Essays on the impact of education on misclassified civic outcomes: studies of Italy and the UK

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ESSAYS ON THE IMPACT OF EDUCATION ON MISCLASSIFIED CIVIC OUTCOMES: STUDIES OF ITALY AND THE UK

By

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Abstract

In this dissertation I examine the impact of education on a range of civic outcomes in Italy and the UK which embody two of the main dimensions of social capital: civic engagement and social trust. The central aim of this thesis is to attain a credible relationship between education and civic outcomes, accounting for diverse issues which may obscure it. Namely, unobservables driving education choices (i.e., endogeneity), and the tendency to under-report sensitive topics and over-report civic opinions (i.e., misclassification). This approach allows me to ascertain the extent to which the causal effect of schooling on the civic indicators is either genuine or is driven mainly by endogeneity and a systematic misreporting by educational levels. I also investigate how these elements vary by contextual factors of the two countries. The contribution in this area is given by utilizing data from these two countries, considering a distinct group of civic outcomes (i.e., civic opinions and civic behaviours) and by dealing with misreporting. Previous research does not explicitly control for misclassification and focuses on civic engagement, one aspect of social capital. Furthermore, I contribute by introducing a hurdle ordered probit with misclassification to account for two issues regarding the distribution of a self-reported ordered outcome, its skewness and its misclassification. The main findings are: (i) for Italy, qualitative overall conclusions regarding the causality of education on civic outcomes are indeed affected when accounting for misclassification: education turns out to be insignificant across civic behaviours, (ii) for the UK, on the contrary, education has significant positive effects on all civic outcomes due to upward biases induced by endogeneity, (iii) both Italy and the UK, however, do not differ substantially overall with regards to misreporting: most civic outcomes are misclassified for either country, and misreporting is more severe for civic behaviours due to a larger influence of social desirability.

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To Sara and Dante.

Contents

Abbreviations

AIC	—	Akaike information criterion
BIC	—	Bayesian information criterion
BOP	—	binary ordered probit
BOPM	—	binary ordered probit with misclassification
CAIC	—	consistent Akaike information criterion
c.d.f.	—	cumulative distribution function
d.g.p.	—	data generation process
HOP	—	hurdle ordered probit
HOPM	—	hurdle ordered probit with misclassification
IV	—	instrumental variables
IV-BOPM	—	instrumental variables binary ordered probit with misclassification
IV-OP	—	instrumental variables ordered probit
IV-OPM	—	instrumental variables ordered probit with misclassification
KLIC	—	Kullback-Leibler information criterion
LR	—	likelihood ratio
LS	—	least squares
ME, MEs	—	marginal effect, marginal effects
ML	—	maximum likelihood
OP	—	ordered probit
OPM	—	ordered probit with misclassification
RD	—	regression discontinuity
RMSE	—	root mean squared error
RMSEall	—	overall root mean squared error
SD	—	social desirability
SDB	—	social desirability bias
Std. dev.	—	standard deviation
ZIOP	—	zero-inflated ordered probit
2SLS	—	two-stage least squares
$\bar{\chi}^2$ statistic	—	chi-bar-squared statistic
$\bar{\chi}^2$ test	—	misclassification test

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Chapter 1
Introduction and summary

1.1. Economic motivation

Education provides varied benefits to society, for instance, increasing productivity, impacting upon individual health and well-being, crime reduction and higher economic growth. The wide range of positive externalities deriving from education can be explained by the relationship between human and social capital, broadly defined as informal rules and norms that, along with the formal rules, establish an institutional framework (Chhibbert (2000)). Indeed, there is evidence which suggests that countries and communities with a higher stock of social capital are more likely to present superior human development (e.g., Poortinga (2006a), Groot et al. (2007), and Snelgrove et al. (2009)) and a higher economic performance (e.g., Maskell (2000), Zak and Knack (2001), Francois (2002), and Halpern (2005)).

In turn, the level of social capital, formally, "networks, together with shared norms, values and understandings which facilitate cooperation within or among groups" (Healy and Cote (2001), p. 41), can be enhanced by increasing schooling levels. For instance, van Oorschot and Finsveen (2009) argue that education is often one of the most important determinants of social capital found in the different empirical studies. Regardless of their income level, higher educated individuals are more likely to participate in social networks, be engaged in politics and volunteering activities, and have a stronger trust in other people (Delhey and Newton (2003), van Oorschot and Arts (2005), Bekkers (2007)).

In this dissertation I examine, for Italy and the UK, the impact of education on a range of civic outcomes that embody some of the main dimensions of social capital. Hence, the chosen working hypothesis is with causality going from human to social capital. Intuitively, higher educated individuals are better informed and more capable when interpreting and processing information, more conscious about the consequences of their actions and others, as well as more likely to be civically engaged, all of these being crucial components of social capital. More specifically, my main interest throughout the dissertation is to attain a "credible" relationship between education and civic outcomes. Unobserved factors driving education choices (i.e., endogeneity) and the tendency of individuals to under-report socially undesirable behaviours (i.e., misclassification), are both elements which contribute to obscure the true relationship between education and civic outcomes. I tackle these issues and also investigate how these elements vary by contextual factors of the two countries. Finally, I propose an extension to discrete choice models to deal with highly skewed responses of a misclassified outcome.

The human to social capital framework has been adopted in several studies which argue that educational attainment increases social capital (see, for instance, La Porta et al. (1997), Glaeser et al. (2000), Curtis et al. (2001), van Oorschot and Arts (2005), Helliwell and Putnam (2007)). There are also cross country investigations that provide evidence on the direct relationship between schooling and social capital. For example, Knack and Keefer (1997) find that trust and civic norms are stronger in nations with more educated populations. Recently, in a study that includes 28 European nations, Gesthuizen et al. (2008) conclude that educational attainment increases nearly all indicators of both formal (participation in formally constituted civic organizations) and informal (social ties between individuals and their friends, families, colleagues, etc.) social capital. The same evidence is contained in the meta analysis study of Huang et al. (2009) who assess the effect of schooling on two of the main dimensions of social capital (i.e., social trust and social participation) in a large number of evaluations, and find that education is a strong and robust correlate of individual social capital. Similarly, Allum et al. (2010), when fitting a measurement model for three elements of social capital (social trust, institutional trust and civic association) using European data, they also find that education is a strong predictor.

There are diverse interpretations on the positive influence of education on the dimensions of social capital.[1] There is consensus in the literature that social capital is an umbrella concept, a multidimensional construct, and therefore multiple indicators are needed if these dimensions are to be measured properly (e.g., Johnston and Percy-Smith (2003), van Oorschot et al. (2006)). Then, due to its multidimensional nature, it is unsurprising that there is no a single cause for shifting social capital. Certainly, many determinants have been identified on each level of analysis. At the micro-level, social capital is affected by personality type, age, family, class, education, work, religion, and consumption habits. At the meso-level, social capital is affected by civil society, school, community, ethnic and social heterogeneity, mobility, transportation habits/infrastructure, and urban design. Finally, at the macro-level, social capital is directly affected by history and culture, social structure and hierarchy, labour-market trends as well as the size and nature of the welfare state.

[1]For an interesting review, see Halpern (2005), Chapter 5. He identifies three levels of social capital: micro (individual), meso (community) and macro (region, national), and argues that education affects social capital primarily at the micro level.

With regards to the geographical distribution of social capital over European regions, research suggests a range of driving forces which are present at different levels of the analysis. At the macro level, for example, an extended welfare state creates a national norm of social solidarity and fellow feeling which is conducive to higher trust levels amongst individuals (Curtis et al. (2001), van Oorschot and Finsveen (2010)). Furthermore, explanations at the meso-level are based on social skills learnt at school and the relatively higher levels of utility that individuals with increasing level of social capital obtain from social interaction (Glaeser et al. (2002)).

Alongside schooling, religion is often cited as another important determinant at the micro-level (Wuthnow (1999), Putnam (2000), Smidt (2003)). There are two general explanations of why religion should foster social capital formation. The first perspective views religiosity primarily as a cultural phenomenon, thereby stressing the effects of religious beliefs, norms, identities, and world views. The second perspective focuses on structural aspects of religiosity and thus on the effects that result from social integration and active participation in religious communities (Traunmüller (2010)). Moreover, because social trust has an important foundation in moral beliefs, different religious identities may explain variations in individuals' propensity to place trust in others. In particular, a country with a dominant protestant culture tends to show a higher level of trustworthiness, while a catholic country tends to display lower levels of trust in others and in institutions (Delhey and Newton (2005), van Oorschot et al. (2006), Bjørnskov (2008)). This is principally explained in the literature (see, e.g., Putnam et al. (1993), Fukuyama (1995), Verba et al. (1995), Lam (2006)) with two arguments. Firstly, by the fact that protestant norms and values extend social trust from close kin to people in general, whereas there is a distrustful familism inherent in catholicism. Secondly, by their respective organisational structure: an egalitarian and horizontal network structure of protestantism which is more conducive to the formation of mutual trust than the hierarchical structure of catholicism. Note that Italy and the UK are distinct as far as religious composition and welfare policies are concerned.

From a theoretical point of view, the sociological literature proposes two theories: the socialisation and resource perspectives (Gesthuizen et al. (2008)) which account for the relationship between education and formal and informal social capital. Firstly, the crucial assumption of the socialisation perspective is that the origins of social capital are rooted in a process by which individuals are subject to devoting their efforts to a collective good, internalising norms. Parents and teachers alike, play an important role in this process as they are socialising agents who teach individuals moral values and stress the importance of being good citizens. Because higher educated individuals are most likely to originated from privileged backgrounds whose parents are more educated too, there is also an intergenerational transmission of social capital (Bekkers (2007)). In short, schooling fosters social capital through a socialisation process at school, at home as well as through social networks. There is, however, a growing body of research which suggests that social attitudes such as trust have a genetic basis (see, e.g., Hatemi et al. (2009)). For example, in a recent paper using samples of twins, Sturgis et al. (2010b) find that interpersonal trust is an important component of personality, with environmental influences having a discernable effect. This questions the hypothesis of the development of trust through the socialization process at an early stage of the life-course. Secondly, the resource perspective predicts a differential impact of education instead, being concentrated in the formal (or visible) aspects of social capital. More educated individuals contribute to the formal sphere of social capital (e.g., donations to and membership of volunteering for organizations) as this allows them to preserve their status position. This is not the case with less publicly or informal activities such as contact with colleagues, neighbours, and offering informal help (Pichler and Wallace (2007)).

It should be noted, however, that it is also probable that economic and social well-being lead to enhanced social capital, with causal effects running in both directions. This is in line with a range of hypotheses. For instance, in the seminal work of Coleman (1988), the connection of human and social capital is through family social capital. In particular, he suggests that communities rich in trust and social connections achieve low rates of high school drop outs, with individuals in families with stronger bonds, more likely to succeed in education since they have easier access to adults' human capital. Moreover, mutual trust is considered by some authors endogenous to certain elements of the social structure (Torsvik (2004)) and social capital itself regarded as context-dependent (Fine (2001)) and, consequently, may provide an environment where schooling thrives.[2] Similarly, this bidirectional connection is further supported by studies (Glaeser et al. (2002), Groot et al. (2007)) that, upon empirical evidence, deem human and social capital as complements. Putnam (2000) assumes that child development is strongly shaped by social capital and states that where there is high social capital there is also high education performance. This simultaneity is clearly highlighted by Durlauf (2002) who critically examines various identification problems of leading studies in the field. In fact, according to Dekker and Uslaner (2001), due to the complexity and contesting nature of social capital, there is growing awareness that social capital can be both cause and effect.

[2]Bjørnskov (2009), on the contrary, proposes a reverse causality where social trust affects schooling's growth by means of lowering transaction costs.

In the thesis, I address the previous criticisms of the human to social capital framework. For example, in Chapters 4 and 5 which contain the empirical analysis of Italy and the UK, I deal with simultaneity (or endogeneity) of education when modeling civic outcomes in line with research in the economic literature (e.g., Dee (2004), Milligan et al. (2004)). Here, the main hypothesis regarding the linkage of schooling and civic engagement stems from the political science field as models of civic participation. I discuss an alternative theoretical model for the association between education and civic opinions (i.e., civic voluntarism) in Section 1.3. I am able to offer a robust relationship between these two elements throughout the thesis, by using alternative models regarding the causality of education and civic outcomes as well as methodologically accounting for empirical concerns raised in the literature (such as misreporting).

1.2. SOCIAL CAPITAL, ITS IMPACT ON WELL BEING AND CIVIC OUTCOMES

TAXONOMY

Social capital is a contested concept. The extent to which elements should be included as part of social capital to accomplish an operationalised definition in empirical research, has been subjected to important debate.[3] I begin this section by discussing in more detail, definitions of social capital and how they are related to the array of civic outcomes studied in this dissertation. As mentioned earlier, I consider the concept of social capital a heuristic notion which provides a conceptual framework to analyze the relationship between education and civic outcomes.

Early seminal studies within the field include the works from Bourdieu (1986), Coleman (1988), and Putnam et al. (1993), Putnam (1995). Albeit with different interpretations (for instance, Bourdieu's concept of social capital emphasises conflicts and the power function), all of these authors stress the crucial role that social networks, trust and norms play to achieve common goals in society.[4] The three features of social capital, networks, norms (to a lesser extent) and trust, are the elements which tend to dominate the conceptual discussion around social capital (Schuller et al. (2000)). I discuss the concepts of trust and networks below.

Within the social capital literature, Fukuyama's work on trust is well acknowledged. He defines trust as: "the expectation that arises within a community of regular, honest and cooperative behaviour based on commonly shared norms on the part

[3]For some interesting reviews of the concept from sociological, political science and economics perspectives, see Schuller et al. (2000), and Prakash and Selle (2004).

[4]A popular definition due to Putnam is: "features of social life –networks, norms, and trust– that enable participants to act together more effectively to pursue shared objectives" (Putnam (1995), p. 66).

of other members of that society" (Fukuyama (1995), p. 26). A nation's well-being, the ability to compete, etc., are mainly explained by this cultural characteristic. Social norms influence people's behaviours by constraining them, lower transaction costs (as it is not needed to write contracts that capture all contingencies), and aid the exchange of information. Shared norms are generalised attitudes towards behaviours that are accepted by most individuals/groups as 'correct' (e.g., giving up a seat in bus to somebody who needs it). Trustworthiness is based on 'commonly shared norms', the norm of reciprocal behaviour. A society that is characterised by generalised reciprocity, defined by Putnam (2000) as widespread and transitive trust and trustworthiness among the members of a large group, is more efficient than a distrustful society as it facilitates collective action for mutual benefit (van Oorschot et al. (2006)).

Social trust is then crucial and, by dividing nations into low and high trust societies, one is able to explain a dissimilar economic progress for each group according to Fukuyama. Because trust and reputation for trustworthiness are instrumental in: increasing the willingness to trade (Uslaner (2002)), lowering transactions' costs (Dasgupta (2000)) and achieving higher institutional quality and lower corruption (Uslaner (2008)), one observes in high-trust societies the development of large scale (and efficient) corporations out of family firms through the medium of the 'rich and complex civic society'. Conversely, in low-trust societies, the limitation on trust leads to enterprise being restricted to the 'family' and the 'rich and complex civic society' to be replaced by a centralised state. Note that Italy is classified as a low-trust society, with small and inefficient organisations and trade carried out under influence and corruption (Fukuyama (1995)).

Furthermore, trust creates networks' externalities. The reciprocal component of trustworthiness allows norms and information to flow across networks and so are an essential part of them. Networks are either based on trust amongst: strangers or distant people (bridging social capital), familiar (bonding social capital), and with people in positions of power (linking social capital) (Woolcock (1998)). The prevalence of particular types of bonding social capital has collateral downside effects. A common example is that of criminal gangs creating bonding social capital. This links naturally to Fukuyama's idea on low-trust societies where limitation of trust leads to enterprise and networks to be restricted to closed-knit groups.

Alternatively, one can look at the problem of trust via the overall institutional environment (Rothstein (2005), Chapter 5). It is very unlikely that individuals would trust the majority of people if institutions do not ensure justice and fairness.[5] There

[5]This is reflected by regional disparities in the level of bonding capital and institutional quality in

is a similar positive correlation between trustworthiness and trust in institutions, in other words, in countries where people trust institutions more, there is also a higher level of civic morality. van Oorschot et al. (2006) state that this result is parallel to the hypothesis of Putnam et al. (1993) by which sheer participation in civic organizations forms habits of cooperation, solidarity and public-spiritedness. On the contrary, bridging social capital is mainly deemed a key factor for a civic society, economic development and good institutions. I now introduce the array of civic outcomes studied in the thesis and also present a taxonomy of these indicators.

The set of questions on civic outcomes (or dependent variables) for Italy are as follows. Firstly, 'interest in politics' and the 'problem of tax evasion', are clearly related to opinions about the political field and are classified as "civic opinions". Secondly, whether the following behaviours are acceptable: 'not paying for your ticket on public transport'[6], 'keeping money obtained by accident when it could be returned' and 'not leaving your name for the owner of a car you accidentally scraped', are denoted as "civic behaviours". This array of civic outcomes fits into the social capital framework proposed by Uphoff (2000), who divides social capital into "structural social capital" (civic engagement) and "cognitive social capital" (social trust). The former type is associated with various forms of social organisation while the latter indicates mental processes and resulting ideas, reinforced by culture and ideology and, more specifically by norms, values and beliefs.

These two categories of social capital are highly interdependent, as each form contributes to the other and both affect behaviour through the mechanism of expectations. Norms, values, attitudes and beliefs, by creating expectations about how people should act, by implication, create expectations about how people will act (Uphoff (2000), p. 218). For example, values and attitudes create an expectation as to whether an individual will keep money or not when it could easily be returned. Moreover, there is evidence (Woolcock and Narayan (2000)) that political interest, political action and measures of trust are associated. Sundquist and Yang (2007) interpret this correlation by arguing that political involvement is an important component of trust and a good indicator of bridging social capital.

Structural forms of social capital are observable and externalised in contrast to cognitive forms. Civic opinions belong to judgments on the political field and hence are externalised through social organisations, but not people's behaviours (at least the ones studied in this thesis) as they are largely influenced by values and beliefs. Another taxonomy of social capital that provides support to my categorisation of civic

Italy which is often cited as a typical empirical example. See Section 2.2 for details.

[6]This variable is also used in Knack and Keefer (1997).

indicators is Krishna (2000). The first dimension is 'institutional capital': structural elements (roles, rules, procedures and organizations) that facilitate mutually beneficial collective action. The second is 'relational capital': values, attitudes, norms, and beliefs that predispose individuals toward cooperation with others. Civic opinions belong to the first and civic behaviours to the second.

Although I use social capital as a framework, it should be noted that there are certain elements omitted from the civic indicators for the Italian case which are measured by statistical offices. For example, social interaction, social networks and social support (usually measured by contact with friends, family, neighbours, etc.) are not captured by the current indicators.[7]

The UK analysis employs more indicators than Italy. But it should be pointed out that, because one of the aims in the analysis of the UK is to provide a validation of the results for Italy, the core group of civic outcomes are equivalent across the two countries. The UK's civic opinions are: 'interest in politics', 'pay attention to politics', 'discuss politics' and being 'active in a voluntary organisation'. Moreover, the three civic behaviours measure the extent to which the following statements are justified: 'failing to report accidental damage done to a parked vehicle', 'keeping money that you have found', and 'avoiding a fare on public transport'. Note that the group of civic behaviours is identical to the ones for Italy. In addition, I include outcomes related to politics, voting and social trust. Namely, whether respondents believe that 'political activity takes too much time and effort', 'family and friends think that voting is a waste of time', 'feel very guilty if not vote', 'neglect my duty as a citizen if not vote', as well as outcomes concerning interpersonal trust and trust in institutions, that is, whether 'most people can be trusted' and whether they 'trust the local government'. These indicators represent another dimension of social capital which is not captured for the previous Italian indicators, such as social participation and interpersonal trust.

Although the array of indicators for the UK fits into the earlier social capital framework of Uphoff (2000), a slightly different framework by van Oorschot et al. (2006) is more suitable, which contains three dimensions for social capital: i) networks, ii) trust, and iii) civism. Each dimension has two aspects. First, in the network dimension, they distinguish participation in voluntary organisations and socialising with family and friends. Second, the trust dimension embodies generalized

[7]The Office of National Statistics (UK) identified five dimensions of social capital (Green and Fletcher (2003)). Namely, views about the local area (e.g., satisfaction with living in the area, problems in area), civic participation (e.g., propensity to vote, action on local and national issues), social networks and support (e.g., contact with friends and relatives), social participation (e.g., involvement in groups and voluntary activities), reciprocity and trust (e.g., trusting other people). The chosen indicators for Italy mainly capture two of those: trust and civic participation.

trust (interpersonal trust, trust in people) and trust in institutions (state institutions such as the health care system, the justice system, parliament, the police, etc.). Individuals' attitudinal and behavioural characteristics are given by the last dimension, civism, that contains as a first aspect, trustworthiness (people's civic commitment and morality) and as a second aspect, people's political engagement (similar to linking social capital). Therefore, most of the thesis' UK indicators belong to the third dimension, civism, with civic behaviours measuring the degree of trustworthiness and civic opinions, the aspect of political engagement. The analysis, however, includes further outcomes for the remaining dimensions of trust and networks. Hence, all three dimensions of social capital are represented. I now turn to a brief discussion of the impact of social capital impact on well being.

There are various mechanisms by which social capital fosters economic growth and individuals' human development. The impact of social capital on these two aspects is the key reason as to why obtaining a credible causal link between education and social capital (the main objective throughout this dissertation) is vital. The overall argument is that social capital influences economic performance through trust as its pivotal element. Trust incentives markets to function efficiently by reducing inter-firm transaction costs (due to reputation and informal sanctions supplementing formal contracts and sanctions), by increasing exchange of knowledge between firms and by enhancing the division of labour by lowering costs of coordination (Maskell (2000)). Yet, a deeper insight into the relationship of "social capital-well being" is achieved by looking at specific effects by levels of social capital. Halpern (2005) divides these effects by the three levels of social capital: individual or micro level; community or meso level; regional, national or macro level.

Firstly, at the individual level, certain types of bonding social capital (e.g., having a supportive family) can have a substantial effect on educational attainment and future earnings. Bridging network social capital is also very helpful in the labour market. For instance, the probability of unemployment decreases if individuals belong to networks of interconnected agents as they have a higher access to and exchange of information. In addition, participation in intercommunity networks reduces incentives for rent seeking and cheating, promoting economic growth (Beugelsdijk and Smulders (2009)). Secondly, the stock of social capital within a community has an impact on house prices as well as the characteristics of a neighbourhood, such as school quality and low crime. Thirdly, social capital at the macro level boosts economic growth partly through its positive effects upon the formal structures of government, as it is strongly associated with lower government corruption[8], higher bureaucratic quality

[8] Several studies (e.g., Glaeser and Saks (2006))) show the negative effects of corruption on economic

and compliance with paying taxes (Halpern (2005)). There are numerous studies that show that social capital affects the level of democracy and economic growth. Dincer and Uslaner (2010) find a positive relationship between trust and growth across U.S. states. Using data from a mixed group of countries (i.e., low, middle, and high-income) Knack and Keefer (1997), Zak and Knack (2001) and Beugelsdijk et al. (2004) find a positive effect of trust on economic growth as well. (See also the previous review of Fukuyama (1995)).

