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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

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2010: Ökonomie der Familie - Session: Public Economics: How do individuals vote and behave?, No. E18-V1

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Schwarz, Gerhard; Pitlik, Hans; Brandl, Bernd; Bechter, Barbara (2010) : Near Is My Shirt, But Nearer Is My Skin: Ideology or Self-Interest as Determinants of Public Opinion on Fiscal Policy Issues, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2010: Ökonomie der Familie - Session: Public Economics: How do individuals vote and behave?, No. E18-V1, Verein für Socialpolitik, Frankfurt a. M.

This Version is available at:

<https://hdl.handle.net/10419/37248>

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Submission to Verein für Socialpolitik, Jahrestagung 2010,
Kiel, Germany

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

This version: 01 March 2010

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.

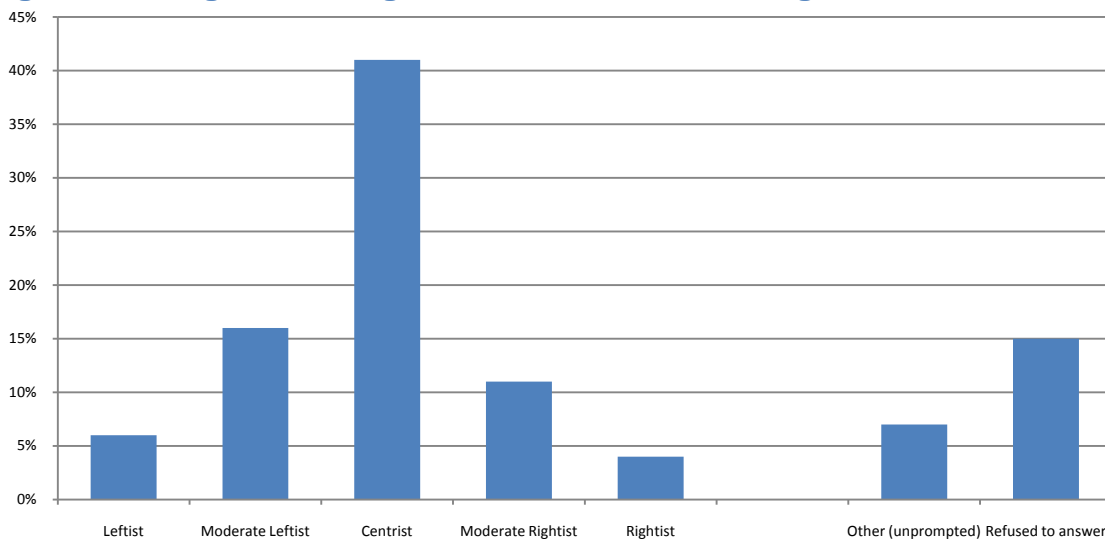
² To prevent order biases the sequence of categories was randomized.

