.5471
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.0897

Iteration 0: log likelihood = -607.53773
 Iteration 1: log likelihood = -594.13749
 Iteration 2: log likelihood = -594.11257
 Iteration 3: log likelihood = -594.11257

Logistic regression Number of obs = 899
 LR chi2(10) = 26.85
 Prob > chi2 = 0.0028
 Log likelihood = -594.11257 Pseudo R2 = 0.0221

f10_5x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
f11_5x	-.4001695	.1411858	-2.83	0.005	-.6768887	-.1234504
s3_1x	.3967122	.2338003	1.70	0.090	-.061528	.8549523
s3_2x	.5120379	.296031	1.73	0.084	-.0681722	1.092248
s3_3x	-.0191488	.319908	-0.06	0.952	-.646157	.6078593
s3_4x	.2284003	.2956028	0.77	0.440	-.3509704	.8077711
s4x	-.0524568	.0737282	-0.71	0.477	-.1969615	.0920479
GrStadt	.0849658	.1579498	0.54	0.591	-.22461	.3945417
s1x	.180612	.1515784	1.19	0.233	-.1164762	.4777002
s2x	-.0382935	.0670906	-0.57	0.568	-.1697887	.0932017
s7x	.1620153	.0588699	2.75	0.006	.0466325	.2773981
_cons	-.7255472	.3085521	-2.35	0.019	-1.330298	-.1207962

Iteration 0: log likelihood = -607.53773
 Iteration 1: log likelihood = -593.92866
 Iteration 2: log likelihood = -593.90419
 Iteration 3: log likelihood = -593.90419

Logistic regression Number of obs = 899
 LR chi2(2) = 27.27
 Prob > chi2 = 0.0000
 Log likelihood = -593.90419 Pseudo R2 = 0.0224

f10_5x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.214743	.3878184	3.13	0.002	.4546328	1.974853
_hatsq	.2805059	.4338523	0.65	0.518	-.569829	1.130841
_cons	.0065248	.1003216	0.07	0.948	-.190102	.2031516

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_6x	1.03	1.01	0.9734	0.0266
s3_1x	2.43	1.56	0.4120	0.5880
s3_2x	1.80	1.34	0.5545	0.4455
s3_3x	1.69	1.30	0.5922	0.4078
s3_4x	3.99	2.00	0.2508	0.7492
s4x	1.70	1.30	0.5900	0.4100
GrStadt	1.08	1.04	0.9271	0.0729
s1x	1.21	1.10	0.8249	0.1751
s2x	2.53	1.59	0.3956	0.6044
s7x	1.27	1.13	0.7867	0.2133

Mean VIF 1.87

	Eigenval	Cond Index
1	5.9202	1.0000
2	1.1414	2.2774
3	1.0139	2.4164
4	1.0014	2.4315
5	0.6845	2.9410
6	0.4956	3.4562
7	0.3996	3.8491
8	0.1717	5.8717
9	0.0786	8.6778
10	0.0614	9.8167
11	0.0317	13.6551

Condition Number 13.6551
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.0881

Iteration 0: log likelihood = -594.32321
 Iteration 1: log likelihood = -565.77168
 Iteration 2: log likelihood = -565.66553
 Iteration 3: log likelihood = -565.66551

Logistic regression Number of obs = 873
 LR chi2(10) = 57.32
 Prob > chi2 = 0.0000
 Log likelihood = -565.66551 Pseudo R2 = 0.0482

f10_6x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_6x	-.8951125	.1447197	-6.19	0.000	-1.178758 - .6111467
s3_1x	.4372341	.2448566	1.79	0.074	-.042676 .9171441
s3_2x	.5459479	.3078542	1.77	0.076	-.0574352 1.149331
s3_3x	-.0251081	.3260715	-0.08	0.939	-.6641965 .6139804
s3_4x	-.2667711	.30728	-0.87	0.385	-.8690288 .3354867
s4x	-.1194084	.0769363	-1.55	0.121	-.2702008 .0313841
GrStadt	.2807228	.1629829	1.72	0.085	-.0387177 .6001634
s1x	.2823244	.1567624	1.80	0.072	-.0249243 .5895731
s2x	.1264928	.0696854	1.82	0.069	-.010088 .2630736
s7x	.0727424	.0604919	1.20	0.229	-.0458195 .1913044
_cons	-.5497192	.3167714	-1.74	0.083	-1.17058 .0711413

Iteration 0: log likelihood = -594.32321
 Iteration 1: log likelihood = -564.80966
 Iteration 2: log likelihood = -564.74673
 Iteration 3: log likelihood = -564.74672

Logistic regression Number of obs = 873
 LR chi2(2) = 59.15
 Prob > chi2 = 0.0000
 Log likelihood = -564.74672 Pseudo R2 = 0.0498

f10_6x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.214831	.2124313	5.72	0.000	.798473 1.631188
_hatsq	.3280926	.2423167	1.35	0.176	-.1468394 .8030245
_cons	-.0533402	.0909631	-0.59	0.558	-.2316245 .1249442

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_7x	1.02	1.01	0.9802	0.0198
s3_1x	2.43	1.56	0.4119	0.5881
s3_2x	1.82	1.35	0.5482	0.4518
s3_3x	1.69	1.30	0.5921	0.4079
s3_4x	3.91	1.98	0.2558	0.7442
s4x	1.69	1.30	0.5906	0.4094
GrStadt	1.08	1.04	0.9289	0.0711
s1x	1.21	1.10	0.8274	0.1726
s2x	2.45	1.57	0.4076	0.5924
s7x	1.26	1.12	0.7930	0.2070

Mean VIF 1.86

	Eigenval	Cond Index
1	6.0195	1.0000
2	1.1321	2.3059
3	1.0114	2.4396
4	1.0010	2.4523
5	0.6820	2.9708
6	0.4626	3.6073
7	0.3485	4.1558
8	0.1700	5.9511
9	0.0779	8.7926
10	0.0619	9.8608
11	0.0330	13.4967

Condition Number 13.4967
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.0921

Iteration 0: log likelihood = -344.06992
Iteration 1: log likelihood = -326.25427
Iteration 2: log likelihood = -325.27808
Iteration 3: log likelihood = -325.27629
Iteration 4: log likelihood = -325.27629

Logistic regression
Log likelihood = -325.27629

Number of obs	=	874
LR chi2(10)	=	37.59
Prob > chi2	=	0.0000
Pseudo R2	=	0.0546

f10_7x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_7x	-1.022696	.2082488	-4.91	0.000	-1.430856 - .6145354
s3_1x	.4589042	.3341138	1.37	0.170	-.195947 1.113755
s3_2x	-.0772627	.4504489	-0.17	0.864	-.9601263 .8056008
s3_3x	-.1502098	.4942807	-0.30	0.761	-1.118982 .8185625
s3_4x	.0278132	.4557076	0.06	0.951	-.8653573 .9209838
s4x	-.0393377	.1077317	-0.37	0.715	-.2504879 .1718125
GrStadt	.105727	.231438	0.46	0.648	-.3478832 .5593371
s1x	-.1256128	.2233989	-0.56	0.574	-.5634666 .312241
s2x	-.1123279	.0973187	-1.15	0.248	-.303069 .0784132
s7x	.0774425	.0860864	0.90	0.368	-.0912838 .2461688
_cons	-1.164632	.4391874	-2.65	0.008	-2.025423 -.3038406