The second motivation in obtaining a credible relationship between education and civic outcomes is founded on the direct effect of social capital on human development. A large body of empirical evidence suggests that distinct levels (or types) of social capital are significant determinants of crucial health outcomes, such as self-rated health and suicides rates (e.g., Subramanian et al. (2002), Helliwell (2006), Poortinga (2006a), Sundquist and Yang (2007)). Recently, Groot et al. (2007) provide evidence that a higher stock of social capital increases people's life satisfaction as well. Social capital affects well being via different channels.[9]

At the individual level, social capital provides social and material support in adverse times. Strong bonding ties, for instance, tend to offer emotional support, which in turn has a positive impact on health, especially mental health, mainly via psychological mechanisms, such as personal control and stress reduction (Ferlander (2007)).[10] At the meso level, socially cohesive communities have better access to local health services because they are more likely to be successful at fighting potential cuts in services and more effective at exercising social control over different health behaviours such as drug abuse. Finally, at the macro level, a deeper trust in a society leads to a higher efficiency of health institutions.

Equivalent mechanisms are proposed by Szreter and Woolcock (2004) but in terms of types of social capital. They argue that bonding social capital is important for the necessary social support; bridging social capital, for solidarity and respect across the social spectrum; and linking social capital for the effective mobilization of political institutions and will. In short, there is a growing body of evidence on how social capital plays an important role in shaping people's health.

A spurious relationship may be obtained if one does not account for measurement error in the causal link of schooling on civic outcomes. Controlling for measurement error in the two components of this association is vital. One could not argue of

growth. Corruption simply acts as an additional tax which slows economic growth (Dincer and Uslaner (2010)).

[9]For more details, see Poortinga (2006b) and references therein.

[10]Although she argues that for the provider it can be stressful and hence have negative health effects. In consequence, she stresses the need to incorporate the mutuality of social relations when looking at the impact of social capital on health.

the benefits of education in terms of economic growth and health via its impact on key facets of social capital (i.e., civic engagement and social trust) if the observed relationship is plagued with inaccuracies. This might be the case for certain civic outcomes used in the thesis as they are self-reported measures which try to recover sensitive information. Therefore, observed responses to civic outcomes and their 'true' responses may differ and are probably misreported. Similarly, education decisions (the other element of the relationship) are likely to be affected by unobserved factors which simultaneously affect answers to civic outcomes. This could also obscure the causal link education-civic outcomes. Measurement error in the relationship may vary at the macro level too as a consequence of the cultural and contextual factors of the two countries.

In summary, misclassification of civic outcomes as well as endogeneity of schooling should be accounted for, otherwise the former reasons (i.e., social capital's impact on economic growth and individuals' health) from the literature may not be applicable. This is why the key and core idea throughout this dissertation is how measurement error affects causality.[11]

1.3. A MODEL OF POLITICAL PARTICIPATION

As previously stated, the array of civic outcomes can be separated into two groups: civic opinions and civic behaviours. The former group represents knowledge of current political issues whereas the latter is guided by trust and enforcing norms. Civic opinions indirectly measure political participation, as individuals who are more interested in politics and discuss political issues are more likely to vote. Crucially, raising a society's interest in politics generally makes its citizens more politically active (Pattie et al. (2003)). Moreover, psychological involvement or participation in politics is highly correlated with individuals' socioeconomic resources (Miller (1992), p. 429). Hence, results for the civic opinions of the dissertation can be related to hypothesis from the economic literature regarding the association of schooling and voting, as well as theories from the political science field, where political engagement is based on a socioeconomic model of participation. This partly allows me to depart from the social capital literature when investigating the 'schooling-civic opinions' causal link, and focusing on the political and economic literature instead.[12] I begin by examining an explanatory model of political activity: civic voluntarism. I use some of its features in the analytical Chapters 4 and 5, particularly when examining endogeneity.

[11] A detailed explanation of the thesis' outline is contained in Section 1.4.

[12] This departure is only partial as social capital is present in most aspects of life. Political engagement is clearly influenced by bonding social capital. For example, younger individuals would be more keen on politics if their parents are politically affiliated.

Verba et al. (1995) investigate the process of political participation proposing a civic voluntarism model[13] that rests on three factors: resources, psychological engagement with politics, and access to networks through which individuals can be recruited to political life. In other words, those who are able to take part, who want to take part, and who are asked to take part, are more likely to do so. Of the three factors they place more emphasis on resources, because causality and interpretability are easier to establish. They argue that certain resources (especially time, money, and civic skills) are necessary for political participation. Educational attainment has a particular primacy to acquire these. In fact, not only does education have a direct impact on political activity, it also affects the acquisition of each of the sets of factors that facilitate participation: the well-educated are more likely to earn higher incomes; to develop civic skills at work, in non-political organisations; to be in social networks through which requests for political activity are mediated; and to be politically interested and knowledgeable (Verba et al. (2005)).

Additionally, an individual's family socioeconomic background also influences all these factors and consequently his future political activity. Verba et al. (2005) offer some explanations of this process.

On the one hand, privileged families are more likely to boast a politically rich home environment dominated by frequent political discussions, with politically active parents acting as role models. Children growing up in such families would clearly have distinguished political orientations, which most probably would make them more psychologically motivated to participate in politics as adults. On the other hand, parents' economic background will ultimately determine their children's socioeconomic position through the education they provide them, which in turn affects their future jobs and income. In turn, their position in society will affect their political activity because, participatory resources such as civic skills developed in school and in adult institutional settings (e.g., jobs) as well as location of recruitment networks, are all more easily attainable to certain society stratum.[14] In other words, the transmission of political activity from generation to generation initially operates through the political richness of the home environment, and then during a child's education by affecting the participatory factors resources, recruitment, and motivation.

The civic voluntarism framework, however, shares several features with the social capital concept that has been discussed in the thesis so far. For example, the input for political psychological motivation is essentially stimulation provided at home, clearly bonding social capital or social capital at the micro level.

[13]See also Brady et al. (1995) and Burns et al. (2001).

[14]Moreover, education can increase analytic ability and allows more educated individuals to have a greater capacity for absorbing and organizing complex political information.

There is also a consensus in the economic literature that education is positively associated with civic outcomes. I introduce a couple of important studies. Dee (2004) shows that schooling has a significant effect on voter participation and support for free speech for the US, as well as in the quality of civic knowledge as measured by the frequency of newspaper readership. He also finds that the impact of schooling holds for different levels of education, both at the post-secondary and the secondary levels, and has a strong and independent effect on most measures of civic engagement and attitudes. Similarly, Milligan et al. (2004) find a strong relationship between education and voting in the US and also evidence that education increases citizens' attention to public affairs and to following politics. Both studies use explanations from the civic voluntarism model when explaining the instrumental variable approach to control for unobservables. For instance, Milligan et al. (2004), discuss unobservables at the home environment level which influences both schooling and civic outcomes. That is, they argue that some parents who encourage their children to participate in civic activities also instill in their children a taste for education. This strand of the economic literature, however, only focuses on one dimension of social capital, ignoring social trust, and does not explicitly account for misclassification. The thesis goes beyond this existing research by including social behaviours and investigating misclassification. This is the key contribution of Chapters 4 and 5.

1.4. DISSERTATION'S OUTLINE, METHODOLOGICAL ISSUES AND CONTRIBUTIONS

The core of the thesis consists of three Chapters which take into account the earlier mentioned issues affecting the causality of education on civic outcomes, so as to attain a convincing association between them. Chapters 4, 5, and 6 are self-contained and can be read independently, hence, separate conclusions are included at the end of each of them. The data and methodological Chapters (i.e., Chapters 2 and 3, respectively) should be read alongside them but, otherwise, they are independent. Chapter 5 could also be seen as a robustness analysis, where some of the key results of Chapter 4 are replicated using a different dataset for the UK. Chapter 7 offers overall conclusions linking all the dissertation's results with the literature review in this introductory Chapter. Below, I present the dissertation's outline and contributions.

As discussed in detail in Section 1.2, the principal reason to concentrate on the current set of civic outcomes is due to their dual impact on economic growth and individuals' health. This holds in the thesis' conceptual framework as the indicators embody key dimensions of social capital. Within this framework, my focus is particularly on the causal effect of schooling since it is considered one of the main factors influencing social capital. On the one hand, this is the key motivation of the thesis from a theoretical outlook. By focusing on Italy and on the UK, I attempt to extend the previous research in this area from both the economic and social capital literature, and I am also able to discern to what extent, causality and the issues which affect the linkage between schooling and civic outcomes, vary by the contextual factors (e.g., welfare policy, wealth, religion, cultural aspects, etc.) of these two countries. From a methodological point of view, on the other hand, the main interest throughout the dissertation is to attain a "credible" relationship between education and civic outcomes, accounting for diverse issues which may obscure it.

Figure 1.1 provides a diagram of the different Chapters. In particular, the Chapters are linked as follows. Let x and y denote observed values of education and civic outcomes, respectively. Since education choices are driven by unobserved factors, one does not observe the true value of schooling x^* and the original relationship f would be biased. One needs to recover the true relationship g by accounting for endogeneity. But g assumes that the true civic outcomes y are observed. However, because civic outcomes are likely to be misreported, Chapters 4 and 5 look at whether the original association of the true variable of interest x^* to outcomes y still holds when one accounts for the tendency to underreport socially undesirable behaviours and overreport socially desirable ones. Thus, I assume that the true values of civic outcomes are not observed: $\omega \neq y$. This response pattern is known in social psychology as social desirability. The causal effect is now denoted by h. Also note that relationship h could be endogenous to each country's social structure. Finally, Chapter 6, explores this in more depth, and proposes an econometric/causality model which takes into account the characteristics of the distribution of a sub-group of civic outcomes. That is, the skewness and misclassification of civic behaviours are introduced in a hurdle model. The remainder of this section discusses each Chapter and its contributions in more detail.

Chapters 4 and 5 attempt to identify the causal effect of education on an array of measures of civic engagement in Italy and in the UK respectively, addressing the endogeneity and misclassification problems. Despite numerous reasons to expect a positive association between education and civic outcomes, estimates may not provide a valid relationship unless one takes into account the potential endogeneity of education. For example, it is likely that parents who foster an interest in further education in their children, also instil into them the importance of being civically responsible. Intelligence is also an unobservable which would simultaneously influence education decisions and levels of trust. Indeed, as argued by Sturgis et al. (2010a) intelligence fosters greater interpersonal trust as more intelligent individuals are more accurate in their assessments of the trustworthiness of others. This means that more

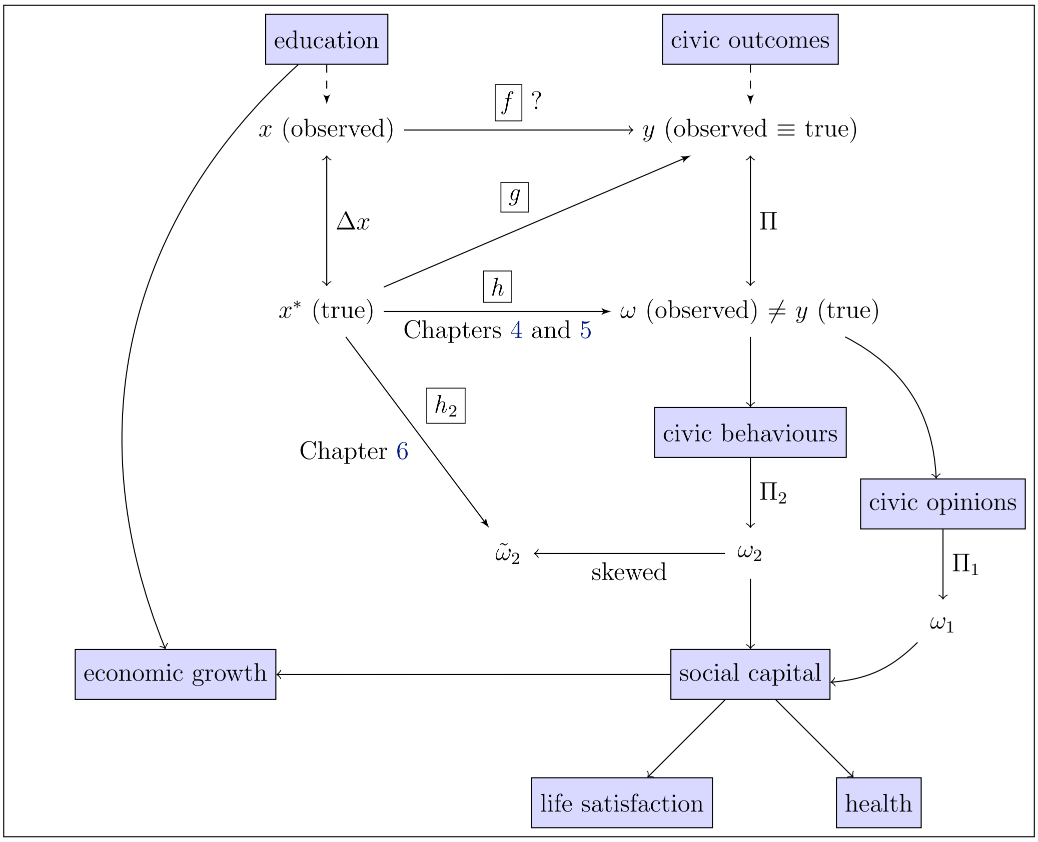

FIGURE 1.1.— Dissertation's outline.

intelligent people are less often betrayed over the life-course and therefore are able to benefit from norms of reciprocity. In line with other approaches (e.g., Oreopoulos (2007), Brunello et al. (2009)), to account for endogeneity I use educational reforms in both countries which are sources of exogenous variation in individuals' level of schooling but are otherwise unrelated to civic outcomes.

These two Chapters also deal with misclassification. Chapter 4, in particular, is an extension of the article Di Pietro and Delprato (2009) because it simultaneously considers misreporting and the potential endogeneity of education. In the former study the focus is on the causal effect of education on an array of measures of civic engagement in Italy, but only addressing the endogeneity problem and associated bias' sources on this relationship. In particular, the aim of Di Pietro and Delprato (2009) is whether the direction of the biases vary across civic indicators.

Misreporting represents deviation between the recorded answer to a survey question and the underlying attribute being measured. This frequently occurs when respondents are asked questions about socially and personally sensitive issues. Typically, individuals would tend to underreport socially undesirable behaviours and over-report socially desirable ones. This is known as social desirability bias in social psychology (see, King and Bruner (2000), Hattie et al. (2006)). In Chapter 4 and Chapter 5, I examine how the causal link, given by the education coefficient in a standard ordered probit, may be affected by misreporting of the self-reported civic outcomes. Following the approach of Abrevaya and Hausman (1999) and Dustmann and van Soest (2004), estimates from an ordered probit are compared with those from an ordered probit with misclassification.[15]

I draw on findings from social psychology and political science when setting up various hypothesis in terms of misclassification patterns, by group of civic outcomes and by educational levels. For instance, numerous arguments in political science support over-reporting of civic opinions (e.g., Bernstein et al. (2001)). The chosen approach allows me to establish the extent to which the causal effect of schooling on the civic indicators is genuine or whether it is mainly driven by a systematic over-reporting of more educated individuals relative to the less educated ones.

As before, the main empirical contribution is given by using an array of civic outcomes and, crucially, to account for misclassification. Previous research studying the causal link of education and civic outcomes does not explicitly control for misclassification and focuses on one aspect of social capital, civic engagement. By including civic behaviours into the analysis I am able to provide evidence on how, after accounting for misreporting, education is related to indicators of social trust. Moreover, because of the two countries' analysis, it is possible to investigate issues such as the extent to which educational effects on social capital differ under varying social structures. I now summarize the Chapters main results.

On the one hand, results for Italy indicate that most civic outcomes are misclassified, and misreporting is more severe for civic behaviours due to a stronger influence of social desirability. Perhaps surprisingly, I accept the hypothesis that education is exogenous, although caution is needed in the interpretation of this result. The key finding of Chapter 4 is, however, that qualitative overall conclusions regarding the causality of education on civic outcomes are indeed affected when accounting for misclassification: education turns out to be insignificant across civic behaviours. This lack of causality suggests two possibilities. It may indicate that social desirability operates differently in the two dimensions of social capital and is a more important issue on measures of civic behaviours than indicators on civic engagement. Alternatively, it may reflect that, at least in Italy, the cultural component of social trust plays a major role than schooling. Both are at odds with the conjecture that

[15] Also, I introduce an IV ordered probit with misclassification to control for the potential endogeneity of education.

they hold in spite of individuals educational levels. Moreover, individuals misreport civic behaviour questions regardless of their education levels, but not in the case of civic opinions where misclassification only holds for more educated individuals. In general, results tend to agree with existing theories from political science and social psychology.

On the other hand, the analysis for the UK in Chapter 5 shows that most civic outcomes are misclassified and, consequently, misreporting is an important empirical issue for this country. Endogeneity is an empirical concern too, as the null hypothesis of exogeneity is rejected for most indicators. The direction of the bias introduced by endogeneity follows the same direction as the one introduced by misreporting, with upward biases in both cases. Except for the Italian case where there is lack of endogeneity, the hypothesis of the civic voluntarism model seems to hold for the UK: unobserved factors which lead individuals to develop a taste for education, are likely to be positively correlated with civic opinions and civic behaviours. In fact, results appear to suggest that the extent of this correlation is such, that the impact of education on civic behaviours becomes statistically significant when accounting for endogeneity. This is the main difference with the Italian case: schooling, in the UK, has significant positive effects on all civic outcomes. Educational achievement emerges as a strong predictor within the three dimensions (network, trust and civism) of social capital. There is a significant misreporting of civic behaviours regardless of the educational level considered and, in the case of civic opinions, only for more educated individuals.

On the whole, Italy and the UK do not differ substantially with regards to misreporting, which indicates that social desirability influences measures of social capital beyond country effects. This might reflect the importance of personal characteristics over regional determinants in explaining differences in people's social capital. This is in line with some studies in the social capital literature that argue about a considerable degree of unity, in terms of aggregate levels of social capital amongst European countries. Additionally, this result is further supported by the emerging literature on the impact of genes on measures of trust.

Chapter 6 consists of a theoretical extension to an ordered response model. I introduce a "hurdle ordered probit with misclassification" to address two problems regarding the distribution of a self-reported ordered outcome: its skewness and its misclassification. The latter issue is motivated by the assumption that the dependent variable measures a sensitive topic (i.e., a civic behaviour) which it is likely to be misclassified. The argument is as before: the bias (social desirability bias) arises since respondents will tend to answer, though unconsciously, according to what is considered to be socially acceptable in order to gain approval of others, and will result in under-reporting undesirable behaviours and over-reporting desirable ones (see, e.g., Paulhus (1991), Tourangeau and Yan (2007)). To account for the high degree of skewness, that is, a substantial proportion of values at one end of its distribution, I propose a hurdle (or two-part) model, which is commonly used in the empirical literature. In fact, combining a binary choice model with an ordered response model is a standard practice in health economics (e.g., Jones (2000), Yen (2005), Madden (2008)).

The hurdle ordered probit with misclassification consists of two parts: (i) a split probit model which divides the distribution into two regimes by the median of the dependent variable, and (ii) an ordered probit with misclassification to deal with misreporting of observed answers in the top half of the scale. In Chapter 6, I carry out an extensive simulation exercise and obtain favourable performance in finite samples. By applying the model to a biased civic behaviour (for Italy) I find that, if the splitting process and measurement error are ignored, inference would be erroneous. This is the first model which accounts for both issues and could potentially be applied to self-reported data in other fields such as happiness and job satisfaction outcomes.

Chapter 2
Data

2.1. INTRODUCTION

In this Chapter I provide a description of the thesis' datasets and reasons why I focus on Italy and the UK. In particular, Section 2.2 contains a review of social capital studies for both countries which emphasises why the Italian and UK cases deserve to be studied and contrasted. Section 2.3 explains the Italian dataset used in Chapter 4 and also in the application section of Chapter 6. Section 2.4 contains the datasets and sources for the UK, which are employed in Chapter 5.

2.2. REASONS TO FOCUS ON ITALY AND THE UK

The focus on Italy is twofold. Firstly, the economic literature on civic returns tends to be centered in works for the US and UK (e.g., Gibson (2001), Dee (2004), Milligan et al. (2004)). Because political institutions efficiency, civic behaviours and enforcing norms are predominantly endogenous to the social structure, it would be rather erroneous to make generalisations exclusively based on these countries. I then attempt to extend the previous research in this area by utilising data from Italy. Providing new evidence is not trivial: normative aspects of culture will strongly impact, for example, on the level of transaction costs and so economic performance of a specific region or country will be directly affected as well (Halpern (2005)). Secondly, the Italian case contains unique features, particulary significant social capital regional differences, which makes it an interesting case worth studying. Indeed, contrary to the economic literature where there is lack of research on Italy, the Italian case is very popular within the social capital literature, since publication of the seminal study on the Italian regions was carried out by Putnam et al. (1993). I aim to contribute to these two strands of research but mainly from an economic perspective, dealing with various issues on the causal link of schooling on civic outcomes. Next, I provide a review of some evidence on Italy from a social capital perspective.

Putnam et al. (1993) argue that the critical factor when explaining differences in the effectiveness of regional governments and economic performance in Italy, is to be found in the different ways in which those regions' societies are organised. Typically, regions are characterised with horizontal structures common in the north and hierarchical forms in the south, and by differences in the extent of civic community, citizen involvement and governmental efficiency. By using four indicators of social capital: numbers of voluntary organizations, local newspaper readers, voter turn-out and preference votes, they find strong correlation between these indicators and government quality across regions in Italy. They attribute the North-South differences mostly to the large number of voluntary associations in northern Italy which explain the region's economic success.[1]

Recently, Sabatini (2008) confirms the finding, that linking social capital of voluntary organisations has positive influences on diverse economic outcomes in Italy.[2] He claims that in southern regions the spill-over effects from membership in organizations to the cooperative values and norms is low, and so there are fewer opportunities to learn civic virtues and democratic attitudes through this channel. This results in lack of trust, fewer cooperative behaviours and more shirking behaviours. In contrast, bonding social capital of strong family ties is more widespread exerting negative effects.[3]

Some authors claim that trust is culturally inherited. Locke (1995) argues that differences in economic performance among regions in Italy are largely accounted for inherited patterns of social interaction among firms. Trust and reciprocity among firms are higher in regions where polycentric networks are the norm, than in those where inherited networks are hierarchical or fragmented. Fukuyama (1995) stresses the need for cooperation between strangers as a medium of success in large firms, as well as the dependence of such cooperation on trust. He contrasts large public firms in high trust countries to smaller family firms that prevail in low-trust societies. As noted earlier in Section 1.2, Italy is classified in his framework as a low-trust society, with small and inefficient organisations, trading under influence and corruption.

The lack of trust in the Italian southern regions exemplifies a situation known in the literature as 'social trap' (Rothstein (2005)). One can look at the problem of trust from the overall institutional environment, where available institutional avenues, reflecting past or prevailing structural conditions, act as limitations on how

[1] According to Putnam et al. (1993), associations function as "schools of democracy" in which cooperative values and trust are easily socialised.

[2] In his study, importantly, there is acknowledgement of the problem of omitted variables and that social capital may be endogenous to institutional and economic performance, rather than a cause of them. He attempts to provide reliable results by using structural equations models.