- 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



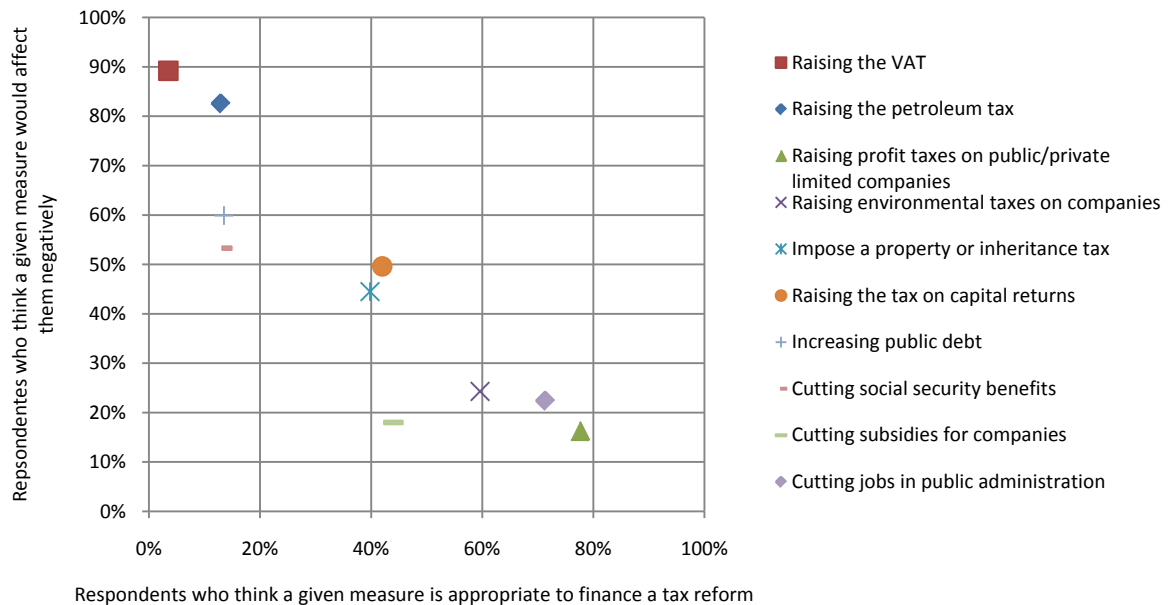
3 Descriptive Statistics

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

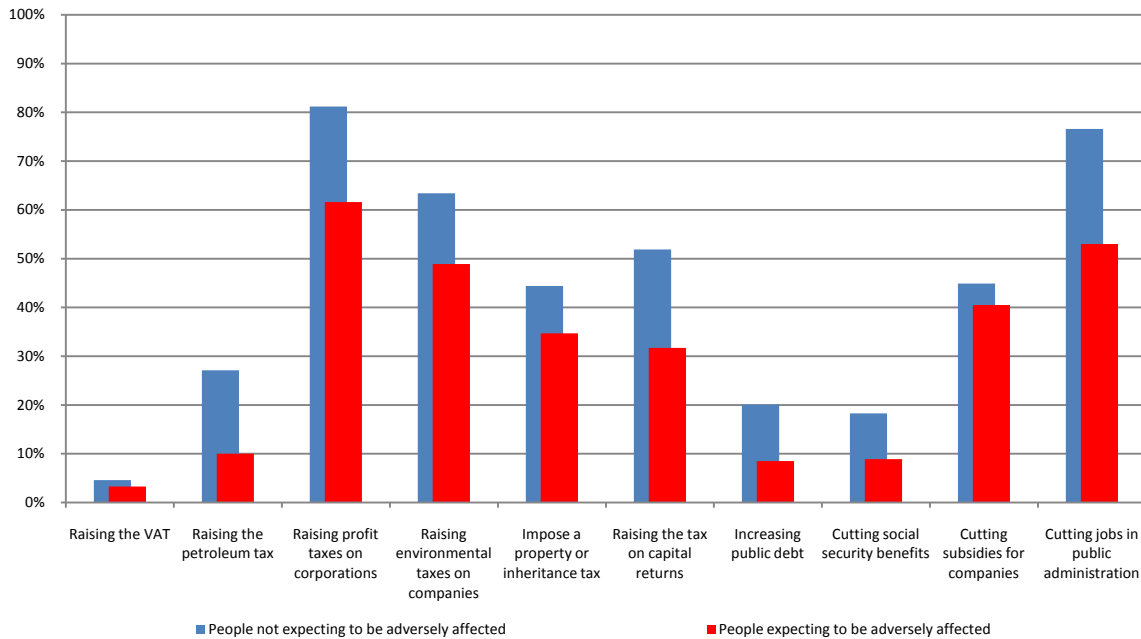
Descriptive analyses reveal a clear adverse correlation between the share of respondents who suppose a given policy measure is appropriate for financing a tax reform (acceptance) and the share of respondents who think this specific measure would have an adverse impact on them (Pearson's Correlation Coefficient = -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

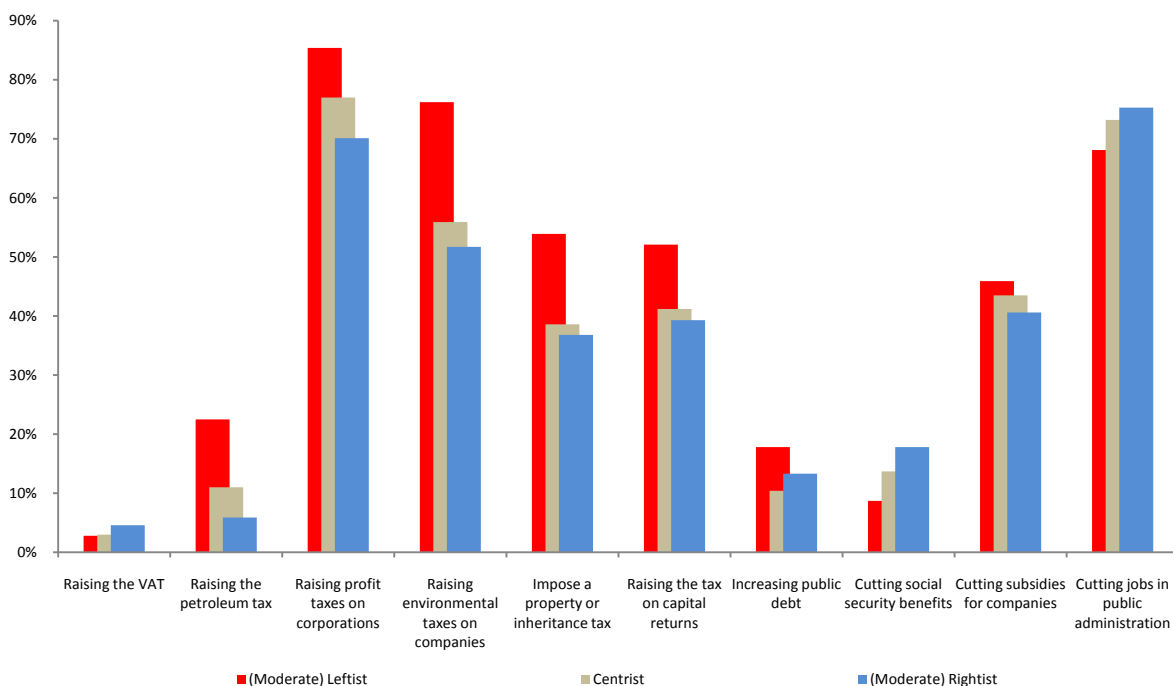


Remarkably this strong correlation does not simply imply that people who fear an adverse impact on themselves oppose a certain measure while people who do not feel affected are in favor of it. Figure 3 clearly shows that the rates of acceptance show a similar pattern for both groups (Pearson's Correlation 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)