Iteration 0: log likelihood = -344.06992
Iteration 1: log likelihood = -327.47914
Iteration 2: log likelihood = -324.12732
Iteration 3: log likelihood = -324.12505

Logistic regression
Log likelihood = -324.12505

Number of obs	=	874
LR chi2(2)	=	39.89
Prob > chi2	=	0.0000
Pseudo R2	=	0.0580

f10_7x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	2.347366	.8980722	2.61	0.009	.5871771 4.107555
_hatsq	.3822891	.2494639	1.53	0.125	-.1066512 .8712294
_cons	1.037413	.7425755	1.40	0.162	-.4180085 2.492834

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_8x	1.04	1.02	0.9588	0.0412
s3_1x	2.40	1.55	0.4168	0.5832
s3_2x	1.81	1.34	0.5535	0.4465
s3_3x	1.67	1.29	0.5980	0.4020
s3_4x	3.90	1.97	0.2565	0.7435
s4x	1.71	1.31	0.5842	0.4158
GrStadt	1.08	1.04	0.9284	0.0716
s1x	1.22	1.10	0.8212	0.1788
s2x	2.49	1.58	0.4014	0.5986
s7x	1.27	1.13	0.7863	0.2137
Mean VIF	1.86			

	Eigenval	Cond Index
1	5.9192	1.0000
2	1.1359	2.2828
3	1.0214	2.4073
4	1.0097	2.4213
5	0.6882	2.9327
6	0.5195	3.3756
7	0.3666	4.0181
8	0.1701	5.8990
9	0.0756	8.8472
10	0.0621	9.7600
11	0.0316	13.6898

Condition Number 13.6898
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.0884

Iteration 0: log likelihood = -347.07741
Iteration 1: log likelihood = -326.89581
Iteration 2: log likelihood = -325.35765
Iteration 3: log likelihood = -325.34791
Iteration 4: log likelihood = -325.34791

Logistic regression Number of obs = 909
LR chi2(10) = 43.46
Prob > chi2 = 0.0000
Log likelihood = -325.34791 Pseudo R2 = 0.0626

f10_8x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_8x	-.8951392	.2140296	-4.18	0.000	-1.31463 - .4756489
s3_1x	.2779367	.339948	0.82	0.414	-.388349 .9442225
s3_2x	-.8450812	.5282317	-1.60	0.110	-1.880396 .1902339
s3_3x	.6436228	.4158423	1.55	0.122	-.1714132 1.458659
s3_4x	-.1018392	.445303	-0.23	0.819	-.9746171 .7709386
s4x	-.109902	.1096884	-1.00	0.316	-.3248873 .1050834
GrStadt	-.2719653	.245954	-1.11	0.269	-.7540263 .2100956
s1x	.4569566	.2292226	1.99	0.046	.0076886 .9062246
s2x	-.0861864	.0963861	-0.89	0.371	-.2750996 .1027268
s7x	.0065798	.0861767	0.08	0.939	-.1623235 .1754831
_cons	-1.110157	.4537949	-2.45	0.014	-1.999579 -.2207355

Iteration 0: log likelihood = -347.07741
Iteration 1: log likelihood = -327.68985
Iteration 2: log likelihood = -323.5615
Iteration 3: log likelihood = -323.55552
Iteration 4: log likelihood = -323.55552

Logistic regression Number of obs = 909
LR chi2(2) = 47.04
Prob > chi2 = 0.0000
Log likelihood = -323.55552 Pseudo R2 = 0.0678

f10_8x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	2.269489	.6690527	3.39	0.001	.95817 3.580809
_hatsq	.3430693	.1728311	1.98	0.047	.0043266 .681812
_cons	1.016964	.6000035	1.69	0.090	-.1590216 2.192949

Collinearity Diagnostics

Variable	VIF	SQRT		R-Squared
		VIF	Tolerance	
f11_9x	1.05	1.03	0.9503	0.0497
s3_1x	2.41	1.55	0.4146	0.5854
s3_2x	1.80	1.34	0.5542	0.4458
s3_3x	1.69	1.30	0.5908	0.4092
s3_4x	3.98	1.99	0.2516	0.7484
s4x	1.68	1.30	0.5960	0.4040
GrStadt	1.07	1.04	0.9304	0.0696
s1x	1.21	1.10	0.8257	0.1743
s2x	2.53	1.59	0.3947	0.6053
s7x	1.26	1.12	0.7909	0.2091
Mean VIF	1.87			

	Eigenval	Cond Index
1	5.5871	1.0000
2	1.1907	2.1662
3	1.0527	2.3038
4	1.0018	2.3616
5	0.7362	2.7549
6	0.6616	2.9060
7	0.4227	3.6357
8	0.1750	5.6501
9	0.0786	8.4332
10	0.0621	9.4870
11	0.0316	13.3004

Condition Number 13.3004
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.0871

Iteration 0: log likelihood = -564.82395
 Iteration 1: log likelihood = -560.84117
 Iteration 2: log likelihood = -560.84009

Logistic regression	Number of obs =	824
	LR chi2(10) =	7.97
	Prob > chi2 =	0.6320
Log likelihood = -560.84009	Pseudo R2 =	0.0071

f10_9x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_9x	-.1356998	.1878592	-0.72	0.470	-.503897 .2324974
s3_1x	-.224569	.2379905	-0.94	0.345	-.6910217 .2418838
s3_2x	-.4615312	.3041973	-1.52	0.129	-1.057747 .1346844
s3_3x	-.458881	.3228488	-1.42	0.155	-1.091653 .1738911
s3_4x	-.4429798	.3024844	-1.46	0.143	-1.035838 .1498787
s4x	.124634	.0749817	1.66	0.096	-.0223275 .2715955
GrStadt	.147615	.1618528	0.91	0.362	-.1696106 .4648405
s1x	.0588716	.1556521	0.38	0.705	-.246201 .3639442
s2x	.0747871	.0695112	1.08	0.282	-.0614524 .2110267
s7x	-.0581373	.0602323	-0.97	0.334	-.1761903 .0599158
_cons	-.4881742	.318784	-1.53	0.126	-1.112979 .1366311

Iteration 0: log likelihood = -564.82395
 Iteration 1: log likelihood = -560.64087
 Iteration 2: log likelihood = -560.63474
 Iteration 3: log likelihood = -560.63474

Logistic regression	Number of obs =	824
	LR chi2(2) =	8.38
	Prob > chi2 =	0.0152
Log likelihood = -560.63474	Pseudo R2 =	0.0074

f10_9x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.6564606	.6426706	1.02	0.307	-.6031506 1.916072
_hatsq	-.7281998	1.139823	-0.64	0.523	-2.962212 1.505812
_cons	-.0121396	.1142327	-0.11	0.915	-.2360316 .2117525

Collinearity Diagnostics

Variable	VIF	SQRT		R-
		VIF	Tolerance	Squared
f11_10x	1.05	1.02	0.9566	0.0434
s3_1x	2.40	1.55	0.4171	0.5829
s3_2x	1.82	1.35	0.5503	0.4497
s3_3x	1.67	1.29	0.5985	0.4015
s3_4x	3.87	1.97	0.2583	0.7417
s4x	1.70	1.30	0.5879	0.4121
GrStadt	1.07	1.03	0.9355	0.0645
s1x	1.22	1.10	0.8220	0.1780
s2x	2.47	1.57	0.4049	0.5951
s7x	1.25	1.12	0.7972	0.2028