[3] Putman traces the differences between the supply of social capital in southern and northern Italy back to several centuries, to a political culture established over a long period of time. Essentially, to independent city-states in the north in the fifteenth-century and to the feudal and autocratic southern region (Rothstein (2005), p. 53). Independent city-states of northern Italy encouraged the formation of such horizontal networks, in contrast to the more authoritarian political regimes of the south.

far one can extend the ambit of trust. A 'social trap' is a situation where individuals, groups or organisations are unable to cooperate owing to mutual distrust and lack of social capital, even where cooperation would benefit all. Examples include pervasive corruption and tax evasion (one of the Italian civic indicators analyzed in Chapter 4), which are more likely to occur in the south.

Note that people will cooperate only if they can trust that others will also cooperate. Public policies which enhance social and economic equality carried out by impartial political institutions would create social capital and trust (Rothstein (2005), Rothstein and Uslaner (2006)).[4] Otherwise lack of trust, an outcome of the dynamic interaction between norms and institutions, leads to bad steady states where trade breaks down, institutions are dysfunctional and beneficial norms are violated (Francois (2008)). Obviously, lower levels of trust would also lead to a higher tolerance of self-interest acts. For instance, tolerance of behaviours such as 'keeping money that you have found' (another indicator analysed) is much lower in Scandinavian countries than in southern European countries (Halpern (2005), p. 66).

Being aware of the reasons behind the process of a declining level of social capital helps to outline various hypothesis. A poor institutional environment in Italy may be the origin of a lack of interest in political issues and to judge as acceptable a lower tax compliance. Lack of cooperation and low trust may also lead individuals to be more tolerant of self-interest acts or bad civic behaviours.

The focus on the UK from an empirical point of view is to validate the evidence on Italy. Although the comparison is also an important concern in the dissertation because, by contrasting their results, diverse appealing questions arise. For example, is causality of education on measures of social capital in these two countries endogenous to their social structures? If so, which differential characteristics of these two countries are associated to different levels of social capital, making the relationship endogenous?

There are various explanations. Social capital levels are reported to be lower in countries that spend less on welfare (Arts et al. (2003)), and some research (e.g., Wuthnow (1999), Smidt (2003), van Oorschot et al. (2006)) stresses that the generation of social capital is linked to religious beliefs. With regards to the role of religion in the formation of social trust, it is acknowledged in the literature that, whereas protestantism fosters generalised social trust, the development of trust in a given population could be impeded by its catholic heritage (Putnam et al. (1993), Fukuyama (1995), Bjørnskov (2008)). In fact, in a recent study for the formation of

[4]This is known in the literature as the institutional performance theory (see, e.g., Allum et al. (2010)).

social trust in Germany, Traunmüller (2010) finds a double positive effect of protestantism: not only do protestants tend to be more trusting, but a protestant context also increases one's trust regardless of individual religious beliefs. These results suggest that both individual religiosity and regional religious contexts matter in the formation of social trust.[5] Note that the fact that the UK is mostly protestant and Italy mainly catholic, would thereby imply higher levels of social trust for the former country. I now explain the theory underlying the linkage between religion and trust, especially the protestant/catholic distinction.

The fundamental idea is that the protestant identity and a regional cultural tradition of protestantism foster generalized social trust by extending the scope of moral communities beyond narrow in-groups toward people in general. Protestant tradition extend virtues such as truth-telling, reliability, and reciprocity beyond the narrow circle of one's own family (Fukuyama (1995)). In regions dominated by protestants, more people would have internalized these norms and thus behave in honest and trustworthy ways when dealing with strangers. This leads to more positive experiences in everyday interactions and encourages the extension of trust to people in general, including strangers. Traunmüller (2010) describes these two positive effects by individual and contextual levels hypotheses.[6] Catholicism, on the contrary, might be conducive to an 'amoral familism', that is, a situation where moral behaviour is only exhibited toward the own in-group but not toward people in general. In catholic dominated populations, then, one would observe less experiences of trustworthiness from strangers' social interactions.

Additionally, the hierarchical and rigid organizational structure of catholicism should be less encouraging to the formation of mutual trust (Putnam et al. (1993)). In fact, in a family orientated country such as Italy, the subjective, cultural dimension of social capital[7] is shaped by bonding social capital and therefore have an elective affinity with particularized trust than with generalized trust, trust in institutions and civic morality (van Oorschot et al. (2006)). This, in turn, may also have an impact on the level of misreporting. The UK, however, has a higher level of wealth (GDP) and more religious diversity as compared to Italy.[8] These are only some illustrative reasons that might influence the type and degree of the linkage of education with dimensions of social capital in either country. Recall that, throughout the thesis,

[5] An equivalent finding is obtained by Lam (2006).

[6] The religiosity of a collective serves as a cultural as well as structural context for individuals and is therefore likely to have an impact on social trust independent from individual religiosity.

[7] That is, the set of values and attitudes of individuals relating to trust, reciprocity and willingness to cooperate.

[8] For a recent analysis of the determinants of generalised and particularised trust for the UK, see Sturgis and Smith (2010).

social capital is conceived as an umbrella concept which is multidimensional, therefore multiple indicators are required for a complete measurement of these dimensions. Because it contains various dimensions, a wide range of results are possible.

Differences in political systems, social norms and expectations amongst European nations would, on the whole, lead to significant countries' effects. Yet this has been called into question. Recent evidence for European countries of Allum et al. (2010) suggest that effects on measures of social trust, and institutional trust happen at the micro level. In particular, they argue that both forms of trust are more akin to personality type variables or value orientations and, therefore, more likely related to the social psychological conception of trust. I finish this section by describing some UK studies on social capital.

Historically, the UK has a long tradition of civic culture with high levels of social trust and political and civic participation. Hall (1999) argues that the UK has not followed USA's lower levels of social capital due to the post war transformation in social structure and the emphasis placed upon the government's policy towards the delivery of social services, as well as the use of non-profit association and volunteering work. At present, however, there has been decline in the UK similar to the USA, France and other Anglo-Saxon countries (Halpern (2009)). The only exception to this erosion of social capital is the group of Scandinavian countries which shows a higher average level of trustworthiness mainly related to their countries wealth and dominant protestant culture (Delhey and Newton (2005), van Oorschot et al. (2006)). Rothstein attributes their higher stock of social capital to the fact that a solidaristic rather than egoistic individualism has appeared in the Scandinavian countries . This "solidaristic individualism" is not present in the UK where there is a shift towards privatisation and egoistic individualism. In the case of "solidaristic individualism" individual autonomy and social responsibility go together. People are willing to support others with different values and causes because this happens on a condition of mutual trust by which they would also be helped and respected in return (Rothstein (2005), p. 78).

Although the nature of politics, government and type of engagement have changed, there is a decreasing tendency in the level of trust of politics and politicians in Britain (Halpern (2009), p. 177), and increasing levels of income inequality. Even though the latter UK's conditions may be akin to Italy, southern European countries are markedly distinct as they tend to show low levels of both formal and informal social capital. Studies on the distribution of social capital in Europe (e.g., Beugelsdijk and van Schaik (2005), Pichler and Wallace (2007)) classified the UK into the western group of countries, which is in between the northern and southern European countries with respect to contextual characteristics. van Oorschot et al. (2006), for instance, consider in their analysis four European regions: north, west, south and east.[9] As mentioned earlier, in the southern region there is lower welfare spending and wealth as well as a catholic majority. In western countries, on the contrary, there is more religious diversity, wealth and more extensive welfare states.

These contextual characteristics of the two countries (at the macro level) normally lead to different types of social capital and distribution amongst individuals. Take, for example, the role of the welfare state. In a recent paper, van Oorschot and Finsveen (2009) go beyond existing theories by stating that the reduction of inequality in social capital is one of the central aims of the welfare state. Central to their argument is that economic and cultural inequality directly translates into inequality in social capital and vice-versa, that is, these two inequalities (re)produces each other. They argue that welfare states can have two basic impacts on the (re)production of social capital inequalities. Firstly, one impact is indirect. Welfare policies seek to reduce large economic inequalities by means of often inter-connected policies such as labor participation, education, healthcare, etc. Secondly, a direct but unintended impact. Welfare policies create a basic security and empowerment which, especially for the more deprived groups in society, may enhance their trust in others, as well as in institutions. Also, they foster a context of national solidarity and fellow feeling, which is conducive to higher trust levels too.[10]

The empirical evidence is inconclusive. Recently, van Oorschot and Finsveen (2010) find that there is no effect of welfare stateness on social capital inequality, although they stress that an analysis relying on a broader range of welfare states might show effect. Similarly, Gesthuizen et al. (2008) do not find consistent patterns on the distribution of social capital by educational expansions and welfare state contexts amongst European nations. But the former authors do find that the influence of education on the dimensions of social capital varies under conditions of educational expansion and social security expenditure. For instance, higher levels of social security expenditure have an effect on the impact of education in voluntary organization membership.

[9]Specifically, the regions are composed as follows: north (Sweden, Finland, Denmark), west (Austria, Belgium, France, Germany, Ireland, The Netherlands and the *United Kingdom*), south (Greece, *Italy*, Portugal and Spain) and east (Bulgaria, Croatia, the Czech Republic, Estonia, Latvia, Lithuania, Poland, Hungary, Slovakia and Slovenia).

[10]Known as the solidarity hypothesis in the literature.

2.3. ITALIAN DATA

In Chapters 4 and 6 (i.e., Section 6.5) of the thesis I use data from the Survey of Household Income and Wealth (SHIW) carried out by the Central Bank of Italy. I rely on a specific section related to civic outcomes which is included in the 2004 wave. Respondents to this section contain household heads born in uneven years.

Five different indicators of civic outcomes are considered for Italy. The first one relates to political engagement. Individuals were asked to report *how interested they are in politics*, with answers taking values 1 to 4, which correspond to 'very', 'fairly', 'not very' and 'not at all', respectively. The second indicator concerns people's opinion on the problem of tax evasion. Specifically, people were asked to *rate the importance of the problem of tax evasion in relation to all the problems faced by the government*. The answer to this question is coded on a 1-5 scale, with 1 being 'very serious', 2 as 'serious', 3 as 'the same as any other', 4 as 'marginal' and 5 as 'non-existent'. In the next three questions respondents were asked to indicate the extent to which the following behaviours were justified: *not paying for your ticket on public transport*, *keeping money you obtained by accident when it would be possible to return it to the rightful owner* and *not leaving your name for the owner of a car you accidentally scraped*. Answers to these questions are given on an ordered 1 to 10 scale, with 'never justifiable' equals to 1 and 'always justifiable' to 10. The order for the responses of the five civic outcomes is reversed so that a high value indicates a higher sense of civic duty. Summary statistics for the civic outcomes are displayed in Table 2.1.

Because the survey only contains the highest educational achievement of the individual and not the number of years spent at the educational institution, I compute a continuous measure of schooling by following similar approaches in the literature (see, for instance, Brunello and Miniaci (1999)). Clearly, years of education are calculated by imputing the number of years required to complete the highest level of educational achievement reported by the individual.

More precisely, the following procedure is used. To obtain a primary school certificate and a lower secondary school diploma 5 and 8 years of education are needed, respectively. For the next education level, that is, upper secondary school, the number of years varies by the type of school attended. In particular, four extra years are needed for teaching school, and a five-year programme for general and technical schools. The number of statutory years required to complete university education varies according to the subject studied as well. To obtain a humanities and social sciences degrees 4 years are required, and for a medicine degree 6 years. Finally, most postgraduate courses tend to last one year in Italy. The average level of education

TABLE 2.1

Descriptive statistics for Italy: SHIW sample for civic outcomes

Variables	Mean	Std. Dev.
Civic outcomes:		
Interest in politics	1.91	0.90
Importance of the problem of tax evasion	4.08	0.81
Not paying ticket on public transport	8.73	1.98
Keeping money and not return it to the rightful owner	8.87	1.91
Not leaving your name for the owner of a car you scraped	8.96	1.86
Education (years of schooling)	9.09	4.39
Demographic variables:		
Household income (in thousand)	31.74	32.19
Age (years)	55.74	15.52
Male = 1	0.63	
Father's education (years of schooling)	4.95	4.19
Mother's education (years of schooling)	4.09	3.73
Married = 1	0.66	
Employed = 1	0.46	
Number of children in the household	0.81	0.97
Area of residence:		
South = 1	0.31	
Center = 1	0.23	
North=1	0.46	
Urbanization:		
Small town (below 20,000) = 1	0.32	
Medium town (between 20,000 and 40,000) = 1	0.20	
Big town (between 40,000 and 500,000) = 1	0.40	
Very big town (above 500,000) = 1	0.08	
Father's occupation:		
Manager or professional	0.05	
Self-employed	0.21	
Not working	0.04	
Others	0.70	
Mother's occupation:		
Manager or professional	0.01	
Self-employed	0.07	
Not working	0.70	
Others	0.22	
Number of observations	3,059	

in the sample is 9.09 years. Additional explanatory variables are: age, household income, gender, parental education and occupation, marital and employment status, number of children in the household, area of residence and urbanisation. The sample size is $N = 3059$. Summary statistics for individual characteristics are presented in Table 2.1.[11]

2.4. UK DATA

I rely on two surveys for the UK analysis in Chapter 5. For civic opinions, I use the British Election Study (BES), 2005 cross section wave[12] and, for civic behaviours, the European Values Study (EVS), waves 1981, 1990 and 1999 for the UK.[13] A description of each data source is provided below.

The BES has been conducted at every General Election since 1964. The purpose of the BES is to study long-term trends in British voting behaviour, to explain the election outcome, party choice and turnout, as well as examining the election effects on British politics. The 2005 BES comprised a series of linked surveys. The main surveys are the pre-campaign and post-election cross-sectional surveys, the self-completion survey and internet follow up surveys.[14] The core survey of the BES uses a national face-to-face probability sample and the primary instrument is a post-election face-to-face survey. I use this entire post-election sample (N= 4161) for England, Scotland and Wales. This sample is composed by a pre-campaign-post election panel with $N = 2959$, as well as a post-election only "topup" of $N = 1202$.

As can be seen in Table 2.2, I consider four civic opinions for the UK, three of them equivalent to 'interest in politics' in Italy. The first one asks respondents: *how much interest do you generally have in what is going on in politics?*, with answers taking values 1 (a great deal), 2 (quite a lot), 3 (some), 4 (not very much) and 5 (none at all). The second and third civic opinions ask whether individuals *pay attention to politics* and whether they *discuss politics with family and friends*, with answers given in a 0 to 10 scale, where 0 means 'pay no attention to politics', and 10 'pay a great deal of attention' and, for the latter civic opinion, 0 means 'very unlikely that would discuss politics' and 10 'very likely that would discuss politics'.

Although not directly linked with political participation, I also consider the vari-

[11]Note the high proportion (70%) that the covariate "father's occupation" falls into the category 'others'. This category contains the following occupation's types: blue-collar worker ($\approx$ 53%), office worker, teacher, junior manager and official.

[12]The last available dataset for the BES is from June 2010, but it is a temporary (beta) release with some information missing.

[13]I do not include the latest cross section data (for 2008) since it has not been released yet for Great Britain.

[14]See, Johnson et al. (2007) for details on the 2005 BES.

TABLE 2.2

Descriptive statistics for the UK: BES sample for civic opinions

Variables	Mean	Std. Dev.
Civic opinions:		
General interest in politics	3.06	1.00
Attention to politics	5.37	2.49
Discuss politics with family and friends	5.26	3.39
Active in a voluntary organisation	1.96	1.15
Education (age finished full-time education):		
15 or younger (=1)	0.34	
16 (=2)	0.26	
17 (=3)	0.09	
18 (=4)	0.08	
19 or older (=5)	0.23	
Demographic variables:		
Age (years)	50.91	17.78
Employed = 1	0.53	
Income	5.43	3.14
Male = 1	0.44	
Married = 1	0.49	
Number of children in the household	0.55	0.96
Heath-Goldthorpe five-category social class variables:		
Socialclass1 (salariat) = 1	0.32	
Socialclass2 (routine non-manual) = 1	0.23	
Socialclass3 (petty bourgeoisie) = 1	0.05	
Socialclass4 (manual foremen and supervisors) = 1	0.09	
Socialclass5 (working class) = 1	0.27	
Country:		
Wales = 1	0.19	
Scotland = 1	0.24	
England = 1	0.57	
Additional outcomes related to politics and voting:		
Political activity takes too much time and effort	3.11	0.94
Family and friends think that voting is a waste of time	2.41	1.01
Feel very guilty if not vote	3.55	1.19
Neglect my duty as a citizen if not vote	3.76	1.07
Additional outcomes about trust:		
Most people can be trusted	6.26	2.03
Trust local government	4.88	1.89
Number of observations	4,161	

able *active in a voluntary organisation* as a fourth indicator, with answers taking values 1 to 4, which correspond to 'very active', 'somewhat active', 'a little active' and 'not at all active/not involved', respectively. By incorporating voluntary activities I am able to investigate the impact of schooling on another dimension of social capital, i.e., social participation (networks).[15] Citizens who choose to join organisations and voluntary associations have more opportunities to meet people, to develop more extensive systems of social relationships, and hence to become more engaged in civic life (Verba et al. (1995)). As noted by Putnam et al. (1993) participation in civic organisations forms habits of cooperation, solidarity and public-spiritedness. Even different levels of participation in voluntary organisations can characterise countries and regions (van Oorschot et al. (2006)).

Furthermore, four extra indicators related to politics and voting, as well as two concerning social trust from the BES 2005 post-election sample, are investigated. Individuals were asked to show how much they agree with the following statements: *it takes too much time and effort to be active in politics and public affairs*, *most of my family and friends think that voting is a waste of time*, *I would feel very guilty if I didn't vote in a general election* and, finally, *I would be seriously neglecting my duty as a citizen if I didn't vote*. Answers to these questions are coded on a 1-5 scale, with 1 (strongly agree), 2 (agree), 3 (neither agree nor disagree), 4 (disagree) and 5 (strongly disagree). Responses to the two indicators about social trust (*most people can be trusted*,[16] *trust local government*) are provided in a 0 to 10 scale, with 0 equals to the lowest level of trust and 10 to the highest level of trust.[17] As before, the order of the responses for all civic outcomes and additional indicators (if necessary) is reversed, so that higher values represent a higher sense of civic duty. Summary statistics for all these outcomes are displayed in Table 2.2.

The BES survey does not provide the education covariate as the number of years spent at a specific educational institution. Instead, the amount of education is represented by an integer defined by the age when the individual finished full-time education.[18] That is, 15 or younger (=1), 16 (=2),..., 19 or older (=5). Additional

[15]In fact, for the Office of National Statistics (ONS) in the UK, *involvement with voluntary organisations* is an aspect of the social participation dimension of social capital that should be measured (see, e.g., Harper (2002)).

[16]This question measures a 'moralistic' type of trust whereas trust in people with whom one is personally familiar is known in the literature as 'strategic' (Uslaner (2002)). See Sturgis and Smith (2010) for a discussion of this kind of data for the UK, as well as the issue of heterogeneity in question interpretation.

[17]As far as the ONS (UK) is concerned (e.g., Babb (2005)) trusting other people and institutions (justice, government, etc.) are also key components of social capital and so they are classified as elements of the reciprocity and trust dimension. Specific research for the UK employing these two indicators are, for instance, Li et al. (2005), Fahmy (2006), and Sturgis et al. (2010a).

[18]Milligan et al. (2004) employ the same definition of schooling from the BES survey.

covariates included in the analysis are similar to the ones for Italy. Specifically, age, employment status, income,[19] gender, marital status, number of children (under 18) in the household, five dummies describing the economic position (social class) of the respondents measured by the five category Goldthorpe-Heath class schema (Heath et al. (1985)), and dummies for each country. Covariates' summary statistics are presented in Table 2.2.

The UK's analysis for civic behaviours is based on the EVS (See Table 2.3). The EVS is a large-scale, cross-national, and longitudinal survey research program on basic human values. It provides insights into the ideas, beliefs, preferences, attitudes, values and opinions of citizens all over Europe. It started in 1981 and is repeated every 9 years. I use cross section data from the 1981, 1990 and 1999 waves, which make an overall sample of $N = 3651$, comparable to the ones from the SHIW (Italy) and BES (UK) datasets. The EVS sample for the UK contains the same three civic behaviours as the ones chosen for Italy.

In the group of civic behaviour questions, respondents were asked to indicate the extent to which the following statements were justified: *failing to report accidental damage done to a parked vehicle*, *keeping money that you have found*, and *avoiding a fare on public transport*. Answers were coded on a 1 to 10 scale, where 1 stands for 'can never be justified' and 10 for 'can always be justified'. Again, answers to these questions are reversed so that 1 and 10 stand for the lowest and highest civic behaviour responsibility, respectively. These questions convey information on the degree of people's trustworthiness by revealing attitudinal and behavioural characteristics of people themselves, but not interpersonal trust. Nonetheless, they are linked because there is a positive correlation between trustworthiness and trust in institutions: in countries where people trust institutions more, there is also a higher level of civic morality (van Oorschot et al. (2006)).

The education variable for the EVS sample is presented in the same terms as in Table 2.2, that is, as an integer for the age when the individual finished full-time education (15 or younger (=1), 16 (=2),...,19 or older (=5)). The other explanatory variables chosen for civic behaviours coincides with the ones used for the UK's civic opinions of the BES sample. Summary statistics for all EVS outcomes and covariates are offered in Table 2.3.

The two countries' data sources are comparable. The SHIW dataset, containing the whole array of civic outcomes, is representative of the whole Italian population and therefore it has been extensively used in leading IV studies of the economic re-

[19]Income stands for the combined annual household income, with answers coded as: 1 if income $<$ 5,000, 2 if income $\in (5,001-10,000)$, 3 if income $\in (10,001-15,000)$,..., and 14 if income $>$ 70,000.

TABLE 2.3

Descriptive statistics for the UK: EVS sample for civic behaviours

Variables	Mean	Std. Dev.
Civic behaviours:		
Failing to report accidental damage done to a parked vehicle	9.00	1.82
Keeping money that you have found	8.56	1.88
Avoiding a fare on public transport	8.73	1.90
Education (age finished full-time education):		
15 or younger (=1)	0.39	
16 (=2)	0.31	
17 (=3)	0.08	
18 (=4)	0.07	
19 or older (=5)	0.15	
Demographic variables:		
Age (years)	44.14	18.70
Employed = 1	0.57	
Income	6.08	2.37
Male = 1	0.46	
Married = 1	0.58	
Number of children in the household	1.92	1.38
Socio-economics status:		
Socialclass1 (upper, upper-middle class) = 1	0.18	
Socialclass2 (middle, non-manual workers) = 1	0.27	
Socialclass3 (manual workers-skilled, semi-skilled) = 1	0.28	
Socialclass4 (manual workers-unskilled, unemployed) = 1	0.27	
Country:		
Wales = 1	0.09	
Scotland = 1	0.10	
England = 1	0.81	
wave: 1981	0.32	
wave: 1990	0.41	
wave: 1999	0.27	
Number of observations	3,651	

turns of schooling (e.g., Brunello and Miniaci (1999), Flabbi (1999), Brandolini and Cipollone (2002)). The UK's group of civic opinions is included in the BES dataset, which is also representative of the British population and a major survey on political issues. Thus, final samples of both surveys share two important characteristics: they are representative of their countries and were conducted almost at the same time, that is, the SHIW in 2004 and the BES in 2005. In connection with civic behaviours, I did not pursue the idea of using the EVS dataset for Italy because I judged more important to gather all civic indicators from the same SHIW dataset for a higher consistency in the within country analysis than to raise comparability across countries.