		Sub- jec- tive self- inter- est	Objective self-interest						Ide- ology	Control variables		
	Pseudo R ²	Expected adverse consequences of measure	Employee in the private sector	Employee in the public sector	Self-employed	Retired	Personal monthly net income	Living in a big city	(Moderate) Leftist	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)

		Sub- jec- tive self- inter- est	Objective self-interest						Ide- ology	Control variables		
	Pseudo R ²	Expected adverse consequences of measure	Occupation						(Moderate) Leftist	Sex	Age	Educational level
			Employee in the private sector	Employee in the public sector	Self-employed	Retired	Personal net income	Living in a big city				
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	Objective self-interest							Ide- ology	Control variables		
	Expected adverse consequences of measure		Occupation										
			Employee in the private sector	Employee in the public sector	Self-employed	Retired	Personal monthly net income	Living in a big city	(Moderate) Leftist		Sex	Age	Educational level
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)

		Objective self-interest						Ideology	Control variables		
	Pseudo R ²	Occupation						(Moderate) Leftist	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	0.06						↓				↑
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 VIF	Tolerance	R- Squared
f11_2x	1.11	1.05	0.9001	0.0999
s3_1x	2.38	1.54	0.4200	0.5800
s3_2x	1.76	1.33	0.5694	0.4306
s3_3x	1.74	1.32	0.5756	0.4244
s3_4x	3.98	2.00	0.2511	0.7489
s4x	1.72	1.31	0.5822	0.4178
GrStadt	1.13	1.07	0.8814	0.1186
leftist	1.06	1.03	0.9397	0.0603
s1x	1.24	1.11	0.8071	0.1929
s2x	2.53	1.59	0.3947	0.6053
s7x	1.27	1.13	0.7881	0.2119

Mean VIF 1.81

	Eigenval	Cond Index
1	6.5431	1.0000
2	1.1420	2.3937
3	1.0181	2.5351
4	1.0037	2.5533
5	0.7946	2.8695
6	0.5778	3.3651
7	0.4235	3.9306
8	0.1906	5.8597
9	0.1451	6.7150
10	0.0722	9.5181
11	0.0611	10.3475
12	0.0282	15.2251

```
Condition Number      15.2251
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix)  0.0771
```

```
Iteration 0: log likelihood = -286.17024
Iteration 1: log likelihood = -246.59782
Iteration 2: log likelihood = -239.58293
Iteration 3: log likelihood = -239.51627
Iteration 4: log likelihood = -239.51621
```

Logistic regression	Number of obs	=	731
	LR chi2(11)	=	93.31
	Prob > chi2	=	0.0000
Log likelihood = -239.51621	Pseudo R2	=	0.1630

f10_2x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_2x	-1.510956	.2863023	-5.28	0.000	-2.072098 - .949814
s3_1x	-.3752664	.3831196	-0.98	0.327	-1.126167 .3756342
s3_2x	.4073186	.4544541	0.90	0.370	-.4833952 1.298032
s3_3x	.19509	.5016955	0.39	0.697	-.7882151 1.178395
s3_4x	-.2120822	.5495433	-0.39	0.700	-1.289167 .8650028
s4x	-.1365356	.1242133	-1.10	0.272	-.3799893 .1069181
GrStadt	.3800618	.2614328	1.45	0.146	-.132337 .8924606
leftist	.1798616	.2481311	2.90	0.004	.2335337 1.20619
s1x	.2556429	.259412	0.99	0.324	-.2527953 .7640811
s2x	-.3066642	.1153993	-2.66	0.008	-.5328426 -.0804857
s7x	.2344837	.09991609	2.36	0.018	.0401318 .4288355
_cons	-.4213856	.5412651	-0.78	0.436	-1.482246 .6394745

```
Iteration 0: log likelihood = -286.17024
Iteration 1: log likelihood = -252.11088
Iteration 2: log likelihood = -243.67399
Iteration 3: log likelihood = -239.49385
Iteration 4: log likelihood = -239.49121
Iteration 5: log likelihood = -239.49121
```

Logistic regression	Number of obs	=	731
	LR chi2(2)	=	93.36
	Prob > chi2	=	0.0000
Log likelihood = -239.49121	Pseudo R2	=	0.1631

	f10_2x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
	hat	1.053141	.2641497	3.99	0.000	.535417 1.570865
	_hatsq	.0184931	.0826283	0.22	0.823	-.1434554 .1804416
	_cons	.0171872	.2293618	0.07	0.940	-.4323536 .4667281

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

	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 .2058
_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_4x	1.04	1.02	0.9621	0.0379
s3_1x	2.41	1.55	0.4154	0.5846
s3_2x	1.77	1.33	0.5656	0.4344
s3_3x	1.77	1.33	0.5647	0.4353
s3_4x	3.97	1.99	0.2522	0.7478
s4x	1.70	1.31	0.5867	0.4133
GrStadt	1.10	1.05	0.9074	0.0926
leftist	1.06	1.03	0.9443	0.0557
s1x	1.23	1.11	0.8137	0.1863
s2x	2.51	1.58	0.3986	0.6014
s7x	1.26	1.12	0.7923	0.2077