Mean VIF 1.85

	Eigenval	Cond Index
1	5.6437	1.0000
2	1.1320	2.2329
3	1.0921	2.2733
4	1.0018	2.3735
5	0.6853	2.8698
6	0.6762	2.8890
7	0.4152	3.6870
8	0.1790	5.6154
9	0.0799	8.4065
10	0.0622	9.5218
11	0.0327	13.1399

Condition Number 13.1399
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.0907

Iteration 0: log likelihood = -534.64679
Iteration 1: log likelihood = -493.68571
Iteration 2: log likelihood = -492.86265
Iteration 3: log likelihood = -492.8599
Iteration 4: log likelihood = -492.8599

```
Logistic regression                                Number of obs =      884
                                                LR chi2(10)      =     83.57
                                                Prob > chi2      =     0.0000
Log likelihood = -492.8599                    Pseudo R2       =     0.0782
```

f10_10x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_10x	-.9848826	.1771747	-5.56	0.000	-1.332139 - .6376265
s3_1x	.0440389	.2533683	0.17	0.862	-.4525539 .5406318
s3_2x	-.6627014	.3201658	-2.07	0.038	-1.290215 -.0351879
s3_3x	.7905213	.4010881	1.97	0.049	.0044031 1.57664
s3_4x	-.1656646	.3317596	-0.50	0.618	-.8159015 .4845723
s4x	.0904708	.0861563	1.05	0.294	-.0783925 .259334
GrStadt	-.4831633	.1748094	-2.76	0.006	-.8257834 -.1405433
s1x	.2517451	.1730717	1.45	0.146	-.0874692 .5909595
s2x	.2286048	.075926	3.01	0.003	.0797925 .3774171
s7x	.1121376	.0659065	1.70	0.089	-.0170368 .241312
_cons	-.230011	.3332646	-0.69	0.490	-.8831976 .4231757

Iteration 0: log likelihood = -534.64679
Iteration 1: log likelihood = -493.84606
Iteration 2: log likelihood = -492.84794
Iteration 3: log likelihood = -492.84303
Iteration 4: log likelihood = -492.84303

```
Logistic regression                                Number of obs =      884
                                                LR chi2(2)       =     83.61
                                                Prob > chi2      =     0.0000
Log likelihood = -492.84303                    Pseudo R2       =     0.0782
```

f10_10x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.031265	.2066476	4.99	0.000	.6262434 1.436287
_hatsq	-.0228766	.1244497	-0.18	0.854	-.2667935 .2210403
_cons	-.000017	.1227629	-0.00	1.000	-.2406279 .240594

Annex 5 – Acceptance of policy measures by several determinants (logit models without ‘objective’ self-interest)

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_lx	1.03	1.01	0.9719	0.0281
left1st	1.03	1.01	0.9741	0.0259
s1x	1.03	1.01	0.9742	0.0258
s2x	1.07	1.04	0.9332	0.0668
s7x	1.06	1.03	0.9463	0.0537
Mean VIF	1.04			

	Eigenval	Cond Index
1	4.5185	1.0000
2	0.6795	2.5788
3	0.4733	3.0898
4	0.1852	4.9397
5	0.1146	6.2797
6	0.0290	12.4873

Condition Number 12.4873
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.9004

Iteration 0: log likelihood = -109.97872
 Iteration 1: log likelihood = -101.96287
 Iteration 2: log likelihood = -99.899653
 Iteration 3: log likelihood = -99.832951
 Iteration 4: log likelihood = -99.832767

Logistic regression
 Number of obs = 761
 LR chi2(5) = 20.29
 Prob > chi2 = 0.0011
 Pseudo R2 = 0.0923

f10_lx	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_lx	-.9351058	.5385789	-1.74	0.083	-1.990701 .1204893
left1st	-.4328064	.4963807	-0.87	0.383	-1.405695 .5400819
s1x	1.338971	.5126939	2.61	0.009	.3341095 2.343833
s2x	-.272612	.131884	-2.07	0.039	-.5311 -.014124
s7x	.2781196	.1689839	1.65	0.100	-.0530827 .6093219
_cons	-3.295133	1.003557	-3.28	0.001	-5.262067 -1.328198

Iteration 0: log likelihood = -109.97872
 Iteration 1: log likelihood = -101.15758
 Iteration 2: log likelihood = -99.75155
 Iteration 3: log likelihood = -99.599853
 Iteration 4: log likelihood = -99.596257
 Iteration 5: log likelihood = -99.596254

Logistic regression
 Number of obs = 761
 LR chi2(2) = 20.76
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0944

f10_lx	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.900437	1.295345	1.47	0.142	-.6383931 4.439267
_hatsq	.1380031	.1936901	0.71	0.476	-.2416225 .5176287
_cons	1.349181	2.04309	0.66	0.509	-2.655201 5.353564

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_2x	1.04	1.02	0.9624	0.0376
left1st	1.04	1.02	0.9648	0.0352
s1x	1.02	1.01	0.9766	0.0234
s2x	1.08	1.04	0.9222	0.0778
s7x	1.05	1.03	0.9496	0.0504
Mean VIF	1.05			

	Eigenval	Cond Index
1	4.4541	1.0000
2	0.6918	2.5374
3	0.4649	3.0953
4	0.1952	4.7772
5	0.1608	5.2638
6	0.0332	11.5787

Condition Number 11.5787
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.8896

Iteration 0: log likelihood = -296.34904
Iteration 1: log likelihood = -260.22364
Iteration 2: log likelihood = -254.46831
Iteration 3: log likelihood = -254.41887
Iteration 4: log likelihood = -254.41885

Logistic regression Number of obs = 763
 LR chi2(5) = 83.86
 Prob > chi2 = 0.0000
Log likelihood = -254.41885 Pseudo R2 = 0.1415

f10_2x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_2x	-1.53728	.2608951	-5.89	0.000	-2.048625 -1.025935
left1st	.7001217	.2374996	2.95	0.003	.2346311 1.165612
s1x	.0642406	.2337293	0.27	0.783	-.3938604 .5223416
s2x	-.3512414	.074843	-4.69	0.000	-.497931 -2.2045518
s7x	.2603965	.0897424	2.90	0.004	.0845046 .4362885
_cons	-.616775	.5139301	-1.20	0.230	-1.624059 .3905094

Iteration 0: log likelihood = -296.34904
Iteration 1: log likelihood = -266.78085
Iteration 2: log likelihood = -256.58373
Iteration 3: log likelihood = -254.37987
Iteration 4: log likelihood = -254.3788

Logistic regression Number of obs = 763
 LR chi2(2) = 83.94
 Prob > chi2 = 0.0000
Log likelihood = -254.3788 Pseudo R2 = 0.1416

f10_2x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.9234887	.2941293	3.14	0.002	.3470058 1.499972
_hatsq	-.026105	.0925449	-0.28	0.778	-.2074897 .1552797
_cons	-.0303598	.245726	-0.12	0.902	-.5119739 .4512544