Chapter 3
Parametric misclassification model

3.1. introduction

A large number of empirical studies in economics and other social disciplines rely on self-reported data. However, there is great consensus that this type of data is generally plagued by measurement error. Measurement error represents deviation between the recorded answer to a survey question and the underlying attribute being measured. There are different sources of measurement error. It may arise from errors in data processing and/or in data collection procedures. Most importantly, it may reflect systematic misreporting or unreliable responses by interviewees. This frequently occurs when respondents are asked questions about socially and personally sensitive issues. Typically, individuals would tend to underreport socially undesirable behaviours and over-report socially desirable ones (Paulhus (1991)). This is known in social psychology as social desirability (SD) or social desirability bias (SDB).

Many studies in empirical economics deal with subjective measures which take ordered categorical values. Examples include research in the fields of 'economics of happiness', 'job satisfaction', 'health satisfaction' and 'subjective evaluations of language fluency', which are typically analysed using ordered response models. Since it is very probable that these self-reported measures or dependent variables suffer from misclassification, parametric procedures ignoring the issue of measurement error are likely to lead to inconsistent estimates for the parameters of interest as they rely on a misspecified distribution of the data (Ramalho (2002)). For instance, in the binary choice case, Hausman et al. (1998) find that, even in the case of a small amount of misclassification, ordinary probit not only yields inconsistent estimates, but it can also overstate the precision of the estimates.

Hence, modifications in the likelihood functions of standard ordered response models are required in order to incorporate measurement error or misclassification probabilities. Namely, an ordered probit (OP) that includes as additional parameters, misclassification probabilities (linking reported and true responses), defines an ordered probit with misclassification (OPM). This parametric model is used throughout the thesis.

Chapter 3 is organised as follows. Section 3.2 contains a methodological review.

Section 3.3 formally introduces the OPM model and the recoded civic outcomes for Italy and the UK, which are used in Chapters 4 and 5. In Section 3.4 I perform a small simulation experiment to illustrate the advantages of the OPM over the OP model. In Section 3.5 I present some misclassification assumptions by group of civic outcomes and educational levels. Finally, Section 3.6 concludes. A formal definition of the testing procedure is included in the Appendix A.

3.2. METHODOLOGICAL MISCLASSIFICATION REVIEW

There is a long tradition on the study of measurement error in statistical research. Earlier references go back to Bross (1954), an analysis of the impact of misclassification on statistical tests and, Bryson (1965), who derives bounds for the bias due to errors of classification on a binomial population. Currently, there is a significant body of research in the statistical literature which accounts for the effect of measurement error on the outcome variable using Bayesian approaches (see, e.g., Paulino et al. (2003); Stamey et al. (2008)). A broad review of measurement error and misclassification in statistics and epidemiology is contained in Gustafson (2004).

In econometrics, the problem was first studied by Aigner (1973) who shows that in the presence of a binary misclassified regressor in a linear regression, least squares (LS) estimate is biased towards zero. Literature in econometrics has mainly dealt with measurement problems on the independent variables, thereby investigating misclassification of regressors. A well known strategy for dealing with this type of misreporting is to use a secondary measurement or an instrumental variable. Recent papers following this approach for nonclassical errors and nonlinear models are, for instance, Mahajan (2006), Schennach (2007) and Hu and Schennach (2008). Misclassification on the dependent variables, however, has received less attention.

First studies on misclassification of responses on qualitative choice models are Lee and Porter (1984), Douglas et al. (1995), and Poterba and Summers (1995). More recently, Hausman et al. (1998) introduce a binary choice model with misclassification and a semiparametric approach to deal with measurement error. Other applications with binary outcomes subject to misclassification are Caudill and Mixon (2005), de Coulon and Wolff (2007), and Ramalho (2007). In the context of panel data, Dustmann and van Soest (2001) analyse the determinants of speaking fluency on the wages of immigrants, distinguishing between time-varying and time-persistent misclassification. Furthermore, Keane and Sauer (2009) explicitly treat classification error using a dynamic discrete choice model of labour supply, examining the hypothesis of endogeneity of fertility and non-labour income. In a related paper, Keane and Sauer (2010) introduce a new simulated maximum likelihood estimation algorithm for estimating dynamic panel data models with misclassification. Methodologically, a similar research to this thesis is Brachet (2008), who proposes a method that addresses both the endogeneity and measurement error problems to estimate the effect of maternal smoking on birth outcomes.[1]

There are different approaches to investigate whether the array of civic outcomes suffer from misclassification. The chosen approach would depend on the kind of measurement error one is interested to model. I assume that there is no error in the underlying latent variable that defines the observed response. Hence, I suppose that y^* is a perfect indicator of civic outcomes. On the contrary, if there is an error in y^*, the OPM would not be able to identify this as it would collapse into the idiosyncratic term. However, one could still identify the error term by using a nonparametric structural approach such as Matzkin (2007).

The OPM model assumes that the wrong outcome is reported and accounts for this by including misclassification probabilities in the standard likelihood function of ordered response models. Given that the main interest is on the misclassification process and estimated coefficients, I use an OPM. Nevertheless, if one is indifferent about the misreporting probabilities and consider them as nuisance parameters, then a semiparametric estimation such as a monotone rank estimator would suffice (see, for instance, Cavanagh and Sherman (1998) and Abrevaya (1999)). This estimator assumes monotonicity and is very useful when the researcher suspects mismeasurement but lacks any additional prior information for forming a reliable model of mismeasurement.

Alternatively, one could model the boundaries as linear functions of observed explanatory variables (i.e., Terza (1985)) or extend this by allowing for random boundaries that vary across individuals as in Das (1995). The latter approach is more appealing when individuals' responses are given in numerical scales which are more likely to suffer from unobserved heterogeneity; this is the case of civic behaviours in the dissertation. However, due to problems with identification given data availability, I did not pursue this extension. Alternatively, a fruitful approach is a chopit model (e.g., Kristensen and Johansson (2008)) but, since anchoring vignettes are not available, one is not able to follow this particular model. As previously mentioned, misreporting probabilities are one of the main objectives of Chapter 4 and Chapter 5, and this is captured by the OPM and the extension I propose in Chapter 6.

[1]A review on different approaches on measurement error models in econometrics can be found, for example, in Bound et al. (2001) and Carroll et al. (2006).

3.3. PARAMETRIC MISCLASSIFICATION MODEL

3.3.1. *OPM*

Here I follow Abrevaya and Hausman (1999) and Dustmann and van Soest (2004) to introduce a parametric misclassification model. I begin by defining an OP model for J categories. The latent variable $y_i^* = \mathbf{x}_i'\beta + \varepsilon_i$ (for $i = 1, ..., N$) is related to the 'observed' (or reported) dependent variable ω_i via a partition of the real line into $J+1$ cutpoints $c_0 \equiv -\infty < c_1 < ... < c_{J-1} < c_J \equiv +\infty$,

$$\omega_i = j \text{ if } c_{j-1} \leq y_i^* < c_j, \text{ for } j = 1, ..., J. \tag{3.1}$$

As the framework is of an OP, I assume that the error term is normally distributed: $\varepsilon_i|\mathbf{x}_i \sim N(0, \sigma^2)$. Let y_i be the 'true' response which is related to the latent variable y_i^* as in the OP model of Eq. (3.1). Under the hypothesis of lack of misreporting, $y_i \equiv \omega_i$, and the true response is observed. However, if there is misreporting, $y_i \neq \omega_i$, and one needs to define a misclassification probability. Let the probability that observations belonging to category j are classified in category k as,

$$\pi_{j,k} = \Pr(\omega_i = k|y_i = j, \mathbf{x}_i) \text{ for } j, k \in (1, ..., J) \text{ and } j \neq k. \tag{3.2}$$

For J discrete outcomes, these misclassification probabilities can be expressed in matrix form as

$$\Pi_J = \begin{pmatrix} \pi_{1,1} & \pi_{1,2} & \cdots & \pi_{1,J} \\ \pi_{2,1} & \pi_{2,2} & \cdots & \pi_{2,J} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{J,1} & \pi_{J,2} & \cdots & \pi_{J,J} \end{pmatrix}, \tag{3.3}$$

where the diagonal elements are the probabilities that observations are correctly classified, and by definition each matrix row adds up to one.

Given this misclassification process, the probability of the observed dependent variable is

$$\Pr(\omega_i = k|\mathbf{x}_i) = \sum_{j=1}^{J} \pi_{j,k} \Pr(y_i = j), \text{ for } k \in (1, ..., J), \tag{3.4}$$

where $\Pr(y_i = j) = \Phi(c_j - \mathbf{x}_i'\beta) - \Phi(c_{j-1} - \mathbf{x}_i'\beta)$; $\Phi(.)$ denotes the univariate normal *c.d.f.*, and σ is fixed to 1. The OPM model includes l $[l = J \times (J-1)]$ additional parameters to be estimated given by the off-diagonal elements of matrix Π_J . Let $\theta = (\beta', c', \pi')'$, where the parameter β excludes the constant term. The cutpoints, misclassification probabilities and beta coefficients can be jointly estimated by the following maximum likelihood function,

$$\ell(\theta) = \sum_{i=1}^{N} \sum_{k=1}^{J} \mathbf{1}(\omega_i = k) \ln\left\{ \sum_{j=1}^{J} \pi_{j,k} \left[\Phi(c_j - \mathbf{x}_i'\beta) - \Phi(c_{j-1} - \mathbf{x}_i'\beta) \right] \right\} \tag{3.5}$$

where $\sum_k \pi_{j,k} = 1$ and $\sigma \equiv 1$.

For the parametric model to be valid, the misclassification process must be correctly specified. In other words, the probabilities of misclassification must be a function only of the subset (defined by the cutpoints in Eq. (3.1)) to which y^* belongs and not of the level of y^*. Otherwise maximum likelihood (ML) estimates would yield inconsistent estimates. Hence, the main identification assumption is that $\pi_{j,k}$ are not a function of the covariates.[2]

Consistency relies on stochastic conditions on the behaviour of the misclassification probabilities which guarantees that $\mathbb{E}(\omega_i|\mathbf{x}_i)$ increases with the index $\mathbf{x}_i'\beta$ for the sign of β to be identified. In terms of the matrix Π_J in (3.3), this condition implies that the elements of the first column must be weakly decreasing as you go down row-by-row, the sum of the elements of the first two columns must be weakly decreasing as you go down row-by-row, and so on. Hence, the implicit assumption is that observational units with larger true values for their dependent variable are more likely to report larger values than observational units with smaller true values (see Abrevaya and Hausman (1999), p. 252, for details).

To test the validity of the OPM, one cannot use a standard test because the null hypothesis places the parameters on the boundary of the parameter space. Instead of using a likelihood ratio/Wald test with a χ^2 distribution, one needs to use a chi-bar-squared distribution ($\bar{\chi}^2$), which is distributed as a mixture of χ^2 distributions (Shapiro (1985)). Given that finding the weights is a difficult numerical problem and also there is not a closed expression form for the weights when the number of restrictions tested is higher than 4, the $\bar{\chi}^2$ statistic is normally simulated. Reasonably accurate estimates of the weights can be easily obtained by Monte Carlo simulation (Andrews (2001), Liu and Wang (2003)).[3]

3.3.2. *OPM for three alternatives and civic outcomes frequencies*

Next, I present the likelihood function along with the stochastic conditions for $J = 3$. This is the model used in Chapters 4 and 5 as civic outcomes are recoded in a

[2] Lewbel (2000), Lemma 2, shows that even when the probabilities of misclassification depend in unknown ways on the covariates, binary models with misclassification are semiparametrically identified. However, he concludes that the estimators are not very practical since they involve up to third order derivatives and repeated applications of nonparametric regression.

[3] See Appendix A for details.

three-point scale.

The matrix of misclassification probabilities is

$$\Pi_3 = \begin{pmatrix} \pi_{1,1} & \pi_{1,2} & \pi_{1,3} \\ \pi_{2,1} & \pi_{2,2} & \pi_{2,3} \\ \pi_{3,1} & \pi_{3,2} & \pi_{3,3} \end{pmatrix}. \tag{3.6}$$

Separating the log-likelihood function for each k (or column of matrix Π_3)

$$\ell(\theta) = \ell(\theta_1) + \ell(\theta_2) + \ell(\theta_3), \tag{3.7}$$

where the parameter vector θ_k contains the coefficients β and the corresponding misclassification probabilities ($\pi_{j,k}$, for fixed k) and cutpoints. Expanding the sum according to Eq. (3.5),

$$\begin{aligned} \ell(\theta_1) = \sum_i \mathbf{1}(\omega_i = 1) \ln\Big\{ & \pi_{1,1}\Phi(c_1 - \mathbf{x}_i'\beta) + \pi_{2,1}\big[\Phi(c_2 - \mathbf{x}_i'\beta) - \Phi(c_1 - \mathbf{x}_i'\beta)\big] \\ & + \pi_{3,1}\big[1 - \Phi(c_2 - \mathbf{x}_i'\beta)\big]\Big\} \\ \ell(\theta_2) = \sum_i \mathbf{1}(\omega_i = 2) \ln\Big\{ & \pi_{1,2}\Phi(c_1 - \mathbf{x}_i'\beta) + \pi_{2,2}\big[\Phi(c_2 - \mathbf{x}_i'\beta) - \Phi(c_1 - \mathbf{x}_i'\beta)\big] \\ & + \pi_{3,2}\big[1 - \Phi(c_2 - \mathbf{x}_i'\beta)\big]\Big\} \\ \ell(\theta_3) = \sum_i \mathbf{1}(\omega_i = 3) \ln\Big\{ & \pi_{1,3}\Phi(c_1 - \mathbf{x}_i'\beta) + \pi_{2,3}\big[\Phi(c_2 - \mathbf{x}_i'\beta) - \Phi(c_1 - \mathbf{x}_i'\beta)\big] \\ & + \pi_{3,3}\big[1 - \Phi(c_2 - \mathbf{x}_i'\beta)\big]\Big\}, \end{aligned} \tag{3.8}$$

subject to $\pi_{11} = 1 - \pi_{12} - \pi_{13}$, $\pi_{22} = 1 - \pi_{21} - \pi_{23}$ and $\pi_{33} = 1 - \pi_{31} - \pi_{32}$. The weakly (sufficient) stochastic condition for $J = 3$ is,

$$\pi_{1,1} \geq \pi_{2,1} \geq \pi_{3,1} \quad \text{and} \quad \pi_{3,3} \geq \pi_{2,3} \geq \pi_{1,3}, \tag{3.9}$$

which is a stronger condition than that needed for $\mathbb{E}(y_i|\mathbf{x}_i)$ to be increasing with $\mathbf{x}_i'\beta$. A necessary condition is,

$$\pi_{1,2} + \pi_{2,1} - \pi_{2,3} + 2\pi_{1,3} < 1 \quad \text{and} \quad \pi_{2,3} + \pi_{3,2} - \pi_{2,1} + 2\pi_{3,1} < 1 \tag{3.10}$$

which is satisfied for small values of the misclassification probabilities (see, Dustmann and van Soest (2004)).

For Italy, the dependent variables (or civic outcomes) are recoded as follows. For interest in politics, the categories 'fairly' and 'very' are grouped together and I recode

TABLE 3.1

Civic outcomes frequencies (Italy)

Variables	Mean
Interest in politics:	
not at all = 1	0.4027
not very = 2	0.3321
fairly or very = 3	0.2651
Importance of the problem of tax evasion:	
non-existent or marginal or the same = 1	0.2144
serious = 2	0.4567
very serious = 3	0.3289
Not paying ticket on public transport:	
always justifiable (1 to 3) = 1	0.0559
occasionally justifiable (4 to 7) = 2	0.1442
never justifiable (8 to 10) = 3	0.7999
Keeping money and not return it to the rightful owner:	
always justifiable (1 to 3) = 1	0.0533
occasionally justifiable (4 to 7) = 2	0.1200
never justifiable (8 to 10) = 3	0.8267
Not leaving your name for the owner of a car you scraped:	
always justifiable (1 to 3) = 1	0.0487
occasionally justifiable (4 to 7) = 2	0.1023
never justifiable (8 to 10) = 3	0.8490
Number of observations	3,059

the three categories as 1 (not at all), 2 (not very) and 3 (fairly or very). Similarly, the variable tax evasion problem is recoded as: 1 (non-existent or marginal or the same), 2 (serious) and 3 (very serious). Lastly, for the civic behaviour variables, I changed the scale 1 to 10 to a 1 to 3 scale, recoding 1 to 3 as 1 (always justifiable), 4 to 7 as 2 (occasionally justifiable), and 8 to 10 as 3 (never justifiable).[4] Table 3.1 presents the resulting civic outcomes frequencies.

For the UK, civic outcomes are also recoded into $J = 3$, grouping categories in the same way as for Italy. For instance, for the dependent variable 'general interest in politics', answers with 'a lot or a great deal' of interest in politics are grouped together (=3), whereas 'not very much' is recoded as 2 and 'not at all' as 1. Likewise, civic behaviours' 1 to 10 scale is changed into a $J = 3$ scale, with 1 to 3 = 1 (always justifiable), 4 to 7 = 2 (occasionally justifiable), and 8 to 10 = 3 (never justifiable). Thus, answers to the civic opinion 'interest in politics' and civic behaviours for Italy and the UK are recoded and labeled equivalently so that their estimations for the two countries are comparable. The remaining outcomes, that is, concerning guilt, time

[4]The reason for combining categories together is due to small sample cells which, if not grouped, the parametric model would not be able to identify. For example, only a 0.57% of respondents answer 'non-existent' for the tax evasion question. Combining categories due to a small number of observations is common in the literature. However, since misreporting may be affected by this recoding, I also present some sensitivity analysis for civic behaviours using a five point scale.

TABLE 3.2

CIVIC OUTCOMES FREQUENCIES (UK)

Variables	Mean
a) Civic opinions:	
General interest in politics:	
not at all = 1	0.0493
not very much = 2	0.2535
lot, or a great deal = 3	0.6972
Attention to politics:	
low (0 to 3) = 1	0.2326
medium (4 to 7) = 2	0.5607
high (8 to 10) = 3	0.2067
Discuss politics with family and friends:	
low (0 to 3) = 1	0.3478
medium (4 to 7) = 2	0.3244
high (8 to 10) = 3	0.3278
Active in a voluntary organisation:	
not at all = 1	0.5112
not very = 2	0.1754
somewhat and very = 3	0.3134
b) Additional outcomes related to politics and voting:	
Political activity takes too much time and effort:	
strongly disagree and disagree = 1	0.3031
neither = 2	0.2857
agree and strongly agree = 3	0.4112
Family and friends think that voting is a waste of time:	
strongly disagree and disagree = 1	0.6799
neither = 2	0.1218
agree and strongly agree = 3	0.1983
Feel very guilty if not vote:	
strongly disagree and disagree = 1	0.2499
neither = 2	0.1202
agree and strongly agree = 3	0.6299
Neglect my duty as a citizen if not vote:	
strongly disagree and disagree = 1	0.1745
neither = 2	0.1062
agree and strongly agree = 3	0.7193
c) Addtional outcomes about trust:	
Most people can be trusted:	
low (0 to 3) = 1	0.1000
medium (4 to 7) = 2	0.5948
high (8 to 10) = 3	0.3052
Trust local government:	
low (0 to 3) = 1	0.1903
medium (4 to 7) = 2	0.7371
high (8 to 10) = 3	0.0726
Number of observations	4,161

Continued on next page

Continued from previous page	
d) Civic behaviours:	
Failing to report accidental damage done to a parked vehicle:	
always justifiable (1 to 3) = 1	0.04
ocasionally justifiable (4 to 7) = 2	0.13
never justifiable (8 to 10) = 3	0.83
Keeping money that you have found:	
always justifiable (1 to 3) = 1	0.05
ocasionally justifiable (4 to 7) = 2	0.14
never justifiable (8 to 10) = 3	0.81
Avoiding a fare on public transport:	
always justifiable (1 to 3) = 1	0.04
ocasionally justifiable (4 to 7) = 2	0.17
never justifiable (8 to 10) = 3	0.79
Number of observations	3,651

and effort when voting, other measures of trusts, etc., are changed in an analogous way.

3.4. MONTE CARLO SIMULATIONS

This section examines the properties of the OP model under misclassification. Simulations for the ML estimator given by Eq. (3.5) for $J = 3$ and $J = 5$ are carried out for different levels of misreporting. I begin by introducing the simulation design and algorithm.

The Monte Carlo design has three covariates: x_1 is drawn from a binomial distribution with probability of success equals to 0.6, x_2 is normally distributed, and x_3 follows a lognormal distribution. The error term is drawn from a standard normal distribution. The latent dependent variable is given by

$$y_i^* = 1.5x_{i1} + 0.6x_{i2} + 1.1x_{i3} + \varepsilon_i. \tag{3.11}$$

The algorithm structure for $J = 3$ is as follows.[5]

1. Draw R times the covariates from the $\mathbf{x}$ distributions outlined above and the error term ε for a sample size N. ($r = 1, ..., R$, are the number of repetitions.)

2. Generate the latent variable using Eq. (3.11).

3. Select the values of the cutpoints c_1 and c_2 as to mimic the distribution of a civic outcome for $J = 3$. Create the 'true' values of the dependent variable according to: $y = 1$ if $y^* \leq c_1$, $y = 2$ if $c_1 < y^* \leq c_2$ and $y = 3$ if $y^* > c_2$ for each repetition.

[5]An identical procedure was implemented for $J = 5$. Only two additional cutpoints and extra conditions for generating the observed dependent variable with misclassification are required.

4. For each r, generate the 'observed' dependent variable with misclassification ω as follows.[6] First, define matrix Π, for instance, a matrix with low misclassification,

$$\Pi_3(low) = \begin{pmatrix} \pi_{1,1} & \pi_{1,2} & \pi_{1,3} \\ \pi_{2,1} & \pi_{2,2} & \pi_{2,3} \\ \pi_{3,1} & \pi_{3,2} & \pi_{3,3} \end{pmatrix}. \tag{3.12}$$

5. Second, for each repetition, draw a uniform vector $\mathbf{u}$ of sample size N and set $\omega = y$.

6. Finally, recode the observed dependent variable ω applying the following rule by each matrix row in Eq. (3.12):

   - if $y = 1$ and $\mathbf{u} < \pi_{1,2}$ recode $\omega = 2$, if $y = 1$ and $\mathbf{u} < \pi_{1,3}$ recode $\omega = 3$;
   - if $y = 2$ and $\mathbf{u} < \pi_{2,1}$ recode $\omega = 1$, if $y = 2$ and $\mathbf{u} < \pi_{2,3}$ recode $\omega = 3$;
   - if $y = 3$ and $\mathbf{u} < \pi_{3,1}$ recode $\omega = 1$, if $y = 3$ and $\mathbf{u} < \pi_{3,2}$ recode $\omega = 2$.

7. For each repetition r, using the observed variable ω with mismeasurement, estimate the model with misclassification using Eq. (3.5) r times until $r = R$.

8. To introduce increasing levels of misclassification, repeat steps 4 to 7 changing Eq. (3.12) to $\Pi_3(medium)$ and $\Pi_3(high)$.

Table 3.3 and Table 3.4 report the Monte Carlo simulations results under low, medium and high misclassification scenarios (for $N = 5000$, $R = 200$).