Mean VIF 1.80

	Eigenval	Cond Index
1	6.0124	1.0000
2	1.1299	2.3068
3	1.0830	2.3562
4	1.0044	2.4466
5	0.8085	2.7270
6	0.6419	3.0606
7	0.5794	3.2212
8	0.3969	3.8921
9	0.1699	5.9484
10	0.0787	8.7406
11	0.0621	9.8410
12	0.0329	13.5137

```
Condition Number      13.5137
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix)  0.0833
```

```
Iteration 0:    log likelihood = -457.62466
Iteration 1:    log likelihood = -420.68702
Iteration 2:    log likelihood = -419.98995
Iteration 3:    log likelihood = -419.9882
Iteration 4:    log likelihood = -419.9882
```

Logistic regression	Number of obs	=	687
	LR chi2(11)	=	75.27
	Prob > chi2	=	0.0000
Log likelihood = -419.9882	Pseudo R2	=	0.0822

	f10_4x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
	f11_4x	-.5475382	.1919157	-2.85	0.004	-.9236861 - .1713903
	s3_1x	-.0810252	.288915	-0.28	0.779	-.6472882 .4852378
	s3_2x	-.0798978	.3736966	0.21	0.831	-.6525341 .1812398
	s3_3x	-.4413382	.3789141	-1.16	0.244	-1.183996 .3013199
	s3_4x	.3428547	.349591	0.98	0.327	-.3423311 1.028041
	s4x	-.083734	.0859076	-0.97	0.330	-.2521097 .0846418
	GrStadt	.5192704	.1996851	2.60	0.009	.1278949 .9106459
	leftist	.7841509	.2000342	3.92	0.000	.392091 1.176211
	s1x	-.0977631	.1846844	-0.53	0.597	-.4597379 .2642116
	s2x	-.3214198	.0818986	-3.92	0.000	-.4819381 -1.609016
	s7x	.0711734	.0706943	1.01	0.314	-.0673849 .2097318
	_cons	1.553662	.3834563	4.05	0.000	.8021011 2.305222

```
Iteration 0:    log likelihood = -457.62466
Iteration 1:    log likelihood = -420.90311
Iteration 2:    log likelihood = -419.81692
Iteration 3:    log likelihood = -419.79683
Iteration 4:    log likelihood = -419.79682
```

Logistic regression	Number of obs	=	687
	LR chi2(2)	=	75.66
	Prob > chi2	=	0.0000
Log likelihood = -419.79682	Pseudo R2	=	0.0827

	f10_4x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
	_hat	.0065598	.1950661	4.65	0.000	.5242373 .1288882
	_hatsq	.0892781	.1455341	0.61	0.540	-.1959635 .3745197
	_cons	-.0155966	.1003413	-0.16	0.876	-.2122619 .1810687

Collinearity Diagnostics

Variable	VIF	SQRT	Tolerance	R-
		VIF		Squared
f11_5x	1.03	1.01	0.9723	0.0277
s3_1x	2.37	1.54	0.4223	0.5777
s3_2x	1.76	1.33	0.5683	0.4317
s3_3x	1.74	1.32	0.5742	0.4258
s3_4x	3.95	1.99	0.2532	0.7468
s4x	1.71	1.31	0.5860	0.4140
GrStadtt	1.10	1.05	0.9098	0.0902
leftist	1.06	1.03	0.9441	0.0559
s1x	1.24	1.11	0.8054	0.1946
s2x	2.53	1.59	0.3956	0.6044
s7x	1.28	1.13	0.7842	0.2158
Mean VIF	1.80			

	Eigenval	Cond Index
1	6.2212	1.0000
2	1.1375	2.3386
3	1.0189	2.4710
4	1.0043	2.4889
5	0.7755	2.8324
6	0.5754	3.2882
7	0.5653	3.3175
8	0.3619	4.1460
9	0.1655	6.1315
10	0.0801	8.8120
11	0.0625	9.9779
12	0.0321	13.9251

Condition Number 13.9251
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.0838

Iteration 0: log likelihood = -489.28726
 Iteration 1: log likelihood = -473.41377
 Iteration 2: log likelihood = -473.3841
 Iteration 3: log likelihood = -473.3841

Logistic regression
 Number of obs = 716
 LR chi2(11) = 31.81
 Prob > chi2 = 0.0008
 Pseudo R2 = 0.0325
 Log likelihood = -473.3841

f10_5x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
f11_5x	-.37283	.1574895	-2.37	0.018	-.6815037	-.0641563
s3_1x	.4002692	.2618037	1.53	0.126	-.1128566	.913395
s3_2x	.7352641	.3410079	2.16	0.031	.0669009	1.403627
s3_3x	.0365507	.3557783	0.10	0.918	-.6607619	.7338633
s3_4x	.3398463	.3328856	1.02	0.307	-.3125975	.9922902
s4x	-.068361	.0818116	-0.84	0.403	-.2287088	.0919868
GrStadtt	-.0698638	.1789291	-0.39	0.696	-.4205584	.2808307
leftist	.5251443	.1734097	3.03	0.002	.1852675	.8650211
s1x	.2607684	.1717603	1.52	0.129	-.0758755	.5974123
s2x	-.0316309	.0747601	-0.42	0.672	-.178158	.1148962
s7x	.1380685	.0654772	2.11	0.035	.0097355	.2664015
_cons	-.7675269	.3503394	-2.19	0.028	-1.454179	-.0808744