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_3x	1.01	1.01	0.9871	0.0129
left1st	1.03	1.02	0.9662	0.0338
s1x	1.02	1.01	0.9767	0.0233
s2x	1.05	1.03	0.9495	0.0505
s7x	1.05	1.03	0.9512	0.0488
Mean VIF	1.04			

	Eigenval	Cond Index
1	3.8425	1.0000
2	0.8640	2.1089
3	0.6231	2.4833
4	0.4479	2.9288
5	0.1787	4.6367
6	0.0438	9.3694

Condition Number 9.3694
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.9162

Iteration 0: log likelihood = -373.56199
 Iteration 1: log likelihood = -356.4683
 Iteration 2: log likelihood = -355.7343
 Iteration 3: log likelihood = -355.73381

Logistic regression
 Number of obs = 714
 LR chi2(5) = 35.66
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0477
 Log likelihood = -355.73381

f10_3x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_3x	-1.045416	.2210326	-4.73	0.000	-1.478631 - .6121997
left1st	.6560987	.2292949	2.86	0.004	.206689 1.105508
s1x	.1049112	.1884771	0.56	0.578	-.2644971 .4743194
s2x	.0370932	.0581893	0.64	0.524	-.0769556 .1511421
s7x	-.1313119	.0722285	-1.82	0.069	-.2728771 .0102533
_cons	1.538983	.3696323	4.16	0.000	.8145172 2.263449

Iteration 0: log likelihood = -373.56199
 Iteration 1: log likelihood = -356.7526
 Iteration 2: log likelihood = -355.72093
 Iteration 3: log likelihood = -355.72002
 Iteration 4: log likelihood = -355.72002

Logistic regression
 Number of obs = 714
 LR chi2(2) = 35.68
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0478
 Log likelihood = -355.72002

f10_3x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.9102548	.5666	1.61	0.108	-.2002608 2.02077
_hatsq	.042681	.2574337	0.17	0.868	-.4618799 .5472418
_cons	.0330936	.3015073	0.11	0.913	-.5578498 .6240369

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_4x	1.01	1.01	0.9899	0.0101
left1st	1.03	1.02	0.9681	0.0319
s1x	1.02	1.01	0.9794	0.0206
s2x	1.05	1.03	0.9494	0.0506
s7x	1.05	1.02	0.9528	0.0472
Mean VIF	1.03			

	Eigenval	Cond Index
1	3.9283	1.0000
2	0.8081	2.2047
3	0.5967	2.5657
4	0.4421	2.9810
5	0.1815	4.6521
6	0.0432	9.5306

Condition Number 9.5306
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.9205

Iteration 0: log likelihood = -480.64598
Iteration 1: log likelihood = -449.17528
Iteration 2: log likelihood = -448.78019
Iteration 3: log likelihood = -448.77974

Logistic regression
Log likelihood = -448.77974

Number of obs	=	719
LR chi2(5)	=	63.73
Prob > chi2	=	0.0000
Pseudo R2	=	0.0663

f10_4x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_4x	-.5766827	.1820406	-3.17	0.002	-.9334756 -.2198897
left1st	.8486372	.1915481	4.43	0.000	.4732099 1.224065
s1x	-.239531	.1619505	-1.48	0.139	-.5569481 .0778862
s2x	-.2404982	.051257	-4.69	0.000	-.3409601 -.1400363
s7x	.0724833	.0617258	1.17	0.240	-.0484971 .1934637
_cons	1.210852	.3248965	3.73	0.000	.5740668 1.847638

Iteration 0: log likelihood = -480.64598
Iteration 1: log likelihood = -449.1765
Iteration 2: log likelihood = -448.39067
Iteration 3: log likelihood = -448.38287
Iteration 4: log likelihood = -448.38287

Logistic regression
Log likelihood = -448.38287

Number of obs	=	719
LR chi2(2)	=	64.53
Prob > chi2	=	0.0000
Pseudo R2	=	0.0671

f10_4x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.8434484	.2195117	3.84	0.000	.4132134 1.273683
_hatsq	.1577894	.1788003	0.88	0.378	-.1926527 .5082315
_cons	-.0184788	.098198	-0.19	0.851	-.2109434 .1739857

Collinearity Diagnostics

Variable	VIF	SQRT		R-Squared
		VIF	Tolerance	
f11_5x	1.02	1.01	0.9772	0.0228
left1st	1.03	1.02	0.9692	0.0308
s1x	1.03	1.01	0.9748	0.0252
s2x	1.07	1.03	0.9375	0.0625
s7x	1.06	1.03	0.9442	0.0558
Mean VIF	1.04			

	Eigenval	Cond Index
1	4.1338	1.0000
2	0.6974	2.4347
3	0.5533	2.7333
4	0.3971	3.2265
5	0.1764	4.8405
6	0.0420	9.9169

Condition Number 9.9169
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.9033

Iteration 0: log likelihood = -510.05745
 Iteration 1: log likelihood = -495.94937
 Iteration 2: log likelihood = -495.93416
 Iteration 3: log likelihood = -495.93416

Logistic regression
 Number of obs = 748
 LR chi2(5) = 28.25
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0277
 Log likelihood = -495.93416

f10_5x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_5x	-.3850581	.1534353	-2.51	0.012	-.6857858 -.0843305
left1st	.5937061	.1667035	3.56	0.000	.2669733 .920439
s1x	.205526	.152556	1.35	0.178	-.0934784 .5045303
s2x	-.0256575	.0474216	-0.54	0.588	-.1186022 .0672872
s7x	.1144832	.0581587	1.97	0.049	.0004943 .228472
_cons	-.649659	.3092255	-2.10	0.036	-1.25573 -.0435881

Iteration 0: log likelihood = -510.05745
 Iteration 1: log likelihood = -495.9348
 Iteration 2: log likelihood = -495.91818
 Iteration 3: log likelihood = -495.91818

Logistic regression
 Number of obs = 748
 LR chi2(2) = 28.28
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0277
 Log likelihood = -495.91818

f10_5x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.033444	.2684348	3.85	0.000	.5073211 1.559566
_hatsq	.0749449	.4191144	0.18	0.858	-.7465042 .896394
_cons	-.0082145	.1048647	-0.08	0.938	-.2137455 .1973166

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_6x	1.02	1.01	0.9773	0.0227
left1st	1.03	1.02	0.9668	0.0332
s1x	1.02	1.01	0.9770	0.0230
s2x	1.06	1.03	0.9431	0.0569
s7x	1.07	1.03	0.9370	0.0630
Mean VIF	1.04			

	Eigenval	Cond Index
1	4.1843	1.0000
2	0.7031	2.4394
3	0.4993	2.8948
4	0.3963	3.2493
5	0.1744	4.8976
6	0.0425	9.9227

```

Condition Number      9.9227
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix)  0.9021

```

```

Iteration 0:  log likelihood = -498.78239
Iteration 1:  log likelihood = -476.98325
Iteration 2:  log likelihood = -476.94036
Iteration 3:  log likelihood = -476.94036

```

```

Logistic regression                Number of obs   =       728
                                   LR chi2(5)         =       43.68
                                   Prob > chi2         =       0.0000
Log likelihood = -476.94036        Pseudo R2      =       0.0438