I use the bias, standard deviation, root mean squared error and overall root mean squared error to compare the OP and OPM estimates. Note that the last quantity summarises the overall performance of the OP and OPM models.

Let θ denotes the true parameter vector, $\hat{\theta}$ the estimated parameter vector, and by θ_k, $\hat{\theta}_k$ I denote any element of these vectors. The measures used for comparison are given by,

$$\begin{aligned} \text{Bias} &= \mathbb{E}(\hat{\theta}_k) - \theta_k; \\ \text{Std. dev.} &= \left[\mathbb{E}\big([\hat{\theta}_k - \mathbb{E}(\hat{\theta}_k)]^2\big)\right]^{\frac{1}{2}}; \\ \text{RMSE} &= \left[\mathbb{E}\big([\hat{\theta}_k - \theta_k]^2\big)\right]^{\frac{1}{2}}; \\ \text{RMSE}_{\text{all}} &= \left[\text{tr}\ \mathbb{E}\big([\hat{\theta} - \theta][\hat{\theta} - \theta]'\big)\right]^{\frac{1}{2}}. \end{aligned} \tag{3.13}$$

[6] A similar idea is proposed by Keane and Sauer (2010) in the context of a dynamic panel data probit.

TABLE 3.3

MONTE CARLO SIMULATIONS RESULTS: Π_3

		OP				OPM			
Parameter	True value	Mean	Std. dev.	RMSE	RMSE-all	Mean	Std. dev.	RMSE	RMSE-all
Low misclassification ($0.025 \leq \pi_{j,k} \leq 0.10$)									
β_1	1.5	1.3613	0.0446	0.1475	0.4206	1.5274	0.0652	0.0711	0.1441
β_2	0.6	0.5428	0.0211	0.0620		0.6107	0.0292	0.0301	
β_3	1.1	0.9562	0.0223	0.1504		1.1210	0.0402	0.0440	
c_1	2	1.8749	0.0488	0.1437		2.0409	0.0694	0.0788	
c_2	4	3.6564	0.0684	0.3583		4.0591	0.1303	0.1388	
$\pi_{1,2}$	0.0250					0.0029	0.0084	0.0225	
$\pi_{1,3}$	0.0250					0.0001	0.0013	0.0249	
$\pi_{2,1}$	0.1000					0.0690	0.0230	0.0392	
$\pi_{2,3}$	0.0375					0.0034	0.0107	0.0345	
$\pi_{3,1}$	0.0750					0.0002	0.0025	0.0748	
$\pi_{3,2}$	0.1000					0.0262	0.0086	0.0745	
Medium misclassification ($0.05 \leq \pi_{j,k} \leq 0.20$)									
β_1	1.5	1.2568	0.0442	0.2487	0.7411	1.5020	0.0715	0.0023	0.0672
β_2	0.6	0.5011	0.0209	0.1016		0.6022	0.0327	0.0026	
β_3	1.1	0.8440	0.0207	0.2600		1.1072	0.0406	0.0092	
c_1	2	1.7932	0.0482	0.2208		2.0005	0.1263	0.0088	
c_2	4	3.3901	0.0653	0.6189		3.9998	0.1571	0.0113	
$\pi_{1,2}$	0.050					0.0363	0.0180	0.0141	
$\pi_{1,3}$	0.050					0.0000	0.0011	0.0500	
$\pi_{2,1}$	0.200					0.1911	0.0539	0.0100	
$\pi_{2,3}$	0.075					0.0585	0.0322	0.0171	
$\pi_{3,1}$	0.150					0.1187	0.0417	0.0325	
$\pi_{3,2}$	0.200					0.1792	0.0366	0.0226	
High misclassification ($0.10 \leq \pi_{j,k} \leq 0.40$)									
β_1	1.5	1.0918	0.0444	0.4118	1.2194	1.5053	0.1046	0.0341	0.0444
β_2	0.6	0.4362	0.0210	0.1652		0.6021	0.0511	0.0117	
β_3	1.1	0.6736	0.0177	0.4296		1.1030	0.0625	0.0182	
c_1	2	1.7091	0.0473	0.3053		2.0070	0.1070	0.0336	
c_2	4	2.9866	0.0607	1.0201		4.0039	0.1865	0.0531	
$\pi_{1,2}$	0.100					0.0905	0.0095	0.0300	
$\pi_{1,3}$	0.100					0.0915	0.0095	0.0297	
$\pi_{2,1}$	0.400					0.3907	0.0076	0.0321	
$\pi_{2,3}$	0.150					0.1367	0.0076	0.0443	
$\pi_{3,1}$	0.300					0.2730	0.0290	0.0900	
$\pi_{3,2}$	0.400					0.3732	0.0307	0.0892	

As can be seen in Table 3.3, the downward bias of the OP estimates increases with the amount of misclassification, ranging from 6% to 13% for $\Pi_3(low)$, and 15% to 39% for $\Pi_3(high)$. Also note that the standard errors for the OPM estimates increase with the level of misclassification, whereas the standard errors for the standard OP do not. Thus, besides inconsistency, the OP model overstates the precision of the estimates. The OPM estimates, however, tend to the true values, have lower root mean squared errors (RMSE) and show a superior overall performance according to the overall root mean squared error (RMSE_{all}) measure.

Simulations for $J = 5$ are contained in Table 3.4 using an upper Π_5 matrix.[7] Qualitative similar results hold. That is, estimates, biases, RMSE and RMSE-all are higher for the OP model, and they increase with the level of misclassification. Additionally, in both designs higher values for $\pi_{j,k}$ are more easily identified, tending to their true values. As expected, the main conclusion from these simulations is that,

[7]Elements below the diagonal are fixed and equal to the upper part, i.e., $\pi_{k,j} = \pi_{j,k}$.

TABLE 3.4

Monte Carlo simulations results: Π_5

		OP				OPM			
Parameter	True value	Mean	Std. dev.	RMSE	RMSE-all	Mean	Std. dev.	RMSE	RMSE-all
Low misclassification ($0.025 \leq \pi_{j,k} \leq 0.15$)									
β_1	1.5	1.2799	0.0393	0.2249	0.9467	1.5258	0.0838	0.0265	0.0613
β_2	0.6	0.5003	0.0199	0.1022		0.6116	0.0409	0.0124	
β_3	1.1	0.6677	0.0227	0.4369		1.1347	0.0633	0.0357	
c_1	0.1	-0.2383	0.0400	0.3446		0.0986	0.2188	0.0042	
c_2	0.8	0.4122	0.0393	0.3946		0.8014	0.2168	0.0048	
c_3	1.4	0.9505	0.0413	0.4562		1.3944	0.1659	0.0069	
c_4	2	1.5708	0.0449	0.4378		1.9807	0.1527	0.0200	
$\pi_{1,2}$	0.025					0.0253	0.1359	0.0050	
$\pi_{1,3}$	0.025					0.0198	0.0803	0.0075	
$\pi_{1,4}$	0.025					0.0083	0.0523	0.0174	
$\pi_{1,5}$	0.025					0.0002	0.0788	0.0248	
$\pi_{2,3}$	0.05					0.0480	0.2108	0.0044	
$\pi_{2,4}$	0.05					0.0440	0.2448	0.0072	
$\pi_{2,5}$	0.05					0.0435	0.1188	0.0074	
$\pi_{3,4}$	0.1					0.1013	0.2417	0.0041	
$\pi_{3,5}$	0.1					0.1081	0.1343	0.0092	
$\pi_{4,5}$	0.15					0.1668	0.0627	0.0177	
Medium misclassification ($0.05 \leq \pi_{j,k} \leq 0.30$)									
β_1	1.5	1.1552	0.0390	0.3571	1.4046	1.5224	0.0804	0.0228	0.1044
β_2	0.6	0.4430	0.0195	0.1616		0.6167	0.0390	0.0172	
β_3	1.1	0.4556	0.0169	0.6475		1.1227	0.0689	0.0233	
c_1	0.1	-0.3897	0.0380	0.4946		0.1013	0.1279	0.0047	
c_2	0.8	0.2294	0.0368	0.5752		0.8040	0.1915	0.0058	
c_3	1.4	0.7184	0.0383	0.6878		1.3898	0.0799	0.0105	
c_4	2	1.3803	0.0417	0.6335		1.9937	0.0727	0.0064	
$\pi_{1,2}$	0.05					0.0481	0.0815	0.0080	
$\pi_{1,3}$	0.05					0.0322	0.0542	0.0191	
$\pi_{1,4}$	0.05					0.0078	0.0482	0.0426	
$\pi_{1,5}$	0.05					0.0004	0.0252	0.0496	
$\pi_{2,3}$	0.1					0.0924	0.2286	0.0095	
$\pi_{2,4}$	0.1					0.0825	0.1518	0.0184	
$\pi_{2,5}$	0.1					0.0904	0.1116	0.0109	
$\pi_{3,4}$	0.2					0.2009	0.1638	0.0051	
$\pi_{3,5}$	0.2					0.2297	0.0476	0.0305	
$\pi_{4,5}$	0.3					0.3594	0.0040	0.0601	
High misclassification ($0.075 \leq \pi_{j,k} \leq 0.45$)									
β_1	1.5	1.0761	0.0398	0.4260	1.6519	1.2653	0.1491	0.3905	0.5777
β_2	0.6	0.4059	0.0199	0.1951		0.5302	0.0619	0.1171	
β_3	1.1	0.3288	0.0140	0.7726		0.7871	0.0262	0.4991	
c_1	0.1	-0.4748	0.0378	0.5776		0.0157	0.1052	0.1557	
c_2	0.8	0.1291	0.0364	0.6738		0.7634	0.1175	0.0688	
c_3	1.4	0.5804	0.0377	0.8226		1.5694	0.1496	0.3178	
c_4	2	1.3186	0.0411	0.6858		2.3064	0.2195	0.4961	
$\pi_{1,2}$	0.075					0.1796	0.0796	0.1924	
$\pi_{1,3}$	0.075					0.0863	0.0481	0.0345	
$\pi_{1,4}$	0.075					0.0425	0.0498	0.0430	
$\pi_{1,5}$	0.075					0.0427	0.0646	0.0430	
$\pi_{2,3}$	0.15					0.2545	0.2333	0.1933	
$\pi_{2,4}$	0.15					0.1367	0.0962	0.0230	
$\pi_{2,5}$	0.15					0.2418	0.0524	0.1656	
$\pi_{3,4}$	0.3					0.3610	0.2111	0.1105	
$\pi_{3,5}$	0.3					0.3768	0.0276	0.1121	
$\pi_{4,5}$	0.45					0.5000	0.0000	0.0500	

although the reduction in biases achieved with the OPM model comes at the expense of increased standard errors, the overall performance of the OPM model (measured by the overall root mean squared error) is far superior than the OP model.

Finally, it should be pointed out that alongside the overall performance of the OP and OPM under a scenario of misclassification, a crucial concern for prediction is how statistical significance of the estimated coefficients varies under the two models. In particular, when moving from the OP to the OPM, the increase in the estimated coefficients should be compared with the higher standard errors. This may lead to a lack of causality of education if the reduction in the bias achieved with the OPM model, is less than the lower precision of the estimated coefficient, formally: $\Delta\hat{\beta}_{\text{ed,OPM}} \ll \Delta\text{se}_{(\hat{\beta}_{\text{ed,OPM}})}$.

3.5. MISCLASSIFICATION ASSUMPTIONS

This section describes the expected misclassification patterns by group of civic outcomes and also by educational levels. The following assumptions are used as a guideline to interpret the misreporting results of Chapters 4 and 5.

Recall the classification of the set of dependent variables into two groups. On the one hand, in the case of Italy, the civic indicators 'interest in politics' and 'problem of tax evasion' are defined as "civic opinions", whereas the outcomes 'not paying for your ticket on public transport', 'keeping money obtained by accident when it could be returned', and 'not leaving your name for the owner of a car you accidentally scraped' are classified as "civic behaviours". For the UK, on the other hand, there are four indicators I term as "civic opinions", that is, 'general interest in politics', 'attention to politics', 'discuss politics with family and friends' and 'active in a voluntary organisation'. Moreover, I consider further outcomes related to civic opinions: whether being involved in politics is time consuming, whether voting is a waste of time, and whether the lack of voting is associated with feelings of guilt and neglecting the duty as a citizen. There are also two additional measures of trust: in people, and in the local government. The three "civic behaviours" for the UK are exactly the same as the ones for Italy: failing to report accidental damage done to a parked vehicle (car damage), keeping money that you have found (keeping money), and avoiding a fare on public transport (avoiding fare).

This distinction between civic opinions and civic behaviours provides a clear framework of what kind of results to expect and hence which hypotheses are more relevant to test in terms of misclassification patterns by civic outcomes. For instance, whether the assumption of monotonicity of correct report for civic behaviours holds, where typically there is under (over) reporting of undesirable (desirable) social behaviours. I now provide some useful constraints on the misclassification process relying on this classification. I also elaborate on how these constraints may vary by schooling levels.

To begin with, note that an implicit restriction is that the estimated misclassification probabilities (off-diagonal elements of $\hat{\Pi}_J$) must be less than one half, to guarantee that the probabilities of correct report (diagonal elements) are positive. The first assumption states that the probability of reporting the true value is higher than that of reporting other values,

Assumption 3.1: $\hat{\pi}_{jj} > \hat{\pi}_{jk}$, *for* $j, k \in (1, ..., J)$ *and* $j \neq k$.

This assumption is very plausible because, intuitively, there is only one way to report the truth, while there are several number of alternative ways to misreport. A sufficient condition for this to hold is that, for each of the observed answers, the probability of correct report is higher than one half.[8] Note that this assumption is the same as Assumption 2.7 in Hu (2008) and constraint two in Swartz et al. (2004), and is consistent with most validation studies on occupational choices (Bound et al. (2001)). For example, in a recent study on the extent of measurement error in self-reported occupation data, Sullivan (2009) finds a lower bound of correct report of 60% across (eight) employment status. Hence, it is expected that for most civic outcomes the observed responses ω would contain enough correct information on the true responses y so that Assumption 3.1 would hold.

The next assumption (monotonicity of correct reporting) is motivated by social psychology. When answering questions related to socially sensitive topics, individuals would typically under-report undesirable behaviours and attitudes and over-report desirable ones. This is due to social desirability, "a pervasive tendency of individuals to present themselves in the most favorable manner relative to prevailing social norms" (King and Bruner (2000), p.80). This is a well known phenomenon which has prompted the development of methodologies to improve the quality of self-report measures in psychological research. For instance, Rasinski et al. (2005), introduce an implicit goal priming methodology to reduce the bias on a series of questions on socially sensitive behaviours involving excessive alcohol consumption. Moreover, this assumption turns out to have identifying power in misclassification models. Molinari (2008) (Assumption 4) shows this when analysing misreporting of participation in welfare programs. Monotonicity of correct report implies that the probabilities of

[8]If $\hat{\pi}_{jj} > 1/2, \forall j \in (1, ..., J)$, the misclassification matrix is strictly diagonally dominant and then invertible. Thus, it guarantees a solution to the misclassification equation system: $P^{\omega} = \hat{\Pi}' P^{y}$. This condition also has been assumed in the literature (see, e.g., Assumption 2.2 in Hu (2008)).

correct report are increasing along the diagonal of $\hat{\Pi}_J$,

Assumption 3.2: $\hat{\pi}_{1,1} < ... < \hat{\pi}_{(J-1),(J-1)} < \hat{\pi}_{J,J}$.

As questions about civic behaviours in the sample are clearly sensitivity topics, I consider Assumption 3.2 to be relevant for this group of civic outcomes. In other words, I believe the misclassification problem to be decreasing, the more civically behaved individuals are according to their reported answers.

Assumption 3.3(i) indicates a differential pattern of misreporting by civic outcomes. The assumption for civic opinions implies that individuals who apparently show more political engagement are more prone to misreporting, because probabilities below the diagonal of $\hat{\Pi}_J$ are significantly higher than the ones above it. This is in line with over-reporting of voting behaviour found in the literature (e.g., Karp and Brockington (2005)).[9] For civic behaviours, however, misreporting probabilities below the diagonal of $\hat{\Pi}_J$ should tend to zero as individuals who report having good civic behaviours will clearly have no incentive to state that they are not so.

Assumption 3.3: *(i) For civic opinions, $\hat{\pi}_{j,k}$ are small on the upper part of $\hat{\Pi}_J (j < k)$. For civic behaviours, $\hat{\pi}_{j,k}$ are small on the lower part of $\hat{\Pi}_J (j > k)$. (ii) For civic behaviours, elements on the upper part of $\hat{\Pi}_J$ are increasing along each row, $\hat{\pi}_{j,j+1} < \hat{\pi}_{j,j+2} < ... < \hat{\pi}_{j,J}$.*

In addition, Assumption 3.3(ii) states that individuals whose truthful civic responsibility are the lowest, tend to report the highest scores. Again, I believe that this can be explained by social desirability bias (e.g., Paulhus (1991)). Individuals' motives (e.g., approval, guilt, embarrassment), or expectancies regarding the evaluative consequences of their behaviours, led them to present themselves in socially acceptable terms in order to gain the approval of others. Thus, this sub-group of respondents would lie and report their answers at the top of the scale rather than at the middle of it. I also consider social desirability bias a plausible hypothesis to expect misreporting to be stronger for civic behaviours than civic opinions.

Finally, Assumption 3.4 describes how misreporting may vary by schooling levels.

Assumption 3.4: *(i) For civic opinions, misreporting is more likely to hold for higher education levels and can mostly be explained by misclassification of answers*

[9] People are often embarrassed to admit that they have failed to meet the basic obligation to vote since voting is considered an essential duty of citizenship and a fundamental right. I am able to examine this hypothesis for the UK because, as previously mentioned, two indicators ask: whether feelings of guilt are present if one does not vote, and also whether one is neglecting his duty as a citizen if he does not vote.

at the top of the scale (i.e., small $\hat{\pi}_{J,J}$). (ii) For civic behaviours, misreporting is equally likely to hold for different education levels and can mostly be explained by misclassification of answers at the bottom of the scale (i.e., small $\hat{\pi}_{1,1}$).

Assumption 3.4(i) relies on an established result from the political science literature: a positive association between voting misreporting and socioeconomic status. There are diverse hypotheses for over-reporting. Alternatively, theories place emphasis on either feelings of guilt (Bernstein et al. (2001)), a desire to look good before the interviewer, or see over-reporting as an expression of satisfaction with the status quo (Silver et al. (1986)). More educated individuals are the most probable to misreport as they are under the most pressure from these factors. Because individuals who are more interested in politics are, overall, more likely to vote, this finding from political science is also applicable to the civic opinions 'interest, attention and discussing politics'. Even in the case of Italy, where there is significant discontent with current politics, more educated individuals will tend to over-report their interest in politics so as to remain consistent with their class interests. Otherwise, any deviation from the group norms by means of not over-reporting would create discomfort for the non-conforming person.

Assumption 3.4(ii) is more conflictive. As mentioned above in Assumption 3.2, it is expected that social desirability would drive the whole sample results for civic behaviours. But, should this still hold regardless of the education level of individuals? Indeed, social psychology provides some support for this assumption. Social psychologists have characterised two types of social norms: injunctive and descriptive. Descriptive norms (called the norms of "is") refer to what is commonly done, and by registering what others are doing, one can usually choose efficiently and well. Injunctive norms (called the norms of "ought") refer to what is commonly approved/disapproved by promising social rewards and punishments (Cialdini et al. (2006)). Studies have demonstrated how descriptive norms affect behaviour in a variety of real world situations (e.g., littering, recycling, climate change). The assumption is based upon empirical evidence showing a strong effect of descriptive norms on behaviours regardless of their background (Nolan et al. (2008)).

In other words, if more or less educated individuals believe most people are misreporting their civic behaviours, the effect of descriptive norms (e.g., everybody lies when answering these questions) would lead them to do so too. This is related to circumstances under which providing normative information backfires, producing the opposite effect (see, for example, Cialdini (2007); Griskevicius et al. (2008)).

I also expect similar misreporting patterns along the lines of Assumption 3.1 to Assumption 3.4 for the UK's additional outcomes related to politics and voting, as well as for measures of trust. Evidently, individuals who had not voted are less likely to accept that they either have feelings of guilt or are neglecting their duty as citizens by not voting and, consequently, they would be more prone to misreport these two indicators. This might also hold across education levels. On the contrary, I believe that the outcome dealing with the 'time constraint of political activity' is less likely to be misreported. But the question on whether 'voting is a waste of time' may suffer from misreporting (depicted by Assumption 3.3(i)), as one may feel embarrassed to judge politics as ineffective and to appear as an egoistic and self-interested voter. With regards to the indicators measuring social trust (specifically, trust in people and trust in the local government), they may be misreported too, following a similar misclassification pattern as civic behaviours. Recall that the formers embody measures of social trust.

I finish Section 3.5 by discussing the extent to which the misclassification problem may vary in the two countries. Formally, would the probabilities of correct report ($\hat{\pi}_{jj}, j \in (1, ..., J)$ of Assumption 3.1) be lower in Italy or in the UK? I think that the issue of lack of trust, mainly in Italy, would lead to bad steady states and social traps, making misreporting perhaps more significant in this country. In fact, a higher tolerance of self-interest acts (as the thesis' civic behaviours variables) is lower in northern European countries. This shows that social trust is partly culturally inherited but can also be fostered by economic equality carried out by impartial political institutions (Rothstein (2005)). The extent to whether Assumption 3.1 to Assumption 3.4 are more valid in either Italy or the UK, however, is a new empirical matter since most of the studies undertaken in this field of misreporting, are based on the individual level rather than cross-country comparison.

3.6. CONCLUSIONS

In this Chapter, I have reviewed why misreporting is a frequent concern with self-reported measures, I have also shown its empirical consequences through simulations, in terms of biased and inconsistent estimates with an overstated precision and lastly, I have presented different approaches to tackle it. The key driving force of misreporting is SDB, the tendency in which individuals present themselves in the most favourable manner relative to prevailing social norms, in order to gain approval of others. This will result in an under-report of undesirable behaviours and an over-report of desirable ones. These systematic unreliable responses by interviewees may therefore yield an invalid relationship between education and social capital.

Chapter 3 outlines the numerous models to deal with misclassification. The chosen approach is related to the type of measurement error one is interested in modeling.

Given that my core aim was on the misclassification process and estimated coefficients, I used an OPM. In other words, my double objective by using the OPM is to pin down the existing misreporting patterns assumed in the literature (mainly from the political and social psychology fields) and how SDB affects causality of schooling.

The OPM model assumes that the wrong outcome is reported, and accounts for this by including misclassification probabilities in the standard likelihood function of ordered response models. For the parametric model to be valid, the misclassification process is subject to different conditions. Namely, an stochastic condition which constrains the level of the elements of the misclassification matrix and that misreporting is not a function of covariates. These conditions, which guarantee identification of the coefficients are, nonetheless, a relative drawback by imposing a rigid structure to the misclassification model. Indeed, being highly parameterised is a disadvantage for the OPM model. The other model applied in Chapters 4 and 5 is the IV-OPM, where the probable endogeneity of schooling within the OPM is accounted for. I used a standard IV technique where the endogenous education variable is replaced by its fitted values from the first stage regression. Here, shortcomings originate from both the nonlinearity of the model and the discreteness of the endogenous regressor.