Iteration 0: log likelihood = -489.28726
 Iteration 1: log likelihood = -473.12081
 Iteration 2: log likelihood = -473.09951
 Iteration 3: log likelihood = -473.09951

Logistic regression
 Number of obs = 716
 LR chi2(2) = 32.38
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0331
 Log likelihood = -473.09951

f10_5x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.111876	.2388361	4.66	0.000	.6437663	1.579986
_hatsq	.2429436	.323668	0.75	0.453	-.3914339	.8773212
_cons	-.0309643	.1008395	-0.31	0.759	-.228606	.1666774

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_6x	1.04	1.02	0.9606	0.0394
s3_1x	2.41	1.55	0.4156	0.5844
s3_2x	1.77	1.33	0.5660	0.4340
s3_3x	1.76	1.33	0.5681	0.4319
s3_4x	4.02	2.00	0.2488	0.7512
s4x	1.70	1.30	0.5872	0.4128
GrStadtt	1.10	1.05	0.9076	0.0924
leftist	1.07	1.03	0.9385	0.0615
s1x	1.24	1.11	0.8084	0.1916
s2x	2.56	1.60	0.3910	0.6090
s7x	1.27	1.13	0.7857	0.2143
Mean VIF	1.81			

	Eigenval	Cond Index
1	6.2672	1.0000
2	1.1401	2.3446
3	1.0257	2.4718
4	1.0044	2.4980
5	0.7930	2.8113
6	0.5722	3.3094
7	0.4821	3.6054
8	0.3788	4.0676
9	0.1640	6.1827
10	0.0791	8.9009
11	0.0617	10.0815
12	0.0317	14.0589

Condition Number 14.0589
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.0805

Iteration 0: log likelihood = -480.38912
 Iteration 1: log likelihood = -451.92743
 Iteration 2: log likelihood = -451.78962
 Iteration 3: log likelihood = -451.78958

Logistic regression
 Number of obs = 700
 LR chi2(11) = 57.20
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0595

f10_6x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_6x	-.9141246	.1630814	-5.61	0.000	-1.233758 - .594491
s3_1x	.5229136	.2732954	1.91	0.056	-.0127355 1.058563
s3_2x	.5466482	.3485297	1.57	0.117	-.1364574 1.229754
s3_3x	-.145348	.3633141	-0.40	0.689	-.8574306 .5667345
s3_4x	-.1459627	.3434362	-0.43	0.671	-.8190853 .5271599
s4x	-.1425367	.0856735	-1.66	0.096	-.3104537 .0253802
GrStadtt	.3580528	.1838861	1.95	0.052	-.0023573 .7184628
leftist	.3843174	.1799657	2.14	0.033	.0315912 .7370436
s1x	.2968322	.1778271	1.67	0.095	-.0517025 .6453669
s2x	.078526	.0777542	1.01	0.313	-.0738694 .2309215
s7x	.0291059	.0673666	0.43	0.666	-.1029303 .1611421
_cons	-.2724398	.3567181	-0.76	0.445	-.9715943 .4267147

Iteration 0: log likelihood = -480.38912
 Iteration 1: log likelihood = -451.56066
 Iteration 2: log likelihood = -451.4532
 Iteration 3: log likelihood = -451.45318

Logistic regression
 Number of obs = 700
 LR chi2(2) = 57.87
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0602

f10_6x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.081263	.1728643	6.25	0.000	.7424548 1.420071
_hatsq	.1675717	.2049359	0.82	0.414	-.2340953 .5692387
_cons	-.0450501	.1012269	-0.45	0.656	-.2434513 .153351

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
fl1_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	Number of obs	=	696
	LR chi2(11)	=	27.36
	Prob > chi2	=	0.0041
Log likelihood = -254.3324	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	Number of obs	=	696
	LR chi2(2)	=	28.33
	Prob > chi2	=	0.0000
Log likelihood = -253.84697	Pseudo R2	=	0.0528

f10_7x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	2.007756	1.032922	1.94	0.052	-0.0167335 4.032245
_hatsq	.2797592	.2807236	1.00	0.319	-.270449 .8299673
_cons	.8059711	.8880234	0.91	0.364	-.9345228 2.546465

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_8x	1.06	1.03	0.9406	0.0594
s3_1x	2.39	1.54	0.4190	0.5810
s3_2x	1.77	1.33	0.5641	0.4359
s3_3x	1.75	1.32	0.5706	0.4294
s3_4x	4.00	2.00	0.2497	0.7503
s4x	1.71	1.31	0.5835	0.4165
GrStadt	1.10	1.05	0.9097	0.0903
leftist	1.06	1.03	0.9442	0.0558
s1x	1.24	1.12	0.8036	0.1964
s2x	2.53	1.59	0.3950	0.6050
s7x	1.27	1.13	0.7891	0.2109
Mean VIF	1.81			

	Eigenval	Cond Index
1	6.2722	1.0000
2	1.1370	2.3487
3	1.0293	2.4685
4	1.0098	2.4922
5	0.7689	2.8560
6	0.5968	3.2418
7	0.4953	3.5586
8	0.3595	4.1768
9	0.1634	6.1957
10	0.0735	9.2375
11	0.0623	10.0353
12	0.0318	14.0462

```
Condition Number      14.0462
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix)  0.0803
```

```
Iteration 0: log likelihood = -273.34912
Iteration 1: log likelihood = -255.6748
Iteration 2: log likelihood = -254.1837
Iteration 3: log likelihood = -254.17551
Iteration 4: log likelihood = -254.17551
```