```

f10_6x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
f11_6x	-.9054108	.1566653	-5.78	0.000	-1.212469	-.5983525
left1st	.4275392	.1721172	2.48	0.013	.0901958	.7648826
s1x	.1493957	.1557306	0.96	0.337	-.1558306	.454622
s2x	-.0317113	.0489434	-0.65	0.517	-.1276385	.0642159
s7x	.0364457	.0597729	0.61	0.542	-.0807071	.1535985
_cons	-.0099962	.3120964	-0.03	0.974	-.6216939	.6017015

```

Iteration 0:  log likelihood = -498.78239
Iteration 1:  log likelihood = -476.98563
Iteration 2:  log likelihood = -476.93957
Iteration 3:  log likelihood = -476.93957

```

```

Logistic regression                Number of obs   =       728
                                   LR chi2(2)         =       43.69
                                   Prob > chi2         =       0.0000
Log likelihood = -476.93957        Pseudo R2      =       0.0438

```

f10_6x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.007224	.2389596	4.22	0.000	.5388716	1.475576
_hatsq	.0143296	.3599623	0.04	0.968	-.6911835	.7198428
_cons	-.0026141	.1078196	-0.02	0.981	-.2139365	.2087084

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_7x	1.01	1.00	0.9937	0.0063
left1st	1.03	1.01	0.9740	0.0260
s1x	1.02	1.01	0.9806	0.0194
s2x	1.05	1.02	0.9537	0.0463
s7x	1.05	1.03	0.9486	0.0514
Mean VIF	1.03			

	Eigenval	Cond Index
1	4.2864	1.0000
2	0.6860	2.4997
3	0.4815	2.9835
4	0.3259	3.6264
5	0.1774	4.9150
6	0.0428	10.0098

Condition Number 10.0098
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.9256

Iteration 0: log likelihood = -279.51577
 Iteration 1: log likelihood = -267.37835
 Iteration 2: log likelihood = -266.82701
 Iteration 3: log likelihood = -266.82623
 Iteration 4: log likelihood = -266.82623

Logistic regression	Number of obs	=	724
	LR chi2(5)	=	25.38
	Prob > chi2	=	0.0001
Log likelihood = -266.82623	Pseudo R2	=	0.0454

f10_7x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
f11_7x	-.9793545	.2287156	-4.28	0.000	-1.427629	-.5310802
left1st	.4459179	.2413635	1.85	0.065	-.0271458	.9189816
s1x	-.0828876	.2280191	-0.36	0.716	-.5297968	.3640216
s2x	-.1258988	.0694697	-1.81	0.070	-.2620569	.0102593
s7x	.0006789	.087427	0.01	0.994	-.1706749	.1720327
_cons	-1.03917	.4429215	-2.35	0.019	-1.90728	-.1710593

Iteration 0: log likelihood = -279.51577
 Iteration 1: log likelihood = -267.48881
 Iteration 2: log likelihood = -265.4534
 Iteration 3: log likelihood = -265.45143

Logistic regression	Number of obs	=	724
	LR chi2(2)	=	28.13
	Prob > chi2	=	0.0000
Log likelihood = -265.45143	Pseudo R2	=	0.0503

f10_7x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	3.224156	1.345735	2.40	0.017	.586564	5.861748
_hatsq	.6041812	.3604779	1.68	0.094	-.1023426	1.310705
_cons	1.848255	1.164206	1.59	0.112	-.4335475	4.130057

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_8x	1.02	1.01	0.9776	0.0224
left1st	1.03	1.01	0.9707	0.0293
s1x	1.03	1.01	0.9715	0.0285
s2x	1.07	1.03	0.9368	0.0632
s7x	1.05	1.03	0.9493	0.0507
Mean VIF	1.04			

	Eigenval	Cond Index
1	4.2017	1.0000
2	0.6719	2.5007
3	0.5250	2.8290
4	0.3798	3.3261
5	0.1815	4.8110
6	0.0401	10.2381

Condition Number 10.2381
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.9060

Iteration 0: log likelihood = -293.05204
Iteration 1: log likelihood = -277.70434
Iteration 2: log likelihood = -276.89303
Iteration 3: log likelihood = -276.89044
Iteration 4: log likelihood = -276.89044

Logistic regression Number of obs = 753
LR chi2(5) = 32.32
Prob > chi2 = 0.0000
Log likelihood = -276.89044 Pseudo R2 = 0.0551

f10_8x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
f11_8x	-.8916461	.2306819	-3.87	0.000	-1.343774	-.4395178
left1st	-.5738425	.2769361	-2.07	0.038	-1.116627	-.0310578
s1x	.3967038	.2282025	1.74	0.082	-.0505649	.8439726
s2x	-.1773823	.0688795	-2.58	0.010	-.3123837	-.0423809
s7x	-.0477612	.0844243	-0.57	0.572	-.2132299	.1177074
_cons	-.7666529	.4443284	-1.73	0.084	-1.637521	.1042149

Iteration 0: log likelihood = -293.05204
Iteration 1: log likelihood = -278.69826
Iteration 2: log likelihood = -276.42016
Iteration 3: log likelihood = -276.41348
Iteration 4: log likelihood = -276.41348

Logistic regression Number of obs = 753
LR chi2(2) = 33.28
Prob > chi2 = 0.0000
Log likelihood = -276.41348 Pseudo R2 = 0.0568

f10_8x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.868984	.8955782	2.09	0.037	.1136825	3.624285
_hatsq	.2376046	.2383889	1.00	0.319	-.229629	.7048383
_cons	.7026791	.7846161	0.90	0.370	-.8351403	2.240498

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_9x	1.02	1.01	0.9776	0.0224
leftist	1.04	1.02	0.9641	0.0359
s1x	1.02	1.01	0.9796	0.0204
s2x	1.07	1.03	0.9357	0.0643
s7x	1.05	1.02	0.9519	0.0481
Mean VIF	1.04			

	Eigenval	Cond Index
1	3.8336	1.0000
2	0.8634	2.1072
3	0.6352	2.4567
4	0.4469	2.9289
5	0.1783	4.6363
6	0.0425	9.4933

Condition Number 9.4933
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.9065

Iteration 0: log likelihood = -474.35896
Iteration 1: log likelihood = -471.70413
Iteration 2: log likelihood = -471.70367

Logistic regression	Number of obs	=	693
	LR chi2(5)	=	5.31
	Prob > chi2	=	0.3792
Log likelihood = -471.70367	Pseudo R2	=	0.0056

f10_9x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_9x	-.0288748	.2048817	-0.14	0.888	-.4304357 .372686
leftist	.1764816	.1714505	1.03	0.303	-.1595551 .5125184
s1x	.2385678	.1558459	1.53	0.126	-.0668847 .5440202
s2x	.0760276	.0491958	1.55	0.122	-.0203943 .1724495
s7x	-.0127043	.0598032	-0.21	0.832	-.1299164 .1045078
_cons	-.6820787	.3179047	-2.15	0.032	-1.305161 -.0589968

Iteration 0: log likelihood = -474.35896
Iteration 1: log likelihood = -471.27498
Iteration 2: log likelihood = -471.27464