There are methodological alternatives to capture measurement error in the human to social capital framework. For instance, semiparametric estimation such as a monotone rank estimator would suffice (e.g., Cavanagh and Sherman (1998) and Abrevaya (1999)), or one could model the boundaries as linear functions of observed explanatory variables (i.e., Terza (1985)), and extend this by allowing for random boundaries that vary across individuals as in Das (1995). In these models, however, one is indifferent about the misreporting probabilities and consider them as nuisance parameters. But as mentioned earlier, misreporting probabilities are one of the main objectives of the Chapters and this is captured by the OPM and extensions. Perhaps one could employ nonparametric versions of the models to deal with endogeneity in nonlinear models and allowing for covariate-dependent misclassification (e.g., Hu and Schennach (2008), Hu (2008)).

A. APPENDIX: MISCLASSIFICATION TEST

In this appendix I outline how to test the null hypothesis H_0: $\pi_{j,k} = 0$ for $j \neq k$ against the alternative H_1: $\pi_{j,k} > 0$, for at least one misclassification probability. In other words, a statistical test for the OP model against the OPM model. Divide the parameter vector θ into three components: the p beta coefficients, the j-1 cut points and the l $[l = J \times (J-1)]$ off-diagonal elements of the matrix of misclassification probabilities Π_J. That is, $\theta = (\beta', c', \pi')'$. Suppose that one wants to test that the l estimated misclassification probabilities are zero against the alternative that they are higher than zero. Stack these l estimated misclassification probabilities $\hat{\pi}_{j,k}$ (for $j \neq k$) in a row vector $\hat{\Psi}_l$. Then, the hypothesis test is:

$$\mathrm{H}_0\text{: } \hat{\Psi}_l = 0 \quad \text{against} \quad H_1\text{: } R\hat{\Psi}_l > 0, \tag{A.1}$$

where R is a (l by l) identity matrix. Since the asymptotic distribution of the LR statistic (or χ^2 statistic as it is distributed) is not defined under null, because under H_0, $\hat{\Psi}_l$ is not an interior point of the parameter space and it is located at its boundary, it is assumed that θ is approximated under the null by a convex cone C (Shapiro (1985), p. 137). Now, by Theorem 2.1 of Shapiro (1985), the χ^2 distribution is replaced by a distribution the $\bar{\chi}^2$. Let $Z \sim N(0, V)$ be a l-dimensional normal random vector, then

$$\bar{\chi}^2(V, R) = Z'V^{-1}Z - \min_{R\hat{\Psi}_l > 0}(Z - \hat{\Psi}_l)'V^{-1}(Z - \hat{\Psi}_l). \tag{A.2}$$

The basic distributional result concerning the random variable $\bar{\chi}^2$ is that is distributed as a mixture of chi-squared distributions, that is,

$$\mathrm{pr}[\bar{\chi}^2(V, R) \leq c] = \sum_{i=0}^{l} \omega_i \mathrm{pr}(\chi_i^2 \leq c). \tag{A.3}$$

Computation of the weights $\omega_i = \omega_i(l, V, R)$ are a difficult numerical problem. For $l > 4$, there is not a closed expression form for the weights, but reasonably accurate estimators of the weights can be obtained by Monte Carlo simulations (see, Liu and Wang (2003), p. 123). Proceed as follows:

1. Generate Z from $Z \sim N(0, V)$.
2. Compute $\bar{\chi}^2(V, R)$.
3. Repeat the first two steps M times.
4. Estimate $\mathrm{pr}(\chi_i^2 \leq c)$ by the proportion of times that $\bar{\chi}^2(V, R) \leq c$.

Chapter 4
Civic outcomes, misclassification and education: the case of Italy

4.1. introduction

In this Chapter, following the approach of Abrevaya and Hausman (1999) and Dustmann and van Soest (2004), I examine how the presence of misclassification affects the impact of education on a number of civic outcomes in Italy. Estimates from an OP are compared with those from an OPM. In order to conclude that education has a causal effect on civic outcomes, as well as to account for misclassification, one also needs to control for the potential endogeneity of education. Thus, an IV ordered probit with misclassification (IV-OPM) is estimated. In line with the approach of Brandolini and Cipollone (2002) and Brunello et al. (2009), a reform of the Italian educational system is used as an instrument for education.

A standard result in the political science literature is that more educated people are more likely to be civically engaged than less educated individuals (e.g., Pattie et al. (2003)). The approach adopted in this Chapter enables me to ascertain the extent to which this result is genuine or whether it is mainly driven by a systematic over-reporting of more educated individuals relative to the less educated ones. Moreover, I am also able to determine whether individuals' persistent tendency to provide socially desirable responses leads to a spurious causal link between education and a range of measures of social trust, as well as how this bias varies by schooling levels.

I apply the parametric techniques (described in detail in Chapter 3) to models using five different measures of civic outcome as dependent variables. Individuals are asked: 1) about their 'interest in politics', 2) to rate 'the importance of the problem of tax evasion relative to all the problems faced by the government', 3) whether they 'would not pay the ticket on public transport', 4) whether they 'would keep money obtained by accident when it would be possible to return it', and 5) whether they 'would leave their name for the owner of a car they accidentally scraped'. Given the distinct nature of these measures, it is possible to classify the first two as "civic opinions" and the last three as "civic behaviours". This classification relies on the two main dimensions of social capital proposed by Uphoff (2000), that is, "structural social capital" (civic engagement) and "cognitive social capital" (social trust). These indicators are recoded in a three-point ordinal scale where higher values indicate a higher sense of civic duty.[1]

The main empirical contribution of Chapter 4 is given by using an array of civic outcomes as well as controlling for misreporting. Previous research studying the causal link of education and civic outcomes do not explicitly control for misclassification and focus on one aspect of social capital, civic engagement. By including civic behaviours into the analysis, this Chapter provides evidence on how, after accounting for misreporting, education is related to indicators of social trust. Furthermore, to the best of my knowledge, this is the first study attempting to simultaneously account for the misclassification and endogeneity biases of education. Hence, I am able to establish the directions of both types of bias on the education parameter.

I find that misclassification is significant across civic outcomes, leading to substantial changes in the estimated effects. Chapter 4's main finding is that, if one does not account for the tendency of individuals to provide socially desirable responses, this leads to a spurious relationship between education and civic behaviours. The contribution highlights how causality varies by group of civic outcomes, with relationships being endogenous to the social structure of the specific country under analysis.

The rest of the Chapter is organized as follows. In Section 4.2 I discuss the IV approach. Section 4.3 contains the empirical results by civic outcomes and educational levels. Finally, Section 4.4 concludes. Recall that the data and the methodology used in this Chapter are contained in the previous Chapters 2 and 3.

4.2. IV APPROACH

In this section I briefly discuss the IV approach and explain why education may be endogenous. For a detailed account of how endogeneity may affect the causal effect of education on measures of civic engagement in Italy, and how the associated bias' sources on this relationship may vary across group of civic outcomes, see the related paper: Di Pietro and Delprato (2009).

Despite numerous reasons to expect a positive association between education and civic outcomes, the OPM estimates may not provide a valid relationship unless one takes into account the potential endogeneity of education. This would be the case if unobserved factors drive both civic awareness and the acquisition of education. For example, it is likely that parents who foster an interest in further education in their children, also stress to them the importance of being civically responsible.

[1] The Italian data used is described in Section 2.3 and the recoding and resulting outcomes' frequencies in Section 3.3.2.

Endogeneity could also originate from the unobservable given by intelligence and, such as determination and drive, would simultaneously influence education decisions and levels of trust. Indeed, as argued by Sturgis et al. (2010a) intelligence fosters greater interpersonal trust as more intelligent individuals are more accurate in their assessments of the trustworthiness of others. This means that more intelligent people are less often betrayed over the life-course and, consequently, they are able to benefit from norms of reciprocity.

To account for endogeneity problems I use an educational reform as a source of exogenous variation in individuals' levels of schooling that is otherwise unrelated to civic outcomes. Milligan et al. (2004) employ an equivalent IV strategy using changes in compulsory school laws to disentangle the impact of education on civic outcomes.[2]

As usual with any IV procedure, I expect that the estimated coefficient of the education covariate to be larger than the ones from the OP or OPM models but with a higher standard error. This is a common outcome when using a two-stage procedure (Wooldridge (2002), p. 104), where one faces a trade-off between inconsistent estimators that have relatively small standard errors and consistent but imprecise estimators. The upward bias in the education coefficient relies on the assumption of a positive correlation between unobservables (e.g., determination, drive, intelligence) and education.[3] This assumption, generally put forward within the literature (see, for instance, Dee (2004), Milligan et al. (2004), Oreopoulos (2006), Oreopoulos (2007)) results in a larger IV coefficient of education than when applying OLS.

Two reforms of the Italian educational system have been used as instruments for schooling. The first reform (Law 1859, 31 December 1962) implied the unification of the previous high school in a single compulsory junior high school (in force from 1963). Before 1962 it was mandatory to complete elementary school (5 years of schooling), whereas from 1962 onwards it became compulsory to attend at least 8 years of schooling. The second reform (Law 910, 11 December 1969) opened university access to all students regardless of the high school track attended. Several papers have employed these reforms to estimate the impact of education on earnings: Brunello and Miniaci (1999) and Brunello et al. (2001) use the latter reform, while Brandolini and Cipollone (2002) and Brunello et al. (2009) exploit the 1962 middle school reform. However, the 1969 reform presents two main weaknesses. Firstly, although it provided

[2]Alternative instruments used in the literature are measures of local accessibility in schools (Dee (2004)) and socioeconomic background variables (Brady et al. (1995)).

[3]In the simplest case of a liner model with one covariate, this can be seen by decomposing the probability limit of the estimated education coefficient as: plim $\hat{\beta}_{ed} = \beta_{ed} + \pi \frac{\text{cov(ed,unob)}}{\text{var(ed)}}$. Note that the bias is positive since the covariance of education and unobservables is positive as well as the independent effect of the unobservables on a civic outcome which is given by π.

an opportunity for a wider university access, it did not represent a truly exogenous increase of years of education. Additionally, its impact can be confused with the previous middle school reform. Thus, I attempt to overcome those limitations by using the 1962 compulsory school reform.

I next turn to the issue of the potential treated group of the 1962 reform and its empirical evidence. As noted by Brandolini and Cipollone (2002), individuals immediately and directly affected by the reform were those without a middle school degree and who were less than 15 years old in 1963, that is, people born between 1949 and 1957. However, instead of using this smaller treated group (around 4% of the sample), most of the studies above have defined the reform using a dummy taking the value of one for people born after 1949, controlling for cohort effects. This is partially due to the low degree of compliance as it almost took 15 years for the reform to take full effect.

Nevertheless, its validity as an instrument is mixed. For instance, Brandolini and Cipollone (2002) find an effect of the 1962 reform in terms of highest qualifications and enrolment ratios, and Fort (2007) for number of years of education. Conversely, Brunello and Miniaci (1999) and Brunello et al. (2001) show a little impact which may be explained by a general increasing trend in education. To a certain extent our evidence agrees with those latter studies.[4]

A common procedure to handle endogeneity in nonlinear models is a control function approach, where estimated residuals from the reduced form are added in the second stage regression to control for endogeneity (e.g., Blundell and Powell (2004)). This method, however, does not work if any of the endogenous regressors are non-continuous. Because the endogenous variable education is discrete, there is not point identification.[5] An alternative is to use fitted values for the endogenous covariate from the first stage regression mimicking two-stage least squares (2SLS). Unfortunately, as first pointed out by Amemiya (1985), this is not generally valid in a nonlinear regression setting with non-additive errors. Measurement error (or endogeneity) of education can no longer be considered as an additively separable disturbance and, therefore, it is not possible to find an instrument which would be correlated with the regressor without being correlated with the composite disturbance

[4] A nonparametric regression of years of education on year of birth did not result in a significant discontinuity at the policy change. However, in a related paper (Di Pietro and Delprato (2009)), there is additional support to use the 1962 reform as an instrument for schooling. For instance, estimates indicate that the reform has shifted the educational distribution from primary school to lower secondary school and it is uncorrelated with underlying trends of increasing education.

[5] Chesher (2007) clearly illustrates this point by providing partial identification results for discrete outcome models. In particular, the identification set in an OP is affected by the discreteness of the outcome and strength of the instrument. See Chesher (2010), Section 3.3, for details.

(see, for an example, Wang and Hsiao (2007), p. 428). Although this is a very important limitation, I still follow a standard (fitted value) IV technique.

I now introduce the IV-OPM. Rewrite the latent variable equation as $y_i^* = \mathbf{z}_{1i}'\beta_1 + \omega_{2i}\beta_2 + \varepsilon_i$, where $\mathbf{x}_i \equiv (\mathbf{z}_{1i}, \omega_{2i})$, and ω_{2i} denotes the observed endogenous schooling variable. A weakly increasing function G transforms the latent variable to the 'true' outcome: $y_i = G(y_i^*)$. The model for the endogenous regressor is determined by a linear regression for the reduced form with an independent error,

$$\omega_{2i} = \alpha_0 + \mathbf{z}_i'\alpha_1 + \nu_i \text{ and } \nu_i \perp \mathbf{z}_i \tag{4.2.1}$$

where $\mathbf{z}_i \equiv (\mathbf{z}_{1i}, \mathbf{z}_{2i})$ is the vector of instruments, and $\mathbf{z}_{2i}$ provides the exclusion restrictions. As usual, I assume that the instrument is uncorrelated with the structural error term, $\mathbb{E}(\mathbf{z}_i'\varepsilon_i) = 0$, and is relevant, $\alpha_1 \neq 0$. The vector of exclusion restrictions, $\mathbf{z}_{2i}$, is constructed from (i) a dummy for the 1962 reform (= reform62), (ii) an interaction of the 1962 reform with the respondent's father's education level (= r62edpad), and (iii) an interaction of the 1962 reform with the respondent's mother's education level (= r62edmad). This selection of instruments is guided by the hypothesis that educational reforms should have, in general, a differential impact by family background which is concentrated among respondents from lower socioeconomic levels (Card (2001)). I use the fitted value of schooling from Eq. (4.2.1) and plug it into the latent variable equation to account for endogeneity.

Estimations from the first stage regression provides support for the choice of the vector of exclusion restrictions. The instruments are relevant as they are significantly correlated with years of schooling: $\hat{\alpha}_{1,\text{reform62}} = 1.71$ (p-value = 0.00), $\hat{\alpha}_{1,\text{r62edpad}} =$ -0.11 (p-value = 0.01) and $\hat{\alpha}_{1,\text{r62edmad}} =$ -0.10 (p-value = 0.06). The negative sign of the interaction variables support the hypothesis that the reform had a differential effect by family background in Italy, with increases in educational attaintment for the cohort born after 1949 among those individuals who have less educated parents. Based on the strength of the first stage equation, the selected instruments are not weak. The F-statistic is 202.29, well above Stock and Yogo (2005) critical values for weak instruments.[6]

It is plausible that, at least in Italy, unobservables that encourage individuals to develop a taste for education (e.g., determination and drive) are likely to be more strongly correlated with civic behaviours. For instance, parents who foster an interest in further education in their children, are more likely to impress upon them the importance of being civically responsible, perhaps to a bigger extent than they stress

[6]Endogeneity tests are discussed in Section 4.3.

to them to pursue an interest in public affairs. This could be explained by social sanctioning on civic behaviours. It should be noted that, both the mixed empirical evidence of the reform found in the literature and the nonlinearity of the OPM model, lead to cautious interpretation of the IV-OPM results.

4.3. RESULTS

Estimates for the ordered response models explained in Section 3.3 are presented in Table 4.1 and Table 4.2. All models are estimated by maximum likelihood and consistent standard errors for the IV-OPM are obtained by bootstrapping. Given that the misclassification probabilities are constrained to be on the unit interval, a constrained maximum likelihood procedure is used. Note that it is acknowledged in the literature that if a parameter is on the boundary of the parameter space, then bootstrapping is inconsistent (see, Andrews (2000)). Nonetheless, most of the estimated misclassification probabilities are far away from their boundaries. Thus, applying the bootstrap method to the constrained models will suffice.

As regards to the bias on the estimated impact of education across models, I anticipate an upward bias on its coefficient as a result of misclassification and/or endogeneity. That is: $\hat{\beta}_{\text{ed,OP}} \ll \hat{\beta}_{\text{ed,IV-OP}} \lesseqgtr \hat{\beta}_{\text{ed,OPM}} \ll \hat{\beta}_{\text{ed,IV-OPM}}$. The model accounting for endogeneity and misreporting would yield, on the one hand, a double positive bias on the schooling coefficient but, on the other hand, a double increase in its standard error. Hence, compared to the OP model, whether the resulting impact is significant or not, would depend on which empirical phenomenon dominates. Nevertheless, the OP should certainly underestimate the impact of schooling on civic outcomes.

4.3.1. *Parametric estimations for civic outcomes*

The first part of Table 4.1 presents the results for the civic opinion ‘interest in politics’. The three sets of parametric estimates of the slope coefficients are generally equivalent in terms of signs and significance levels. Because the main interest is on the education coefficients and misclassification probabilities, I briefly discuss the results of the other explanatory variables.

The coefficient on age is statistically significant across models, with older individuals being more likely to have an interest in politics than younger individuals; this result is in line with the literature (Algan and Cahuc (2006)). Interest in politics increases with age at a decreasing rate. As shown in some studies (e.g., Brady et al. (1995)), there are significant gender differences in civic participation, with males more likely to follow public affairs (Dow (2009)). A positive association of income

TABLE 4.1

Parametric estimates for civic opinions (Italy)

	Interest in politics			Tax evasion		
Variables	OP	OPM	IV-OPM	OP	OPM	IV-OPM
Education	0.0908**	0.175**	0.2146*	0.0244**	0.1446*	0.1603
	(0.0066)	(0.0477)	(0.1284)	(0.0063)	(0.0744)	(0.1662)
Age	0.0524**	0.0973**	0.0715**	0.033**	0.128	0.1354
	(0.0095)	(0.0356)	(0.0293)	(0.009)	(0.0893)	(0.111)
$\text{Age}^2/100$	-0.0445**	-0.0815**	-0.0591**	-0.0203**	-0.053	-0.0615
	(0.0086)	(0.0311)	(0.0291)	(0.0081)	(0.093)	(0.1117)
Male	0.3164**	0.6188**	0.6177**	0.0195	-0.0334	-0.0932
	(0.0485)	(0.1994)	(0.2063)	(0.0469)	(0.4063)	(0.4432)
Father's education	-0.0065	-0.0011	-0.0257	0.0121	0.0897	0.0712
	(0.0083)	(0.0198)	(0.0573)	(0.0081)	(0.1255)	(0.127)
Mother's education	0.0276**	0.0648**	0.051	0.0107	0.1711	0.1699
	(0.0091)	(0.0252)	(0.0353)	(0.0089)	(0.1547)	(0.1668)
Income	0.0015**	0.024**	0.0428**	0.0007	0.048	0.0621
	(0.0007)	(0.0079)	(0.0154)	(0.0006)	(0.0426)	(0.0533)
Number of children	-0.0755**	-0.2555**	-0.3258**	0.0214	-0.0479	-0.0888
	(0.0259)	(0.0942)	(0.1032)	(0.0251)	(0.3406)	(0.3165)
Married	0.0938*	0.1168	0.0509	0.1621**	1.2115	1.0447
	(0.0533)	(0.1162)	(0.1589)	(0.0515)	(0.8081)	(0.7978)
Center	-0.0837	-0.379**	-0.4194**	0.3799**	2.5361*	2.4444*
	(0.0597)	(0.1518)	(0.1595)	(0.0578)	(1.317)	(1.3876)
North	0.0475	-0.0719	-0.1481	0.1254**	0.5417	0.3996
	(0.0509)	(0.1265)	(0.1517)	(0.0493)	(0.6227)	(0.563)
$\hat{c}_1$	2.3091**	4.4156**	4.1681**	0.9696**	6.5619**	7.0145**
	(0.2593)	(1.3383)	(1.2158)	(0.2471)	(1.608)	(1.8964)
$\hat{c}_2$	3.2924**	6.514**	6.4494**	2.2448**	9.922**	9.9186**
	(0.2616)	(2.0614)	(1.9698)	(0.2491)	(0.4173)	(0.4393)
$\hat{\pi}_{1,2}$		0.0864	0.0731		0.3483**	0.4118**
		(0.0652)	(0.0542)		(0.1698)	(0.1506)
$\hat{\pi}_{1,3}$		0.0029	0.0013		0.1078	0.1124
		(0.0079)	(0.0055)		(0.1326)	(0.1268)
$\hat{\pi}_{2,1}$		0.2049**	0.2091*		0.3493**	0.3906**
		(0.1013)	(0.1095)		(0.0916)	(0.1107)
$\hat{\pi}_{2,3}$		0.204**	0.2418**		0.1849**	0.156
		(0.0899)	(0.0642)		(0.086)	(0.1076)
$\hat{\pi}_{3,1}$		0.1691**	0.2055**		0.1247**	0.1319**
		(0.0321)	(0.0317)		(0.0191)	(0.0172)
$\hat{\pi}_{3,2}$		0.2074**	0.228**		0.455**	0.4533**
		(0.0401)	(0.0452)		(0.0232)	(0.0281)
Log-likelihood	-3037.29	-3003.59	-3060.15	-3144.52	-3118.45	-3123.48
$\bar{\chi}^2$ (P-value)		1.560 (0.051)	6.302 (0.008)		0.302 (0.480)	0.369 (0.367)
$\chi^2(1)$ (P-value)			0.110 (0.740)			0.011 (0.916)

** significant at 5 % and * significant at 10 %.
Standard errors are given in parentheses.
Bootstrapped OPM and IV-OPM, 100 number of repetitions. Log-likelihood is the average over 100 repetitions.

and mother's education agrees with the socioeconomic literature and the theory of civic voluntarism from political science. Belonging to a larger family and living in the central region have a detrimental effect on being interested in politics. Moreover, misclassification of this self-reported outcome not only introduces a positive bias on most of the coefficients of around 50%, but also an increase in all standard errors. This agrees with the simulations in Section 3.4 which show that the OP model yields biased estimates with higher RMSE. The same also holds when one controls for endogeneity in the IV-OPM model.

A likelihood ratio (LR) test which is distributed as chi-bar squared ($\bar{\chi}^2$) confirms that the OPM which allows for misclassification errors outperforms the OP. The $\bar{\chi}^2$ statistic is 1.56 with a probability value of 5%, so the null hypothesis that the misclassification probabilities are equal to zero is rejected.[7]

Perhaps surprisingly, the null of exogeneity of education is accepted. Because the interest lies solely in the potential endogeneity of education, I use a Hausman test only for this parameter.[8] The $\chi^2(1)$ statistic is 0.11 (p-value = 0.74). Note that I also arrive to the same conclusion in the IV-OP model. The estimated coefficient for education in the IV-OP model is 0.16 (p-value = 0.001), and the $\chi^2(1)$ equals 1.94 with probability 0.17. As in other settings, a test on a subset of parameters can lead to a conclusion different from that of a test on all parameters, although this is not surprising if one takes into account evidence of the IV-strategy and the nonlinearly of the models. Nevertheless, results are consistent in the sense that the lack of endogeneity holds, regardless of whether one considers either true or reported answers. Also, the education coefficient in the OPM and IV-OPM models does not lead to different conclusions as well as the models' $\bar{\chi}^2$ tests. Hence, I rely on the OPM model to discuss the estimates of the misclassification probabilities.