Logistic regression	Number of obs	=	721
	LR chi2(11)	=	38.35
	Prob > chi2	=	0.0001
Log likelihood = -254.17551	Pseudo R2	=	0.0701

	f10_8x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
	f11_8x	-.9182604	.245707	-3.74	0.000	-1.399837 - .4366836
	s3_1x	.1676866	.386877	0.43	0.665	-.5905784 .9259517
	s3_2x	-.4410568	.5602256	-0.79	0.431	-1.539079 .6569653
	s3_3x	.6927721	.4745904	1.46	0.144	-.237408 1.622952
	s3_4x	-.016997	.5168362	-0.03	0.974	-1.029977 .9959833
	s4x	-.1831846	.1234806	-1.48	0.138	-.4252022 .0588331
	GrStadt	-.0593064	.2732316	-0.22	0.828	-.5948305 .4762177
	leftist	-.5407952	.2935375	-1.84	0.065	-1.116118 .0345277
	s1x	.4722305	.264573	1.78	0.074	-.0463231 .990784
	s2x	-.1452428	.1087218	-1.34	0.182	-.3583336 .0678481
	s7x	-.0015756	.0966527	-0.02	0.987	-.1910114 .1878601
	_cons	-.6267806	.5063046	-1.24	0.216	-1.619119 .3655582

```
Iteration 0:    log likelihood = -273.34912
Iteration 1:    log likelihood = -257.59448
Iteration 2:    log likelihood = -253.30715
Iteration 3:    log likelihood = -253.29626
Iteration 4:    log likelihood = -253.29626
```

Logistic regression	Number of obs	=	721
	LR chi2(2)	=	40.11
	Prob > chi2	=	0.0000
Log likelihood = -253.29626	Pseudo R2	=	0.0734

f10_8x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.871682	.6679095	2.80	0.005	.562603 3.18076
_hatsq	.2400832	.1759443	1.36	0.172	-.1047614 .5849278
_cons	.6707242	.5908411	1.14	0.256	-.4873032 1.828752

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_9x	1.07	1.04	0.9323	0.0677
s3_1x	2.38	1.54	0.4197	0.5803
s3_2x	1.79	1.34	0.5599	0.4401
s3_3x	1.76	1.33	0.5692	0.4308
s3_4x	4.08	2.02	0.2449	0.7551
s4x	1.70	1.30	0.5899	0.4101
GrStad1	1.10	1.05	0.9112	0.0888
leftist	1.07	1.03	0.9389	0.0611
s1x	1.24	1.11	0.8085	0.1915
s2x	2.59	1.61	0.3854	0.6146
s7x	1.27	1.13	0.7871	0.2129
Mean VIF	1.82			

	Eigenval	Cond Index
1	5.9151	1.0000
2	1.1927	2.2270
3	1.0899	2.3297
4	1.0035	2.4279
5	0.8087	2.7044
6	0.6845	2.9397
7	0.5782	3.1984
8	0.3894	3.8977
9	0.1664	5.9615
10	0.0778	8.7187
11	0.0619	9.7715
12	0.0319	13.6129

Condition Number 13.6129
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix) 0.0780

Iteration 0: log likelihood = -453.26151
 Iteration 1: log likelihood = -448.90752
 Iteration 2: log likelihood = -448.90581

Logistic regression	Number of obs	=	662
	LR chi2(11)	=	8.71
	Prob > chi2	=	0.6485
Log likelihood = -448.90581	Pseudo R2	=	0.0096

f10_9x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f11_9x	.0068012	.217672	0.03	0.975	-.4198282 .4334305
s3_1x	-.3199154	.2651928	-1.21	0.228	-.8396838 .199853
s3_2x	-.4926285	.3475371	-1.42	0.156	-1.173789 .1885318
s3_3x	-.6283894	.3613006	-1.74	0.082	-1.336526 .0797469
s3_4x	-.5029098	.3425901	-1.47	0.142	-1.174374 .1685544
s4x	.1131987	.0822663	1.38	0.169	-.0480403 .2744376
GrStad1	-.0113556	.1816979	-0.06	0.950	-.3674769 .3447657
leftist	.1749939	.177729	0.98	0.325	-.1733486 .5233364
s1x	.1822719	.1761276	1.03	0.301	-.1629319 .5274756
s2x	.1122901	.0779601	1.44	0.150	-.0405088 .2650891
s7x	-.0392612	.067488	-0.58	0.561	-.1715352 .0930128
_cons	-.6913961	.3573799	-1.93	0.053	-1.391848 .0090557

Iteration 0: log likelihood = -453.26151
 Iteration 1: log likelihood = -448.42019
 Iteration 2: log likelihood = -448.40718
 Iteration 3: log likelihood = -448.40718

Logistic regression	Number of obs	=	662
	LR chi2(2)	=	9.71
	Prob > chi2	=	0.0078
Log likelihood = -448.40718	Pseudo R2	=	0.0107

f10_9x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.4870005	.6162227	0.79	0.429	-.7207739 1.694775
_hatsq	-1.03008	1.038071	-0.99	0.321	-3.064663 1.004502
_cons	-.0093925	.1185666	-0.08	0.937	-.2417787 .2229938