Logistic regression	Number of obs	=	693
	LR chi2(2)	=	6.17
	Prob > chi2	=	0.0458
Log likelihood = -471.27464	Pseudo R2	=	0.0065

f10_9x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.956293	1.12327	1.74	0.082	-.2452754 4.157861
_hatsq	1.816485	1.959265	0.93	0.354	-2.023604 5.656574
_cons	.0690417	.1571853	0.44	0.660	-.2390358 .3771193

Collinearity Diagnostics

Variable	VIF	SQRT		R-Squared
		VIF	Tolerance	
f11_10x	1.01	1.00	0.9932	0.0068
leftist	1.03	1.01	0.9730	0.0270
s1x	1.03	1.01	0.9728	0.0272
s2x	1.06	1.03	0.9474	0.0526
s7x	1.05	1.03	0.9510	0.0490
Mean VIF	1.03			

	Eigenval	Cond Index
1	3.8981	1.0000
2	0.7869	2.2257
3	0.6621	2.4264
4	0.4290	3.0143
5	0.1803	4.6492
6	0.0436	9.4548

Condition Number 9.4548
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.9193

Iteration 0: log likelihood = -433.47263
 Iteration 1: log likelihood = -406.72292
 Iteration 2: log likelihood = -406.22705
 Iteration 3: log likelihood = -406.22683

Logistic regression
 Number of obs = 736
 LR chi2(5) = 54.49
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0629

f10_10x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_10x	-1.097461	.1955387	-5.61	0.000	-1.48071 - .7142124
leftist	-.3170437	.1899047	-1.67	0.095	-.6892501 .0551628
s1x	.4193061	.1748668	2.40	0.016	.0765711 .762041
s2x	.2167636	.0544796	3.98	0.000	.1099856 .3235416
s7x	.1310754	.0663373	1.98	0.048	.0010566 .2610942
_cons	-.0715567	.3347001	-0.21	0.831	-.7275568 .5844433

Iteration 0: log likelihood = -433.47263
 Iteration 1: log likelihood = -405.34079
 Iteration 2: log likelihood = -404.81169
 Iteration 3: log likelihood = -404.81065
 Iteration 4: log likelihood = -404.81065

Logistic regression
 Number of obs = 736
 LR chi2(2) = 57.32
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0661

f10_10x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.468805	.3189911	4.60	0.000	.8435939 2.094016
_hatsq	-.2974565	.1764526	-1.69	0.092	-.6432972 .0483841
_cons	-.0676197	.1632644	-0.41	0.679	-.387612 .2523726

Annex 6 – Acceptance of policy measures by several determinants (logit models without ‘objective’ self-interest)

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_lx	1.03	1.01	0.9719	0.0281
left1st	1.03	1.01	0.9741	0.0259
s1x	1.03	1.01	0.9742	0.0258
s2x	1.07	1.04	0.9332	0.0668
s7x	1.06	1.03	0.9463	0.0537
Mean VIF	1.04			

	Eigenval	Cond Index
1	4.5185	1.0000
2	0.6795	2.5788
3	0.4733	3.0898
4	0.1852	4.9397
5	0.1146	6.2797
6	0.0290	12.4873

Condition Number 12.4873
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.9004

Iteration 0: log likelihood = -109.97872
Iteration 1: log likelihood = -101.96287
Iteration 2: log likelihood = -99.899653
Iteration 3: log likelihood = -99.832951
Iteration 4: log likelihood = -99.832767

Logistic regression
Number of obs = 761
LR chi2(5) = 20.29
Prob > chi2 = 0.0011
Pseudo R2 = 0.0923
Log likelihood = -99.832767

f10_lx	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_lx	-.9351058	.5385789	-1.74	0.083	-1.990701 .1204893
left1st	-.4328064	.4963807	-0.87	0.383	-1.405695 .5400819
s1x	1.338971	.5126939	2.61	0.009	.3341095 2.343833
s2x	-.272612	.131884	-2.07	0.039	-.5311 -.014124
s7x	.2781196	.1689839	1.65	0.100	-.0530827 .6093219
_cons	-3.295133	1.003557	-3.28	0.001	-5.262067 -1.328198

Iteration 0: log likelihood = -109.97872
Iteration 1: log likelihood = -101.15758
Iteration 2: log likelihood = -99.75155
Iteration 3: log likelihood = -99.599853
Iteration 4: log likelihood = -99.596257
Iteration 5: log likelihood = -99.596254

Logistic regression
Number of obs = 761
LR chi2(2) = 20.76
Prob > chi2 = 0.0000
Pseudo R2 = 0.0944
Log likelihood = -99.596254

f10_lx	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.900437	1.295345	1.47	0.142	-.6383931 4.439267
_hatsq	.1380031	.1936901	0.71	0.476	-.2416225 .5176287
_cons	1.349181	2.04309	0.66	0.509	-2.655201 5.353564

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_3x	1.01	1.01	0.9871	0.0129
leftist	1.03	1.02	0.9662	0.0338
s1x	1.02	1.01	0.9767	0.0233
s2x	1.05	1.03	0.9495	0.0505
s7x	1.05	1.03	0.9512	0.0488
Mean VIF	1.04			

	Eigenval	Cond Index
1	3.8425	1.0000
2	0.8640	2.1089
3	0.6231	2.4833
4	0.4479	2.9288
5	0.1787	4.6367
6	0.0438	9.3694

Condition Number 9.3694
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det (correlation matrix) 0.9162

Iteration 0: log likelihood = -373.56199
Iteration 1: log likelihood = -356.4683
Iteration 2: log likelihood = -355.7343
Iteration 3: log likelihood = -355.73381

Logistic regression
Log likelihood = -355.73381

Number of obs =	714
LR chi2(5) =	35.66
Prob > chi2 =	0.0000
Pseudo R2 =	0.0477

f10_3x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_3x	-1.045416	.2210326	-4.73	0.000	-1.478631 - .6121997
leftist	.6560987	.2292949	2.86	0.004	.206689 1.105508
s1x	.1049112	.1884771	0.56	0.578	-.2644971 .4743194
s2x	.0370932	.0581893	0.64	0.524	-.0769556 .1511421
s7x	-.1313119	.0722285	-1.82	0.069	-.2728771 .0102533
_cons	1.538983	.3696323	4.16	0.000	.8145172 2.263449

Iteration 0: log likelihood = -373.56199
Iteration 1: log likelihood = -356.7526
Iteration 2: log likelihood = -355.72093
Iteration 3: log likelihood = -355.72002
Iteration 4: log likelihood = -355.72002

Logistic regression
Log likelihood = -355.72002

Number of obs =	714
LR chi2(2) =	35.68
Prob > chi2 =	0.0000
Pseudo R2 =	0.0478

f10_3x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.9102548	.5666	1.61	0.108	-.2002608 2.02077
_hatsq	.042681	.2574337	0.17	0.868	-.4618799 .5472418
_cons	.0330936	.3015073	0.11	0.913	-.5578498 .6240369

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_4x	1.01	1.01	0.9899	0.0101
left1st	1.03	1.02	0.9681	0.0319
s1x	1.02	1.01	0.9794	0.0206
s2x	1.05	1.03	0.9494	0.0506
s7x	1.05	1.02	0.9528	0.0472
Mean VIF	1.03			

	Eigenval	Cond Index
1	3.9283	1.0000
2	0.8081	2.2047
3	0.5967	2.5657
4	0.4421	2.9810
5	0.1815	4.6521
6	0.0432	9.5306