Misclassification probabilities satisfy the stochastic conditions of Eqs. (3.9) and (3.10). Although this outcome is (statistically) misreported, there is sufficient correct information in the sample on 'interest in politics' for Assumption 3.1 to hold, with probabilities of correct report being higher than one half.[9] People are more likely to tell the truth than to lie about how keen they are in politics. However, misreporting for reported answers taking the value 2 (not very) and 3 (fairly/very) are significant and Assumption 3.3 holds too. While the probability of correct report for the answer (not at all) $\hat{\pi}_{1,1}$ is 0.91, the values for $\hat{\pi}_{2,2}$ and $\hat{\pi}_{3,3}$ are 0.59 and 0.62, respectively. In

[7]The LR test is not distributed as a χ^2 because the test is one-sided and the vector of misclassification probabilities is on the boundary of the parameter space under the null hypothesis. See Appendix A.

[8]The Hausman test in the application is given by: $\mathrm{H} = \frac{(\hat{\beta}_{\mathrm{ed,OPM}} - \hat{\beta}_{\mathrm{ed,IV\text{-}OPM}})^2}{\mathrm{se}^2_{(\hat{\beta}_{\mathrm{ed,IV\text{-}OPM}})} - \mathrm{se}^2_{(\hat{\beta}_{\mathrm{ed,OPM}})}} \sim \chi^2(1)$.

[9]For ease of exposition, estimated probabilities are also displayed in matrix form in Table 4.4.

other words, individuals who apparently show more political engagement are more likely to misreport. This is consistent with findings from political science that support over-reporting of civic opinions. Although there is discontent with current public affairs in Italy, feelings of guilt, stigma or satisfaction with the status quo make individuals over-state their reported attention to public affairs (Karp and Brockington (2005)). Moreover, misclassification plays a major role in the magnitude of the effect of schooling, i.e., its coefficient increases from 0.09 to 0.18. If inference were carried out by calculating marginal effects based upon the OP estimates, it would be very misleading. This highlights the importance of accounting for misreporting.

Estimations for the variable 'the problem of tax evasion' are presented in the second part of Table 4.1. Because the null of non-misreporting is accepted, I mention some covariates using the OP. Individuals living in the north and central regions tend to express a deeper concern regarding the problem of tax evasion, as well as people who are older or married. As expected, since higher educated individuals should be better informed regarding tax evasion in Italy, education has a direct and significant relationship with this civic opinion. Higher educated people tend to judge tax evasion as more problematic. As before, there is not evidence of endogeneity in either the IV-OPM or IV-OP. (For the latter model the $\chi^2(1) = 0.02$, p-value $= 0.88$).

The main result for this civic opinion is that it is not misclassified according to the $\bar{\chi}^2$ p-value. Firstly, the fact that reported and true answers to this question tend to agree could be due to the widespread knowledge of considerable evasion in the Italian tax system (Fiorio and D'Amuri (2005)). In fact, amongst major OECD countries, Italy presents the highest levels of tax evasion, around 28% (Schneider (2000)). One explanation is given by Brosio et al. (2002). They argue that tax evasion is tacitly accepted as a compensation for the welfare loss deriving from too high centrally set tax rates, particularly in poorer regions where this welfare burden is stronger. Secondly, unlike 'interest in politics', factors such as guilt and stigma are not likely to be operating. In the remainder of this section, I turn my attention to the other three civic indicators.

Table 4.2 contains the results for civic behaviours. The first one 'not paying for your ticket on public transport' is abbreviated as 'not paying ticket'. Besides a small effect of schooling, very few covariates are significant (only regional dummies in the OP model). Intuitively, honest behaviour based on shared norms in a society (social trust) should not markedly diverge across background family variables (e.g., parents education, family income). The null hypothesis of non-misreporting is rejected ($\bar{\chi}^2 = 6.94$, p-value $= 0.00$), and the necessary stochastic condition in (3.10) holds. Again, the null of exogeneity of education is accepted for both the IV-OPM and IV-OP models.[10] Moreover, because $\hat{\pi}_{2,3} > \hat{\pi}_{2,2}$ (see also Table 4.4), Assumption 3.1 does not hold and the OP estimates are extremely biased. That is, observed answers taking the value of 2 do not contain enough information on true responses. Assumption 3.1 may be invalid as it mainly stems from educational and occupational data, but not from indicators of social trust which suffer from SD.

While Assumption 3.2 (monotonicity of correct report) does not strictly hold, there is enough evidence to suggest that this variable suffers from SDB (e.g., King and Bruner (2000)). The largest misclassification probabilities are $\hat{\pi}_{1,3}$ and $\hat{\pi}_{2,3}$. This means, in turn, that people whose reported answers show a lower degree of social trust are more concerned in presenting themselves in socially acceptable terms and, consequently, they tend to lie about how they would react to this hypothetical situation. Albeit, $\hat{\pi}_{1,2}$ and $\hat{\pi}_{1,3}$ are not significant according to their t-tests,[11] Assumption 3.3(i) and Assumption 3.3(ii) are relevant. Elements below the diagonal of $\hat{\Pi}_3$ are small: individuals who report that they are more likely to pay for public transport, are not likely to lie, since they do not have any incentive (or pressure) to state that they would not do so otherwise. This is not the case, however, for lower civically behaved individuals.

The impact of education on the outcome 'not paying ticket' becomes insignificant when controlling for misreporting ($\hat{\beta}_{\text{ed,OPM}} = 0.11$, p-value $= 0.37$). This is one of the crucial results of this Chapter. Methodologically, the absence of causality is due to a very high amount of misreporting which increases schooling's standard error more than the coefficient's bias. The OP overestimation of the estimate's precision for this self-reported outcome is a key empirical issue in this context. From a conceptual point of view this result is explained by a significant SDB, where individuals under-report a socially undesirable behaviour. If one does not account for this, an erroneous causal link would have been obtained. This is supported by research in social psychology which has introduced various mechanisms to reduce this type of bias (e.g., Rasinski et al. (2005)). A possible explanation is that, the lower level of trust in Italy leads to a higher tolerance of self-interest acts, regardless of education levels. Indeed, tolerance of civic behaviours such as not paying the ticket on a public transport is much lower in Scandinavian countries than in southern European countries (Halpern (2005), p. 66). Thus, education does not seem to enhance an honest and cooperative behaviour.[12]

[10]Similarly to the previous tests for the two civic opinions, the IV estimate of education becomes very imprecise compared to the gain in consistency using the IV approach. Thus, the $\chi^2(1)$ is small and the null accepted. This is also true for the other two civic behaviours.

[11]Note that t-tests on misreporting probabilities are not strictly valid (Dustmann and van Soest (2004), p. 317).

[12]I check whether this result holds for a different social structure, that is, using UK samples in

TABLE 4.2.— Parametric estimates for civic behaviours (Italy)

	Not paying ticket			Keeping money			Not leaving name		
Variables	OP	OPM	IV-OPM	OP	OPM	IV-OPM	OP	OPM	IV-OPM
Education	0.0318**	0.108	0.1835	0.0251**	0.1322	0.2236	0.0228**	0.0403	0.0812
	(0.0081)	(0.1213)	(0.394)	(0.0086)	(0.1175)	(0.2344)	(0.009)	(0.0543)	(0.1731)
Age	0.0173	-0.0003	-0.0093	-0.0122	-0.7629**	-0.6611**	-0.0104	-0.0508	-0.0834
	(0.0113)	(0.1003)	(0.0888)	(0.012)	(0.2351)	(0.2835)	(0.0126)	(0.0604)	(0.1268)
$Age^2/100$	-0.0059	0.0293	0.0431	0.0166	0.8468**	0.7316**	0.0154	0.0653	0.1027
	(0.0103)	(0.1072)	(0.0985)	(0.0108)	(0.2615)	(0.3144)	(0.0114)	(0.0583)	(0.1452)
Male	0.0268	-0.0997	-0.0738	-0.0875	-0.9783	-0.7291	-0.0391	-0.1897	-0.1467
	(0.0584)	(0.5764)	(0.3654)	(0.0612)	(1.0816)	(1.0921)	(0.0641)	(0.4129)	(0.5625)
Father's education	-0.0091	-0.0734	-0.0854	-0.0094	-0.1425	-0.0494	-0.0004	0.0106	-0.0083
	(0.0104)	(0.1184)	(0.2099)	(0.0107)	(0.216)	(0.3443)	(0.0113)	(0.0823)	(0.1233)
Mother's education	0.0046	0.0631	0.0066	-0.0022	0.2445	0.0378	-0.0006	0.0313	0.0408
	(0.0114)	(0.1355)	(0.1306)	(0.0117)	(0.3574)	(0.356)	(0.0124)	(0.0955)	(0.1347)
Income	0.0013	0.0823	0.076	0.0068**	0.6519**	0.5868**	0.005**	0.0451	0.0561
	(0.0009)	(0.0791)	(0.0562)	(0.0017)	(0.1912)	(0.2164)	(0.0018)	(0.0335)	(0.0536)
Number of children	0.0305	-0.0332	-0.09	0.0558*	1.9812	1.6396**	0.0713**	0.1569	0.1322
	(0.031)	(0.1394)	(0.2778)	(0.033)	(0.801)	(0.7616)	(0.0341)	(0.1623)	(0.1925)
Married	-0.0279	-0.8013	-0.622	-0.0454	-4.1902**	-4.3239**	-0.0843	-0.5861	-0.728
	(0.0648)	(0.8531)	(0.659)	(0.0677)	(1.244)	(1.3714)	(0.0713)	(0.5533)	(0.7916)
Center	0.3448**	1.56	1.3786	0.2452**	3.8882**	3.8463**	0.3865**	1.4197	1.7349
	(0.0707)	(1.2944)	(1.1903)	(0.0741)	(1.0382)	(1.1165)	(0.0771)	(1.0827)	(1.3872)
North	0.472**	1.3658	1.2978*	0.4291**	4.4094**	4.001**	0.5843**	2.0477	2.0953
	(0.0609)	(0.9714)	(0.785)	(0.0643)	(0.9975)	(1.2289)	(0.067)	(1.3789)	(1.4213)
$\hat{c}_1$	-0.2597	0.2692	0.9644	-1.2008**	-7.0531**	-6.0124*	-1.1135**	-1.2864	-1.7228
	(0.304)	(2.53)	(2.7003)	(0.3268)	(3.3964)	(3.6103)	(0.3418)	(1.6816)	(2.2809)
$\hat{c}_2$	0.5157*	2.3955	2.8845	-0.5019	-5.4859	-4.3217	-0.4569	0.021	-0.1976
	(0.3036)	(2.1679)	(2.4726)	(0.3259)	(3.5046)	(3.755)	(0.341)	(1.5604)	(1.9393)
$\hat{\pi}_{1,2}$		0.0986	0.1105		0.2677**	0.2578**		0.1581	0.1328
		(0.1751)	(0.1787)		(0.0436)	(0.0718)		(0.2178)	(0.1994)
$\hat{\pi}_{1,3}$		0.2379	0.2689		0.4884**	0.4628**		0.3951**	0.3334
		(0.2401)	(0.2421)		(0.0568)	(0.1283)		(0.1976)	(0.2303)
$\hat{\pi}_{2,1}$		0.0412	0.0466		0.0235	0.0381		0.1293	0.116
		(0.0674)	(0.0944)		(0.0859)	(0.1018)		(0.1815)	(0.1651)
$\hat{\pi}_{2,3}$		0.4789**	0.4877**		0.4105**	0.3914**		0.4507**	0.4515**
		(0.0983)	(0.0716)		(0.1534)	(0.1781)		(0.1456)	(0.1427)
$\hat{\pi}_{3,1}$		0.0419**	0.0433**		0.0433**	0.0434**		0.0291**	0.0314**
		(0.0121)	(0.0101)		(0.0037)	(0.0041)		(0.01)	(0.0078)
$\hat{\pi}_{3,2}$		0.0814**	0.0867**		0.0972**	0.0967**		0.0527**	0.0559**
		(0.0337)	(0.0218)		(0.0057)	(0.0067)		(0.0202)	(0.0173)
Log-likelihood	-1831.39	-1816.95	-1820.05	-1681.23	-1666.89	-1667.78	-1517.57	-1508.40	-1509.53
$\bar{\chi}^2$ (P-value)		6.942 (0.000)	15.328 (0.000)		1.796 (0.085)	2.771 (0.074)		6.631 (0.003)	8.950 (0.001)
$\chi^2(1)$ (P-value)			0.041 (0.840)			0.203 (0.652)			0.062 (0.803)

See references in Table 4.1.

Estimates for the second civic behaviour 'keeping money' are analogous to 'not paying ticket' (see columns (4)-(6) of Table 4.2). The OP estimate of education shows only a small effect and it is exogenous. Nearly all $\hat{\pi}_{j,k}$ are different from zero based on their t-values, in particular, $\hat{\pi}_{1,2}$ and $\hat{\pi}_{1,3}$ are now significant. Even with a p-value of 8.5% for the misclassification test statistics, the amount of misreporting is large. The model is consistent since the estimated probabilities fulfill the stochastic condition of Eq. (3.10). Let's examine the misclassification assumptions of Section 3.5.

Lying is more likely than telling the truth for answers at the bottom of the scale so that Assumption 3.1 fails: $\hat{\pi}_{1,1} < \hat{\pi}_{1,2} < \hat{\pi}_{1,3}$. Note that for this indicator the monotonicity of correct report (Assumption 3.2) holds, i.e., probabilities of correct report are increasing along the diagonal of $\hat{\Pi}_3$. This arises as lying is less frequent by more civically behaved individuals according to the hypothesis that SDB drives misreporting, with $\hat{\pi}_{j,k}$ (for $j > k$) being small. Moreover, because $\hat{\pi}_{1,3} > \hat{\pi}_{1,2}$, individuals whose truthful civic responsibility is the lowest, tend to report the highest scores (see Assumption 3.3(ii)). The overall interpretation of the estimation results for this indicator is very similar to the previous civic behaviour. Certainly, SDB also leads to a lack of causality of education on 'keeping money' (i.e., $\hat{\beta}_{\text{ed,OPM}} = 0.13$, p-value = 0.26) and the upward bias and standard error of education in column (5) are pretty close to those in column (2).

Results for the third civic behaviour are displayed in the last three columns of Table 4.2. Estimates and tests are in line with the other two indicators of social trust. Education is insignificant in the OPM model, exogenous by the $\chi^2(1)$ statistic from IV-OPM and IV-OP models, and there is statistical evidence to accept the null hypothesis that the dependent variable 'not leaving name' is misclassified ($\bar{\chi}^2$ = 6.63, p-value = 0.00). There are also analogous results concerning estimated misclassification probabilities and how they fit Assumption 3.1 to Assumption 3.3. (Compare $\hat{\Pi}_3$ for the three outcomes in part (a) of Table 4.5). That is, individuals motives (e.g., approval, guilt, embarrassment) lead to a high misreporting of reported answers at the bottom of the scale. In short, SDB operates equally across the array of civic behaviours.

Considered together, estimates for civic outcomes highlight two main findings. On one hand, because of SDB, indicators capturing aspects of social trust are more likely to suffer from misreporting to a larger extent than indicators on civic engagement. On the other hand, the amount of under-reporting of a socially undesirable behaviour can be so powerful that it makes a key causal relationship statistically non-significant. This follows, in turn, from the hypothesis that the cultural dimension

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of social trust plays a major role than education. I investigate this further in Section 4.3.3 by splitting the sample into low and high educational levels and examining their misreporting patterns.

4.3.2. *Sensitivity analysis for civic behaviours*

In this section I examine whether the main results of civic behaviours are affected by recoding observations in three categories. Recall that estimates in Table 4.2 were obtained by changing a 1 to 10 scale to a 1 to 3 scale, and by grouping and recoding 1 to 3 (=1), 4 to 7 (=2) and 8 to 10 (=3). To provide further support to these previous results I also carry out the same analysis using a five point scale. Observations were recoded in five categories as follows: (1,2)=1, (3,4)=2,..., (9,10)=5, and an OPM model is estimated using a full Π_5 as to measure misclassification across the whole scale.

Table 4.3 contains the results for the five point scale. These results are in line with previous estimations. For the three outcomes the OPM outperforms the OP[13] and the estimated effect of schooling is not significant when accounting for misreporting. Thus, the main finding is still valid and therefore not affected by the earlier recoding. Although there is an important positive bias introduced by misclassification in $\hat{\beta}_{\text{ed,OPM}}$, the large increase in its standard errors renders the relationship of education with any of the three civic behaviours non-statistically significant. Again, this is due to SDB, with respondents providing biased answers so as to gain social approval.

The estimated $\hat{\Pi}_5$ matrices are, overall, qualitatively similar to $\hat{\Pi}_3$. First, Assumption 3.1 fails for $J = 5$ too. For instance, the probabilities of correct report, which are less than a half for the variable 'not leaving name', are $\hat{\pi}_{2,2}$ (=0.15), $\hat{\pi}_{3,3}$ (=0.28) and $\hat{\pi}_{4,4}$ (=0.42). Second, the monotonicity of correct report assumption partially holds for the two outcomes. That is, for 'not paying ticket' $\hat{\pi}_{3,3} < \hat{\pi}_{4,4} < \hat{\pi}_{5,5}$ and, for 'not leaving name', $\hat{\pi}_{2,2} < \hat{\pi}_{3,3} < \hat{\pi}_{4,4} < \hat{\pi}_{5,5}$. Lastly, Assumption 3.3(i) remains valid for all outcomes. To sum up, misreporting behaviours are not affected by the $J = 3$ recoding and $\hat{\Pi}_5$ matrices are in agreement with most hypotheses set out in Assumption 3.1 to Assumption 3.3.

4.3.3. *Parametric estimations for civic outcomes by education level*

The next issue to be examined is how the whole sample results are driven by misreporting of certain educational levels. Is it the case, for instance, that the previously found lack of causality amongst education and social trust measures could be

[13]The $\bar{\chi}^2$ p-values for 'keeping money' and 'not leaving name' are below 5%, but for 'not paying ticket' the null is only rejected at 10%.

TABLE 4.3

Sensitivity analysis for civic behaviours (Italy): Π_5

	Not paying ticket		Keeping money		Not leaving name	
	OP	OPM	OP	OPM	OP	OPM
Education	0.0327**	0.1229	0.0284**	0.0637	0.0269**	0.2493
	(0.0073)	(0.1386)	(0.0076)	(0.0411)	(0.0078)	(0.1825)
$\hat{\pi}_{1,2}$		0.0849**		0 †		0.0636
		(0.0352)				(0.0481)
$\hat{\pi}_{1,3}$		0.0778*		0 †		0.0761*
		(0.0409)				(0.0426)
$\hat{\pi}_{1,4}$		0.0564		0 †		0.0625
		(0.0489)				(0.0484)
$\hat{\pi}_{1,5}$		0.0696		0 †		0.0716
		(0.0453)				(0.0451)
$\hat{\pi}_{2,1}$		0.0254		0.0285		0.0025
		(0.048)		(0.05)		(0.0118)
$\hat{\pi}_{2,3}$		0.1815		0.1243		0.1389
		(0.1463)		(0.0971)		(0.0846)
$\hat{\pi}_{2,4}$		0.0419		0.0454		0.2783**
		(0.0909)		(0.0619)		(0.1078)
$\hat{\pi}_{2,5}$		0.1937		0.0698		0.4303**
		(0.1748)		(0.0888)		(0.1473)
$\hat{\pi}_{3,1}$		0.0362		0.0248		0.0388
		(0.0299)		(0.0292)		(0.0435)
$\hat{\pi}_{3,2}$		0.0568		0.059		0.1308
		(0.0447)		(0.0503)		(0.1079)
$\hat{\pi}_{3,4}$		0.2091**		0.0352		0.0508
		(0.0667)		(0.0755)		(0.0919)
$\hat{\pi}_{3,5}$		0.4855**		0.1756		0.4974**
		(0.0592)		(0.1168)		(0.0167)
$\hat{\pi}_{4,1}$		0.0087		0.0379		0.0513
		(0.0128)		(0.0262)		(0.0479)
$\hat{\pi}_{4,2}$		0.076		0.1133**		0.0206
		(0.0628)		(0.051)		(0.0384)
$\hat{\pi}_{4,3}$		0.1677**		0.0184		0.0222
		(0.0803)		(0.0522)		(0.0492)
$\hat{\pi}_{4,5}$		0.4479**		0.4963**		0.4843**
		(0.1335)		(0.0169)		(0.0645)
$\hat{\pi}_{5,1}$		0.0132**		0.0093**		0.0133**
		(0.002)		(0.0039)		(0.0026)
$\hat{\pi}_{5,2}$		0.0309**		0.0159**		0.0233**
		(0.0043)		(0.0055)		(0.0031)
$\hat{\pi}_{5,3}$		0.0665**		0.0635**		0.044**
		(0.0058)		(0.0064)		(0.0043)
$\hat{\pi}_{5,4}$		0.1137**		0.0803**		0.0925**
		(0.0113)		(0.0123)		(0.0085)
Log-likelihood	-2750.79	-2734.29	-2589.41	-2580.06	-2378.19	-2354.03
$\bar{\chi}^2$ (P-value)		2.726 (0.095)		5.129 (0.038)		5.180 (0.013)

The 1 to 10 scale is changed to a 1 to 5 scale, with (1,2)=1, (3,4)=2,..., (9,10)=5, and Π_5.
** significant at 5 % and * significant at 10 %.
Standard errors are given in parentheses.
Bootstrapped OPM, 100 number of repetitions. Log-likelihood is the average over 100 repetitions.
† estimate at lower bound.

TABLE 4.4

Parametric estimates for civic opinions by education level (Italy): Π_3

Interest in politics			Tax evasion		
a) Whole sample (N = 3059)					
0.9107	0.0864	0.0029	0.5439	0.3483**	0.1078
0.2049**	0.5911	0.204**	0.3493**	0.4658	0.1849**
0.1691**	0.2074**	0.6235	0.1247**	0.455**	0.4203
$\bar{\chi}^2$ (P-value): 1.560 (0.051)			$\bar{\chi}^2$ (P-value): 0.302 (0.480)		
b) At least primary school (N = 982)					
0.8938	0.0984**	0.0078	0.6482	0.1626	0.1892**
0.2485**	0.5219	0.2296**	0.1392	0.6494	0.2114**
0.2169**	0.11	0.6731	0.0743	0.1794*	0.7463
$\bar{\chi}^2$ (P-value): 0.498 (0.275)			$\bar{\chi}^2$ (P-value): 0.329 (0.152)		
c) At least secondary school (N = 2077)					
0.8172	0.0995	0.0833	0.4273	0.4283**	0.1444**
0.1003	0.727	0.1727**	0.0773	0.5585	0.3642**
0.2163**	0.233**	0.5507	0.1525**	0.3998**	0.4477
$\bar{\chi}^2$ (P-value): 3.161 (0.010)			$\bar{\chi}^2$ (P-value): 0.557 (0.163)		

Bootstrapped OPM estimates, 100 number of repetitions.
Whole sample estimates are from Table 4.1.
Sub-samples results control for the same covariates of Table 4.1 apart from education.
Diagonal elements of $\hat{\Pi}_3$ are 1 minus the sum of $\hat{\pi}_{j,k}$ across rows.
** significant at 5 % and * significant at 10 %.

explained by high misreporting regardless of individuals schooling levels? Additionally, do only more educated people over-report civic opinions because, for example, they are more concerned with their class interests? In this section I attempt to answer these questions. The main hypothesis I rely on is contained in Assumption 3.4. Results are presented in Table 4.4 and Table 4.5 which contain OPM estimates for two sub-samples: low schooling level (at least primary school) and high schooling level (at least secondary school).