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_10x	1.06	1.03	0.9476	0.0524
s3_1x	2.37	1.54	0.4213	0.5787
s3_2x	1.79	1.34	0.5585	0.4415
s3_3x	1.73	1.32	0.5769	0.4231
s3_4x	3.93	1.98	0.2543	0.7457
s4x	1.71	1.31	0.5841	0.4159
GrStadt	1.09	1.05	0.9147	0.0853
leftist	1.06	1.03	0.9467	0.0533
s1x	1.24	1.12	0.8032	0.1968
s2x	2.51	1.58	0.3985	0.6015
s7x	1.26	1.12	0.7955	0.2045
Mean VIF	1.80			

	Eigenval	Cond Index
1	5.9867	1.0000
2	1.1331	2.2985
3	1.1058	2.3268
4	1.0093	2.4355
5	0.7654	2.7966
6	0.6892	2.9472
7	0.5749	3.2269
8	0.3893	3.9217
9	0.1714	5.9095
10	0.0793	8.6895
11	0.0625	9.7839
12	0.0330	13.4777

```
Condition Number      13.4777
Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix)  0.0829
```

```
Iteration 0: log likelihood = -423.31279
Iteration 1: log likelihood = -389.01683
Iteration 2: log likelihood = -388.30468
Iteration 3: log likelihood = -388.30315
Iteration 4: log likelihood = -388.30315
```

Logistic regression	Number of obs	=	708
	LR chi2(11)	=	70.02
	Prob > chi2	=	0.0000
Log likelihood = -388.30315	Pseudo R2	=	0.0827

f10_10x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
f11_10x	-.9673482	.2028759	-4.77	0.000	-1.364978	-.5697188
s3_1x	.2473249	.2852318	0.87	0.386	-.3117191	.8063689
s3_2x	-.5326851	.3639809	-1.46	0.143	-1.246074	.1807043
s3_3x	.796065	.4380097	1.82	0.069	-.0624184	1.654548
s3_4x	-.0301894	.3790557	-0.08	0.937	-.773249	.7127461
s4x	.0422723	.0953207	0.44	0.657	-.1445529	.2290974
GrStad	-.4976017	.1972875	-2.52	0.012	-.884278	-.1109253
leftist	-.2369422	.1955418	-1.21	0.226	-.6201971	.1463127
s1x	.3469719	.1969894	1.76	0.078	-.0391203	.7330641
s2x	.2400413	.0856197	2.80	0.005	.0722297	.4078529
s7x	.1448	.0741193	1.95	0.051	-.0004712	.2900712
_cons	-.3018396	.3715728	-0.81	0.417	-1.030109	.4264297

```
Iteration 0: log likelihood = -423.31279
Iteration 1: log likelihood = -389.20229
Iteration 2: log likelihood = -388.29023
Iteration 3: log likelihood = -388.28598
Iteration 4: log likelihood = -388.28598
```

Logistic regression	Number of obs	=	708
	L.R chi2(2)	=	70.05
	Prob > chi2	=	0.0000
Log likelihood = -388.28598	Pseudo R2	=	0.0827

f10_10x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.1036637	.2356121	4.40	0.000	.5748453 1.498428
_hatsq	-.0255112	.1376084	-0.19	0.853	-.2952188 .241964
_cons	-.0004869	.1388518	-0.00	0.997	-.2726314 .2716576

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
slx	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
slx	.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
Log likelihood = -347.22471      Pseudo R2      =      0.0463

```

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
Log likelihood = -347.09167      Pseudo R2      =      0.0466

```

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
Log likelihood = -436.90538      Pseudo R2      =      0.0725

```

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
Log likelihood = -436.4136      Pseudo R2      =      0.0735

```

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
GrStad		-.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	-.3472616 -.0214432
	GrStad	.3856085	.1782415	2.16	0.031	.0328616 .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

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

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

	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

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

```
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
```

	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 VIF	Tolerance	R- Squared
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
Log likelihood = -124.64687	Pseudo R2	=	0.1036

	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
	s2_2x	-.8363936	.7757693	-1.08	0.281	-2.356873	.6840862
	s3_3x	-1.105469	.8753234	-1.26	0.207	-2.821071	.6101335
	s3_4x	-1.219853	.8514097	0.25	0.803	-1.456747	1.880718
	s4_4x	-.0700955	.1905369	-0.37	0.713	-.4435411	.30335
	GrStad	.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	.1141375
	s7x	.3460981	.1594046	2.17	0.030	.0336708	.6585525
	_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
Log likelihood = -124.28321	Pseudo R2	=	0.1062