Condition Number 9.5306
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.9205

Iteration 0: log likelihood = -480.64598
Iteration 1: log likelihood = -449.17528
Iteration 2: log likelihood = -448.78019
Iteration 3: log likelihood = -448.77974

Logistic regression
Log likelihood = -448.77974

Number of obs	=	719
LR chi2(5)	=	63.73
Prob > chi2	=	0.0000
Pseudo R2	=	0.0663

f10_4x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_4x	-.5766827	.1820406	-3.17	0.002	-.9334756 -.2198897
left1st	.8486372	.1915481	4.43	0.000	.4732099 1.224065
s1x	-.239531	.1619505	-1.48	0.139	-.5569481 .0778862
s2x	-.2404982	.051257	-4.69	0.000	-.3409601 -.1400363
s7x	.0724833	.0617258	1.17	0.240	-.0484971 .1934637
_cons	1.210852	.3248965	3.73	0.000	.5740668 1.847638

Iteration 0: log likelihood = -480.64598
Iteration 1: log likelihood = -449.1765
Iteration 2: log likelihood = -448.39067
Iteration 3: log likelihood = -448.38287
Iteration 4: log likelihood = -448.38287

Logistic regression
Log likelihood = -448.38287

Number of obs	=	719
LR chi2(2)	=	64.53
Prob > chi2	=	0.0000
Pseudo R2	=	0.0671

f10_4x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.8434484	.2195117	3.84	0.000	.4132134 1.273683
_hatsq	.1577894	.1788003	0.88	0.378	-.1926527 .5082315
_cons	-.0184788	.098198	-0.19	0.851	-.2109434 .1739857

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_5x	1.02	1.01	0.9772	0.0228
left1st	1.03	1.02	0.9692	0.0308
s1x	1.03	1.01	0.9748	0.0252
s2x	1.07	1.03	0.9375	0.0625
s7x	1.06	1.03	0.9442	0.0558
Mean VIF	1.04			

	Eigenval	Cond Index
1	4.1338	1.0000
2	0.6974	2.4347
3	0.5533	2.7333
4	0.3971	3.2265
5	0.1764	4.8405
6	0.0420	9.9169

Condition Number 9.9169
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det (correlation matrix) 0.9033

Iteration 0: log likelihood = -510.05745
Iteration 1: log likelihood = -495.94937
Iteration 2: log likelihood = -495.93416
Iteration 3: log likelihood = -495.93416

Logistic regression Number of obs = 748
LR chi2(5) = 28.25
Prob > chi2 = 0.0000
Log likelihood = -495.93416 Pseudo R2 = 0.0277

f10_5x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_5x	-.3850581	.1534353	-2.51	0.012	-.6857858 -.0843305
left1st	.5937061	.1667035	3.56	0.000	.2669733 .920439
s1x	.205526	.152556	1.35	0.178	-.0934784 .5045303
s2x	-.0256575	.0474216	-0.54	0.588	-.1186022 .0672872
s7x	.1144832	.0581587	1.97	0.049	.0004943 .228472
_cons	-.649659	.3092255	-2.10	0.036	-1.25573 -.0435881

Iteration 0: log likelihood = -510.05745
Iteration 1: log likelihood = -495.9348
Iteration 2: log likelihood = -495.91818
Iteration 3: log likelihood = -495.91818

Logistic regression Number of obs = 748
LR chi2(2) = 28.28
Prob > chi2 = 0.0000
Log likelihood = -495.91818 Pseudo R2 = 0.0277

f10_5x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.033444	.2684348	3.85	0.000	.5073211 1.559566
_hatsq	.0749449	.4191144	0.18	0.858	-.7465042 .896394
_cons	-.0082145	.1048647	-0.08	0.938	-.2137455 .1973166

Collinearity Diagnostics

Variable	VIF	SQRT		R-Squared
		VIF	Tolerance	
f11_6x	1.02	1.01	0.9773	0.0227
left1st	1.03	1.02	0.9668	0.0332
s1x	1.02	1.01	0.9770	0.0230
s2x	1.06	1.03	0.9431	0.0569
s7x	1.07	1.03	0.9370	0.0630
Mean VIF	1.04			

	Eigenval	Cond Index
1	4.1843	1.0000
2	0.7031	2.4394
3	0.4993	2.8948
4	0.3963	3.2493
5	0.1744	4.8976
6	0.0425	9.9227

Condition Number 9.9227
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.9021

Iteration 0: log likelihood = -498.78239
Iteration 1: log likelihood = -476.98325
Iteration 2: log likelihood = -476.94036
Iteration 3: log likelihood = -476.94036

Logistic regression

Number of obs	=	728
LR chi2(5)	=	43.68
Prob > chi2	=	0.0000
Pseudo R2	=	0.0438

Log likelihood = -476.94036

f10_6x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_6x	-.9054108	.1566653	-5.78	0.000	-1.212469 - .5983525
left1st	.4275392	.1721172	2.48	0.013	.0901958 .7648826
s1x	.1493957	.1557306	0.96	0.337	-.1558306 .454622
s2x	-.0317113	.0489434	-0.65	0.517	-.1276385 .0642159
s7x	.0364457	.0597729	0.61	0.542	-.0807071 .1535985
_cons	-.0099962	.3120964	-0.03	0.974	-.6216939 .6017015

Iteration 0: log likelihood = -498.78239
Iteration 1: log likelihood = -476.98563
Iteration 2: log likelihood = -476.93957
Iteration 3: log likelihood = -476.93957

Logistic regression

Number of obs	=	728
LR chi2(2)	=	43.69
Prob > chi2	=	0.0000
Pseudo R2	=	0.0438

Log likelihood = -476.93957

f10_6x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.007224	.2389596	4.22	0.000	.5388716 1.475576
_hatsq	.0143296	.3599623	0.04	0.968	-.6911835 .7198428
_cons	-.0026141	.1078196	-0.02	0.981	-.2139365 .2087084

Collinearity Diagnostics

Variable	VIF	SQRT		R-Squared
		VIF	Tolerance	
f11_7x	1.01	1.00	0.9937	0.0063
left1st	1.03	1.01	0.9740	0.0260
s1x	1.02	1.01	0.9806	0.0194
s2x	1.05	1.02	0.9537	0.0463
s7x	1.05	1.03	0.9486	0.0514

Mean VIF 1.03

	Eigenval	Cond Index
1	4.2864	1.0000
2	0.6860	2.4997
3	0.4815	2.9835
4	0.3259	3.6264
5	0.1774	4.9150
6	0.0428	10.0098

Condition Number 10.0098

Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.9256

Iteration 0: log likelihood = -279.51577
Iteration 1: log likelihood = -267.37835
Iteration 2: log likelihood = -266.82701
Iteration 3: log likelihood = -266.82623
Iteration 4: log likelihood = -266.82623

Logistic regression	Number of obs =	724
	LR chi2(5) =	25.38
	Prob > chi2 =	0.0001
Log likelihood = -266.82623	Pseudo R2 =	0.0454

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
f11_7x	-.9793545	.2287156	-4.28	0.000	-1.427629	-.5310802
left1st	.4459179	.2413635	1.85	0.065	-.0271458	.9189816
s1x	-.0828876	.2280191	-0.36	0.716	-.5297968	.3640216
s2x	-.1258988	.0694697	-1.81	0.070	-.2620569	.0102593
s7x	.0006789	.087427	0.01	0.994	-.1706749	.1720327
_cons	-1.03917	.4429215	-2.35	0.019	-1.90728	-.1710593

Iteration 0: log likelihood = -279.51577
Iteration 1: log likelihood = -267.48881
Iteration 2: log likelihood = -265.4534
Iteration 3: log likelihood = -265.45143

Logistic regression	Number of obs =	724
	LR chi2(2) =	28.13
	Prob > chi2 =	0.0000
Log likelihood = -265.45143	Pseudo R2 =	0.0503

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	3.224156	1.345735	2.40	0.017	.586564	5.861748
_hatsq	.6041812	.3604779	1.68	0.094	-.1023426	1.310705
_cons	1.848255	1.164206	1.59	0.112	-.4335475	4.130057

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_8x	1.02	1.01	0.9776	0.0224
left1st	1.03	1.01	0.9707	0.0293
s1x	1.03	1.01	0.9715	0.0285
s2x	1.07	1.03	0.9368	0.0632
s7x	1.05	1.03	0.9493	0.0507

Mean VIF 1.04

	Eigenval	Cond Index
1	4.2017	1.0000
2	0.6719	2.5007
3	0.5250	2.8290
4	0.3798	3.3261
5	0.1815	4.8110
6	0.0401	10.2381

Condition Number 10.2381
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det (correlation matrix) 0.9060

Iteration 0: log likelihood = -293.05204
Iteration 1: log likelihood = -277.70434
Iteration 2: log likelihood = -276.89303
Iteration 3: log likelihood = -276.89044
Iteration 4: log likelihood = -276.89044

Logistic regression	Number of obs	=	753
	LR chi2(5)	=	32.32
	Prob > chi2	=	0.0000
Log likelihood = -276.89044	Pseudo R2	=	0.0551

f10_8x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_8x	-.8916461	.2306819	-3.87	0.000	-1.343774 - .4395178
left1st	-.5738425	.2769361	-2.07	0.038	-1.116627 - .0310578
s1x	.3967038	.2282025	1.74	0.082	-.0505649 .8439726
s2x	-.1773823	.0688795	-2.58	0.010	-.3123837 - .0423809
s7x	-.0477612	.0844243	-0.57	0.572	-.2132299 .1177074
_cons	-.7666529	.4443284	-1.73	0.084	-1.637521 .1042149

Iteration 0: log likelihood = -293.05204
Iteration 1: log likelihood = -278.69826
Iteration 2: log likelihood = -276.42016
Iteration 3: log likelihood = -276.41348
Iteration 4: log likelihood = -276.41348

Logistic regression	Number of obs	=	753
	LR chi2(2)	=	33.28
	Prob > chi2	=	0.0000
Log likelihood = -276.41348	Pseudo R2	=	0.0568

f10_8x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.868984	.8955782	2.09	0.037	.1136825 3.624285
_hatsq	.2376046	.2383889	1.00	0.319	-.229629 .7048383
_cons	.7026791	.7846161	0.90	0.370	-.8351403 2.240498

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_9x	1.02	1.01	0.9776	0.0224
leftist	1.04	1.02	0.9641	0.0359
s1x	1.02	1.01	0.9796	0.0204
s2x	1.07	1.03	0.9357	0.0643
s7x	1.05	1.02	0.9519	0.0481

Mean VIF 1.04

	Eigenval	Cond Index
1	3.8336	1.0000
2	0.8634	2.1072
3	0.6352	2.4567
4	0.4469	2.9289
5	0.1783	4.6363
6	0.0425	9.4933

Condition Number 9.4933
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.9065

Iteration 0: log likelihood = -474.35896
 Iteration 1: log likelihood = -471.70413
 Iteration 2: log likelihood = -471.70367

Logistic regression
 Number of obs = 693
 LR chi2(5) = 5.31
 Prob > chi2 = 0.3792
 Pseudo R2 = 0.0056
 Log likelihood = -471.70367

f10_9x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_9x	-.0288748	.2048817	-0.14	0.888	-.4304357 .372686
leftist	.1764816	.1714505	1.03	0.303	-.1595551 .5125184
s1x	.2385678	.1558459	1.53	0.126	-.0668847 .5440202
s2x	-.0760276	.0491958	-1.55	0.122	-.0203943 .1724495
s7x	-.0127043	.0598032	-0.21	0.832	-.1299164 .1045078
_cons	-.6820787	.3179047	-2.15	0.032	-1.305161 -.0589968

Iteration 0: log likelihood = -474.35896
 Iteration 1: log likelihood = -471.27498
 Iteration 2: log likelihood = -471.27464

Logistic regression
 Number of obs = 693
 LR chi2(2) = 6.17
 Prob > chi2 = 0.0458
 Pseudo R2 = 0.0065
 Log likelihood = -471.27464

f10_9x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.956293	1.12327	1.74	0.082	-.2452754 4.157861
_hatsq	1.816485	1.959265	0.93	0.354	-2.023604 5.656574
_cons	.0690417	.1571853	0.44	0.660	-.2390358 .3771193

Collinearity Diagnostics

Variable	VIF	SQRT		R-Squared
		VIF	Tolerance	
f11_10x	1.01	1.00	0.9932	0.0068
leftist	1.03	1.01	0.9730	0.0270
s1x	1.03	1.01	0.9728	0.0272
s2x	1.06	1.03	0.9474	0.0526
s7x	1.05	1.03	0.9510	0.0490
Mean VIF	1.03			

	Eigenval	Cond Index
1	3.8981	1.0000
2	0.7869	2.2257
3	0.6621	2.4264
4	0.4290	3.0143
5	0.1803	4.6492
6	0.0436	9.4548

Condition Number 9.4548
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.9193

Iteration 0: log likelihood = -433.47263
 Iteration 1: log likelihood = -406.72292
 Iteration 2: log likelihood = -406.22705
 Iteration 3: log likelihood = -406.22683

Logistic regression
 Number of obs = 736
 LR chi2(5) = 54.49
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0629

f10_10x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_10x	-1.097461	.1955387	-5.61	0.000	-1.48071 - .7142124
leftist	-.3170437	.1899047	-1.67	0.095	-.6892501 .0551628
s1x	.4193061	.174868	2.40	0.016	.0765711 .762041
s2x	.2167636	.0544796	3.98	0.000	.1099856 .3235416
s7x	.1310754	.0663373	1.98	0.048	.0010566 .2610942
_cons	-.0715567	.3347001	-0.21	0.831	-.7275568 .5844433

Iteration 0: log likelihood = -433.47263
 Iteration 1: log likelihood = -405.34079
 Iteration 2: log likelihood = -404.81169
 Iteration 3: log likelihood = -404.81065
 Iteration 4: log likelihood = -404.81065

Logistic regression
 Number of obs = 736
 LR chi2(2) = 57.32
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0661

f10_10x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.468805	.3189911	4.60	0.000	.8435939 2.094016
_hatsq	-.2974565	.1764526	-1.69	0.092	-.6432972 .0483841
_cons	-.0676197	.1632644	-0.41	0.679	-.387612 .2523726