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 VIF	Tolerance	R- Squared
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 .0961167
	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
GrStad		.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	Number of obs	=	847
	LR chi2(10)	=	43.58
	Prob > chi2	=	0.0000
Log likelihood = -424.07135	Pseudo R2	=	0.0489

	f10_3x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
	f11_3x	-.969981	.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
	s4_1x	.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	Number of obs	=	847
	LR chi2(2)	=	45.20
	Prob > chi2	=	0.0000
Log likelihood = -423.26167	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	Tolerance	R-
		VIF		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	Tolerance	R-
		VIF		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	Tolerance	R-
		VIF		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 - .611467
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	Number of obs	=	874
	LR chi2(10)	=	37.59
	Prob > chi2	=	0.0000
Log likelihood = -325.27629	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	.4555076	0.06	0.951	-.8653573	.9209838
	s4x	-.0393377	.1077317	-0.37	0.715	-.2504879	.1718125
	GrStadtd	.105727	.231438	0.46	0.648	-.3478832	.5593371
	s1x	-.1256128	.2233989	-0.56	0.574	-.5634666	.3122441
	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	Number of obs	=	874
	LR chi2(2)	=	39.89
	Prob > chi2	=	0.0000
Log likelihood = -324.12505	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	-.45805812	.5282317	-1.60	0.110	-1.880396 .1902339
	s3_3x	.6436228	.4158423	1.55	0.122	-.1714132 1.458659
	s3_4x	-.1018392	.4455303	-0.23	0.819	-.9746171 .7709386
	s4x	-.109902	.1096884	-1.00	0.316	-.3248873 .1050834
GrStadt		-.2719653	.245954	-1.11	0.269	-.7504263 .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 .1754381
_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 VIF	Tolerance	R- Squared
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
GrStad		.147615	.1618528	0.91	0.362	-.1696106 .4648405
	s1x	.0588716	.1556521	0.38	0.705	-.242601 .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 VIF	Tolerance	R- 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
GrStad:	-.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	Tolerance	R-
		VIF		Squared
f11_1x	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
 Log likelihood = -99.832767 Pseudo R2 = 0.0923

f10_1x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
f11_1x	-.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
 Log likelihood = -99.596254 Pseudo R2 = 0.0944

f10_1x	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
leftist	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
	leftist	.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	-.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 = -254.37888
```

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
 Log likelihood = -355.73381 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
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
 Log likelihood = -355.72002 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
leftist	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	Number of obs	=	719
	LR chi2(5)	=	63.73
	Prob > chi2	=	0.0000
Log likelihood = -448.77974	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
leftist		.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		1.120852	.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	Number of obs	=	719
	LR chi2(2)	=	64.53
	Prob > chi2	=	0.0000
Log likelihood = -448.38287	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
leftist	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
leftlist	.5937061	.1667035	3.56	0.000	.2669733	.9204399
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	0.0749449	.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
leftlist	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
leftist		.4275392	.1721172	2.48	0.013	.0901598	.7648826
	s1x	.1493957	.1557306	0.96	0.337	-.0519306	.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	.601701

```
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
leftist	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
leftist		.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	.0484627	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
leftlist	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
	leftist	-.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	-.0477762	.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_x	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 7.048383
	_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
leftlist	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	-.195551 .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 VIF	Tolerance	R- Squared
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
Log likelihood = -406.22683	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
Log likelihood = -404.81065	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_1x	1.03	1.01	0.9719	0.0281
leftlist	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
Log likelihood = -99.832767	Pseudo R2	=	0.0923

f10_1x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
f11_1x	-.9351058	.5385789	-1.74	0.083	-1.990701	.1204893
leftist	-.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
Log likelihood = -99.596254	Pseudo R2	=	0.0944

f10_1x	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.900437	1.295345	1.47	0.142	-.6383931	4.439267
_hatsq	1.1380031	.1936901	0.71	0.476	-.2416225	.5176287
_cons	1.349181	2.04309	0.66	0.509	-2.655201	5.353564

Variable	VIF	SQRT VIF	Tolerance	R- Squared
f11_2x	1.04	1.02	0.9624	0.0376
leftist	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
leftist	.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	-.204588
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 = -254.37888
```

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
 Log likelihood = -355.73381 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
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
 Log likelihood = -355.72002 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
leftist	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	Number of obs	=	719
	LR chi2(5)	=	63.73
	Prob > chi2	=	0.0000
Log likelihood = -448.77974	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
leftist		.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		1.120852	.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	Number of obs	=	719
	LR chi2(2)	=	64.53
	Prob > chi2	=	0.0000
Log likelihood = -448.38287	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
leftist	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
leftlist	.5937061	.1667035	3.56	0.000	.2669733	.9204399
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		0.0749449	.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
leftist	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
leftlist	.4275392	.1721172	2.48	0.013	.0901958 .7648826
s1x	.1493957	.1557306	0.96	0.337	-.1598306 .4546222
s2x	-.0317113	.0489434	-0.65	0.517	-.1276385 .0642159
s7x	.0364457	.0597729	0.61	0.542	-.0807071 .1535985
_cons	-.0009962	.3120964	-0.03	0.974	-.6216939 .6107015

```
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	0.143296	.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
fill_7x	1.01	1.00	0.9937	0.0063
leftist	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
	leftist	.4459179	.2413635	1.85	0.065	-.0271458 .9189816
	s1x	-.0828876	.2280191	-0.36	0.716	-.5297968 .3640216
	s2x	-.1258988	.0694677	-1.81	0.070	-.2620569 .1020593
	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
leftlist	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
leftist		-.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	-.0477762	.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 7.048383
	_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
leftlist	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	SQR VIF	Tolerance	R- Squared
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
Log likelihood = -406.22683	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	.109856 .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
Log likelihood = -404.81065	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 .0438341
_cons	-.0676197	.1632644	-0.41	0.679	-.387612 .2523726