First, consider the civic opinions' estimates of Table 4.4. The outcome 'the problem of tax evasion' is not misclassified by either less or more educated respondents (both $\bar{\chi}^2$ are non-significant at the 5% level). The previous absence of misreporting for the whole sample is further confirmed with the OPM results by education level. The extensive tax evasion in Italy seems to be acknowledged by both groups, and there is no reason to expect that psychological factors such as guilt and stigma should vary amongst these two sub-samples. Conversely, for the other civic opinion 'interest in politics', misreporting of the whole sample is driven by higher educated individuals. The $\bar{\chi}^2$ p-value of the OPM using the sub-sample of people with at least primary school is 0.28, whilst the sub-sample composed of people with at least secondary school is 0.01.

TABLE 4.5

Parametric estimates for civic behaviours by education level (Italy): Π_3

Not paying ticket			Keeping money			Not leaving name		
a) Whole sample (N = 3059)								
0.6635	0.0986	0.2379	0.2439	0.2677**	0.4884**	0.4468	0.1581	0.3951**
0.0412	0.4799	0.4789**	0.0235	0.566	0.4105**	0.1293	0.42	0.4507**
0.0419**	0.0814**	0.8767	0.0433**	0.0972**	0.8595	0.0291**	0.0527**	0.9182
$\bar{\chi}^2$ (P-value): 6.942 (0.000)			$\bar{\chi}^2$ (P-value): 1.796 (0.085)			$\bar{\chi}^2$ (P-value): 6.631 (0.003)		
b) At least primary school (N = 982)								
0.3805	0.2623**	0.3572**	0.6099	0.2033**	0.1868**	0.5928	0.1682**	0.239**
0.1332	0.7007	0.1661	0.0888	0.7399	0.1713	0.0201	0.6235	0.3564**
0.0489**	0.1311**	0.82	0.0607**	0.1005**	0.8388	0.0471**	0.0741**	0.8788
$\bar{\chi}^2$ (P-value): 3.262 (0.004)			$\bar{\chi}^2$ (P-value): 2.288 (0.031)			$\bar{\chi}^2$ (P-value): 3.281 (0.003)		
c) At least secondary school (N = 2077)								
0.3039	0.3616**	0.3345*	0.4018	0.3037**	0.2945**	0.4095	0.2937**	0.2968**
0.1782	0.5877	0.2341	0.1808	0.531	0.2882*	0.1454	0.5807	0.2739
0.0241*	0.0457	0.9302	0.0205*	0.0743**	0.9052	0.0197**	0.0381*	0.9422
$\bar{\chi}^2$ (P-value): 5.315 (0.002)			$\bar{\chi}^2$ (P-value): 1.163 (0.236)			$\bar{\chi}^2$ (P-value): 5.730 (0.009)		

See references in Table 4.4.

The above results confirm Assumption 3.4(i) that relates misreporting of civic engagement indicators (in this case over-reporting) to socioeconomic status. It is found that, similarly to a well-studied civic indicator in the political science literature (i.e., voting behaviour), more educated individuals are under the most pressure regarding feelings of guilt, stigma or class interests (e.g., Bernstein et al. (2001)). Therefore, they are more likely to misreport (over-report) how keen they are on politics.[14] This can easily be inferred from the probability of correct report for reported answers equal to 3 (interest in politics: fairly/very). Nearly half of those are misreported, that is, $\hat{\pi}_{3,3} = 0.55$. The conjecture from these estimations is that, the dissimilar misreporting pattern by education level which is only present for the group of high schooling individuals, may be the reason why I still obtain a significant causality link between education and interest in politics.

Next, I repeat this analysis for civic behaviours in Table 4.5. A key feature of these results is that for nearly all OPM estimations I find strong evidence to conclude that civic behaviours are misreported, despite the schooling attainment considered.[15] The misclassification tests agree with the hypothesis outlined in Assumption 3.4(ii)

[14]In Chapter 5, for the UK, I am able to directly examine this hypothesis by looking at questions related to stigma and feelings of guilt related to the lack of voting.

[15]Out of the six OPM models estimated, only the $\bar{\chi}^2$ p-value is above 5% for the civic behaviour 'keeping money', using the higher schooling level sub-sample. This is probably why, for this outcome, the null that all $\hat{\pi}_{j,k} = 0$ is rejected for the whole sample at a 8.5% significance level.

which states that misreporting is equally likely to hold for different education levels.

The main argument I believe may explain this result, is drawn from empirical research in social psychology which tends to find a strong impact of descriptive social norms (see, e.g., Cialdini et al. (2006)). Civic behaviours are regulated by social norms, which are divided into injunctive (the norms of "ought") and descriptive (the norms of "is"). I find the hypothesis that descriptive norms affect behaviours in real life, quite appealing in the current application.[16] Respondents choose (or report) their answers by registering what is generally done by most people in those situations and then would under-report their behaviours. Another alternative explanation is that, at least for Italy, the cultural dimension of social trust (which is defined by the array of civic behaviours variables) exerts a stronger influence than schooling. From a methodological point of view, the fact that misreporting holds for both educational levels produces itself, a non-significant link between education and the group of social trust outcomes.

In comparing estimations by educational levels for each outcome, one can assert that all $\hat{\pi}_{j,k}$ are very similar in terms of their values and statistical significance. In particular, for all civic behaviours, $\hat{\pi}_{1,2}$ and $\hat{\pi}_{1,3}$ are quite large and significant at 5% by their t-values. In other words, Assumption 3.2 is still valid for either less or more educated individuals. (See diagonal elements in parts (b) and (c) of Table 4.5.) This is also reflected in the small values of $\hat{\pi}_{j,k}$ below $\hat{\Pi}_3$ diagonal (i.e., Assumption 3.3(i)). Summarised, the results indicate homogenous misreporting patterns across the whole sample and schooling levels.

The above analysis for Italy suggests three results regarding misclassification by educational level present in the data: (i) misreporting of civic opinions is related to socioeconomic status, that is to say, over-report is more probable to hold the higher the educational attainment of an individual, (ii) the amount to which respondents under-report socially undesirable behaviours is not a function of their socioeconomic backgrounds, so that SBD drives misreporting despite schooling levels, and (iii) the former result may indicate why education is significant, even allowing for misclassification, whereas I believe that the latter finding plays a crucial important role in the absence of causality of education and measures of civic behaviours.

4.4. CONCLUSIONS

This Chapter has examined the causal effect of education on civic outcomes in Italy for a range of civic measures. Its particular concern was how misclassification of the self-reported dependent variables affected this relationship. By using an array

[16] For related research in social psychology, see, for instance, Cialdini (2007) and Nolan et al. (2008).

of civic outcomes, this enabled me to extend previous research and to study how SDB affected the causal link of education and indicators of social trust, i.e., civic behaviours. I also investigated the bias introduced by endogeneity of schooling by using an IV-OPM. Another issue explored in Chapter 4 was to discern whether the misclassification bias could be mainly explained by a sub-group defined by a certain education level.

In line with previous studies that use other types of self-reported dependent variables, my findings show that self-reported measures in Italy are prone to suffer from misreporting. This leads to seriously biased parameter estimates as well as to an overestimation of their precision, which can obscure key empirical causality links. Thus, correcting for misclassification in self-reported assessments of civic awareness is crucial. Furthermore, the direction of the bias on the impact of education on civic outcomes induced by misclassification, follows the same direction as the one introduced by endogeneity, with positive biases in both cases. But, perhaps surprisingly, I accept the hypothesis that education is exogenous in the IV-OPM models, although caution is needed in the interpretation of this result due to our IV strategy and the non-linearity of the model.

Most importantly, qualitative overall conclusions are affected by incorporating misclassification. That is, education increases civic awareness for civic opinions but modifies the relationship between schooling and civic behaviours, becoming statistically non-significant. This lack of causality suggests two possibilities. It may indicate that SDB operates differently within the two dimensions of social capital and is a more important issue regarding measures of civic behaviours than indicators on civic engagement. This is in line with empirical studies which show that the aspects of social capital tend to positively correlated, although correlations are usually quite low (Rothstein (2001), Johnston and Percy-Smith (2003), van Oorschot et al. (2006)). Alternatively, it may reflect that, at least in Italy, the cultural component of social trust plays a more crucial role than schooling. Both explanations are at odds with the hypothesis that they hold in spite of individuals educational levels.

More specifically, out of the five civic outcomes analysed for Italy, there is only lack of evidence of misclassification for the civic opinion 'the problem of tax evasion'. Therefore, a clear improvement over the standard OP is achieved for most civic variables. Moreover, the misclassification problem is severer for civic behaviours and empirically explained by the assumption of monotonicity of correct report, which justifies the classification of civic outcomes into two groups. The whole sample results are supported by estimates of both schooling levels, but not for civic opinions where I only found that misclassification holds for more educated individuals. On the contrary, civic behaviours are misreported regardless of which education level is considered. The misclassification bias for civic behaviours obeys to an under-report of the lower civically behaved group whereas, for 'interest in politics', the group that apparently show a higher degree of political engagement are more prone to over-report it. These misreporting patterns obtained are in line with existing theories from social psychology and political science.

Chapter 5

Civic outcomes, misclassification and education: the case of the UK

5.1. Introduction

Differences in political systems, social norms, cultural aspects and expectations across European countries, would lead to specific country effects with regards to distribution of types of social capital. Mutual trust, for instance, is considered by some authors endogenous to certain elements of the social structure (Torsvik (2004)). Endogeneity, or the dynamic interaction between norms and institutions, may lead to social traps; that is, to situations where individuals, groups or organisations are unable to cooperate owing to mutual distrust and lack of social capital, even where cooperation would benefit all (Rothstein (2005), Francois (2008)). These bad steady states, where institutions are dysfunctional and beneficial norms are violated, are often the case in southern European countries such as Italy, which is classified within the group of low trust societies by Fukuyama (1995). The impact of schooling on different dimensions of social capital, then, may be endogenous to a country's social structures too. If the relationship of education with dimensions of social capital is country specific, it may also be true that the two elements which may obscure it (i.e., endogeneity and misclassification) would have a differential impact by country. In other words, the extent of the problem of endogeneity and misreporting in the human to social capital framework, might be country specific.

This is why the UK analysis is included in the thesis: as a way to validate the results for Italy, but also to investigate the extent to which simultaneity and misreporting are influenced by macro characteristics. I believe, that finding out whether unobservables behind education choices and social desirability (SD) are local to social structures is vital.

There is mixed evidence on the distribution of social capital across Europe. The main argument of the previous Sections 1.1 and 2.2 is that there are macro or compositional characteristics in a specific country (e.g., religion diversity, level of economic equality, etc.), and institutional policies (educational expansions, welfare policies, etc.), which determine the level and generation of social capital. Thus, it is often argued that public policies which enhance social and economic equality carried out by impartial political institutions, would create social capital and trust (Rothstein (2005), Rothstein and Uslaner (2006)). On the one hand, welfare policies are an example of the latter, as their aim is to reduce large economic inequalities by means of interconnected policies regarding social protection, labour participation, education, etc. Moreover, welfare policies create a context of national solidarity and fellow feeling, which is conducive to increasing trust levels too, and also offer a role model for adherence to social norms of cooperation and mutual support (van Oorschot and Finsveen (2009)). For example, van Oorschot and Arts (2005) find that more social security expenditure increases informal social capital (contact frequency with friends and family). The reduction of large cultural and human capital inequalities, on the other hand, mostly results from education policy. Compositional characteristics also play a role. Countries with protestant religious traditions and ethnic homogeneity seem to exhibit higher levels of generalised social trust (Delhey and Newton (2005)). Because all these contextual effects differ across Europe, one would expect, in theory, significant country effects in the generation of social capital, as well as how education is linked to civic outcomes in Italy and in the UK.

Nonetheless, recent empirical studies do not seem to find significant country effects to support the hypothesis of an unequal distribution of aggregate levels of social capital for Europe (van Oorschot et al. (2006)). They also do not find significant impacts on social capital stemming from dissimilar welfare state contexts. In other words, the common conclusion is that, after accounting for country fixed effects, original associations tend to disappear. More specifically, van Oorschot et al. (2006) conclude that social capital tends to be higher only in Scandinavia. The rest of the European countries and regions do not differ substantially in aggregate levels of social capital since they have common elements such as that they are modern, relatively affluent, and have more or less comprehensive (post) industrial welfare states. Upon this evidence, one could argue that the aggregate levels of civic outcomes used in this thesis are then similarly distributed between Italy and the UK and, hence, the validation exercise would show up analogous results for these two countries. In short, this may suggest an equal influx of endogeneity and misclassification into the schooling-civic outcomes relationship.

The basic aim of Chapter 5 is, therefore, to disentangle all these forces, providing a cross-national perspective on whether the relationship between education and civic outcomes might vary when accounting for issues of endogeneity and misreporting.

Many empirical UK studies on social capital deal with its determinants.[1] Li et al.

[1]See also Section 2.2 for more references.

(2005) analyse the socio-cultural determinants of three types of social capital (neighbourhood attachment, social network and civic participation) and their impact on social trust. These results show that education is highly significant on social networks, civic participation and generalised trust, but not significant in neighbourhood attachment. Educational attainment is also an important predictor for increasing levels of civic action for young people (Fahmy (2006)), and people with higher qualifications show higher trust too (Sturgis et al. (2010a)). Similarly to the research on other countries, these studies find that education is a consistent predictor for measures of social capital in the UK relying on different data sources.[2] Yet, they do not control for endogeneity and misreporting and focus on particular dimensions of social capital.

In this Chapter, I study how misreporting impacts on the causality of schooling on various measures of social capital in the UK. Social desirability bias (SDB), the tendency by which individuals would tend to under-report socially undesirable behaviours and over-report socially desirable ones (Paulhus (1991)), may produce systematic unreliable responses by interviewees and therefore an invalid relationship between education and social capital. As in the analysis for Italy in Chapter 4, I rely on results from the parametric discrete choice models (described in Chapter 3), that is, estimates of an OP are compared with those from an OPM and IV-OPM. In line with the literature (e.g., Milligan et al. (2004)), a reform of the British educational system is used as an instrument to account for endogeneity.

The models are then applied to an array of measures capturing different dimensions of social capital. Civic opinions are: 'interest in politics', 'pay attention to politics', 'discuss politics' and being 'active in a voluntary organisation'. The three civic behaviours are: 'failing to report accidental damage done to a parked vehicle', 'keeping money that you have found', and 'avoiding a fare on public transport'. I also include as outcomes whether respondents believe that 'political activity takes too much time and effort', 'family and friends think that voting is a waste of time', 'feel very guilty if not vote', 'neglect my duty as a citizen if not vote', as well as outcomes concerning interpersonal trust and trust in institutions. The framework by van Oorschot et al. (2006), containing three dimensions for social capital (networks, trust, and civism), fits this group of UK indicators. Most of them belong to the third dimension, civism, with civic behaviours measuring the degree of trustworthiness and, civic opinions, the aspect of political engagement. These indicators are recoded in a

[2] Li et al. (2005) use the British Household Panel Survey (BHPS); Fahmy (2006) the General Household Survey (GHS); and Sturgis et al. (2010a) the National Child Development Study (NCDS) and the 1970 British Cohort Study (BCS70).

three-point ordinal scale where higher values indicate a higher sense of civic duty.[3]

The analysis in this Chapter shows that most civic outcomes are misclassified and, consequently, misreporting is an important empirical issue for the UK too. Likewise endogeneity, since the null hypothesis of exogeneity is rejected for most indicators. The direction of the bias introduced by endogeneity follows the same direction as the one introduced by misreporting, with upward biases in both cases. In other words, unobserved factors which lead individuals to develop a taste for education, are also positively correlated with civic opinions and civic behaviours. In fact, results appear to suggest that the extent of this correlation is such that, the impact of education on civic behaviours becomes statistically significant when accounting for endogeneity. This is the main difference with the Italian case: schooling has significant positive effects on all civic outcomes in the UK. Chapter 5's main finding is that educational achievement emerges as a strong predictor for the different dimension of social capital. Additionally, estimations by educational levels show a significant misreporting of civic behaviours regardless of the schooling level considered, but, for civic opinions, misreporting only holds for the group of more educated individuals.

Chapter 5 is structured as follows. I address the IV approach below, in Section 5.2. Section 5.3 provides the main empirical results by group of civic outcomes, education levels, and a sensitivity analysis for civic behaviours. Conclusions are included in Section 5.4. The data and methodology used are contained in Chapters 2 and 3.

5.2. IV APPROACH

In this section, I discuss the approach in dealing with endogeneity. As previously stated, unless one takes into account unobserved factors that simultaneously influence education decisions and civic outcomes, the OPM estimates may not provide a valid relationship. Indeed, it is likely that parents who foster an interest in further education in their children, also stress to them the importance of being civically responsible. Explanations on the impact of unobservables are linked to the civic voluntarism model, especially by the resources and psychological factors. For example, privileged families are more likely to boast a politically rich home environment dominated by frequent political discussions, with politically active parents acting as role models. Moreover, intelligence is another unobservable which is found to foster levels of trust and clearly impacts upon education decisions as well.

I rely on an educational reform in the UK which provided an exogenous variation in individuals years of schooling but it is otherwise unrelated to civic outcomes. There are two changes in educational law within the UK mentioned in the literature:

[3]For details on the recoding process, see Section 3.3.2.

the first reform, implemented in 1947, raised the minimum leaving school age from 14 to 15 years-old; the second reform raised the minimum age again in 1972, from 15 to 16. Both reforms have been used extensively in the economic literature as instruments. Milligan et al. (2004), for instance, employ them to produce IV estimates of the probability of voting in the UK and in broader measures of civic engagement (attention to public affairs, follow politics, etc.). They find that the reforms had a remarkably rapid influence on educational attainment as well as that education improves participation, not only measured by voter turnout, but also within these broader measures. Similarly, Oreopoulos (2006) finds that the change in compulsory school laws had a powerful and immediate effect upon the number of years that the subpopulation of people affected by the reforms stay at school, which translates into a 14% higher earnings. In sum, studies tend to find a strong validity using these UK reforms as instrumental variables.

I concentrate only on the 1972 reform because the BES and EVS samples have, as the lowest value for education variable (age finished full-time education) 15 or younger, and therefore the exogenous increase in the schooling age from 14 to 15 of the first reform 1947 would not be captured by the data. People directly affected by the reform were those who in 1972, were 15 years old, or one might alternatively consider people who were at school in 1972, and so were between 6 and 15 years old in 1972. This latter treated group is of a fair size, approximately 20% of the BES sample and around 23% of the EVS sample. As in the other studies, I define the reform using a dummy taking the value of one, for people born on or after 1957 (= reform72).

I now present some checks on the validity of the reform.[4] Recall that the BES and EVS samples are employed to estimate the impact of education on civic opinions and civic behaviours, respectively. Firstly, I examine whether there is a discontinuity at the time of the policy change. Figure 5.1 illustrates the remarkable influence of the raising of the minimum leaving school age on educational attainment in the UK, and thus the evidence coincides with those previous studies (e.g., Milligan et al. (2004)). Figure 5.1 also shows that the fraction of individuals leaving school at age 15 fell from 25% in 1972 to less than 16% in 1973, whereas for the EVS sample, the decrease was from 23% to 3%. And although the proportion of students leaving full-time education at age 15 was decreasing leading up to the reform (depicted in the figure as the vertical line at year 1957), the discontinuity of this proportion at the time of the reform is significant.

Additionally, I present further evidence by applying a regression discontinuity

[4]Endogeneity tests are contained in Section 5.3.

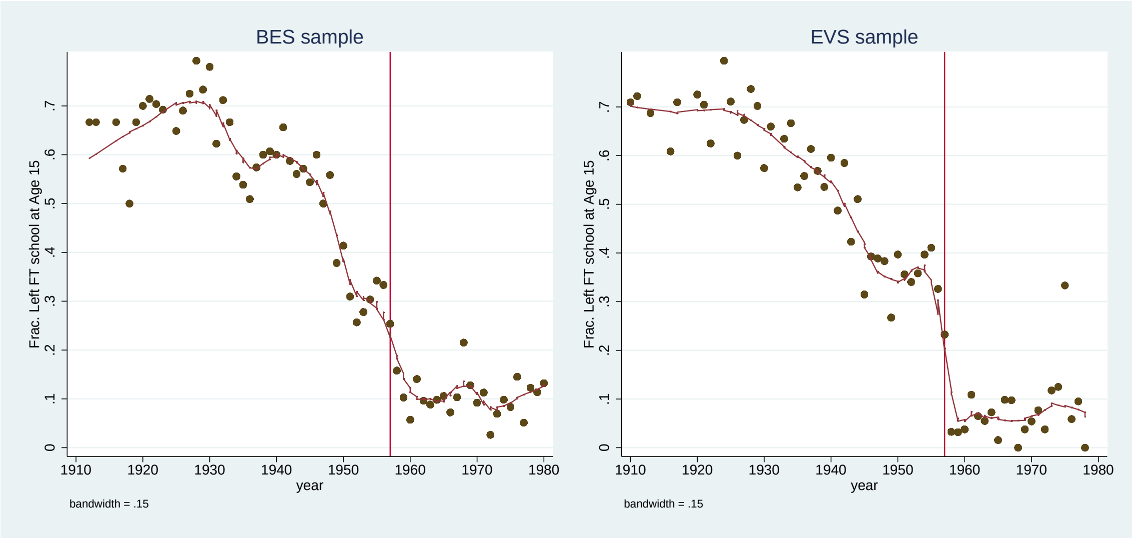

FIGURE 5.1.— Nonparametric regression of education on year of birth.

(RD) approach. In sharp RD designs, the jump in y (i.e., fraction left full-time education at age 15) at the cutoff point $Z_0 = 0$ ($\equiv$ birth - 1957) is the estimate of the causal impact of X^T (assignment to treatment depends on a variable Z being above a cutoff Z_0). Local Wald estimates (equivalent to a local IV estimate) of the casual impact are obtained by local linear regressions on both sides of the cutoff point Z_0, which are negative and significant for the proportion of individuals leaving full-time education at 15 for either sample. For the BES sample the estimate is -0.076 (p-value = 0.000), and, for the EVS sample, the local estimate is -0.029 (p-value = 0.000). Local linear regressions for 20 years before and after the reform are shown in Figure 5.2, where it can be seen a large discontinuity at $Z_0 = 0$ for the BES sample. In summary, there is enough evidence from the UK samples of a considerable exogenous change in the schooling variable.

Secondly, as outlined by Card (2001), because educational reforms are generally intended to reduce the inequality on the distribution of schooling in the population, I then check if the reform had been concentrated amongst the individuals who originate from lower socioeconomic levels. Certainly, this seems to be the case for either data source when running separate regressions by social classes. For the BES sample, the dummy for the reform is only significant and positive for lower social classes: socialclass4 (manual foremen and supervisors, $\hat{\alpha}_{1,\text{reform72}} = 0.61$, p-value = 0.01) and socialclass5 (working class, $\hat{\alpha}_{1,\text{reform72}} = 0.40$, p-value = 0.00). For the EVS sample, the coefficient for the reform dummy is significant and positive for all social classes, except from the socialclass1 (upper and upper-middle class) where $\hat{\alpha}_{1,\text{reform72}} = 0.08$

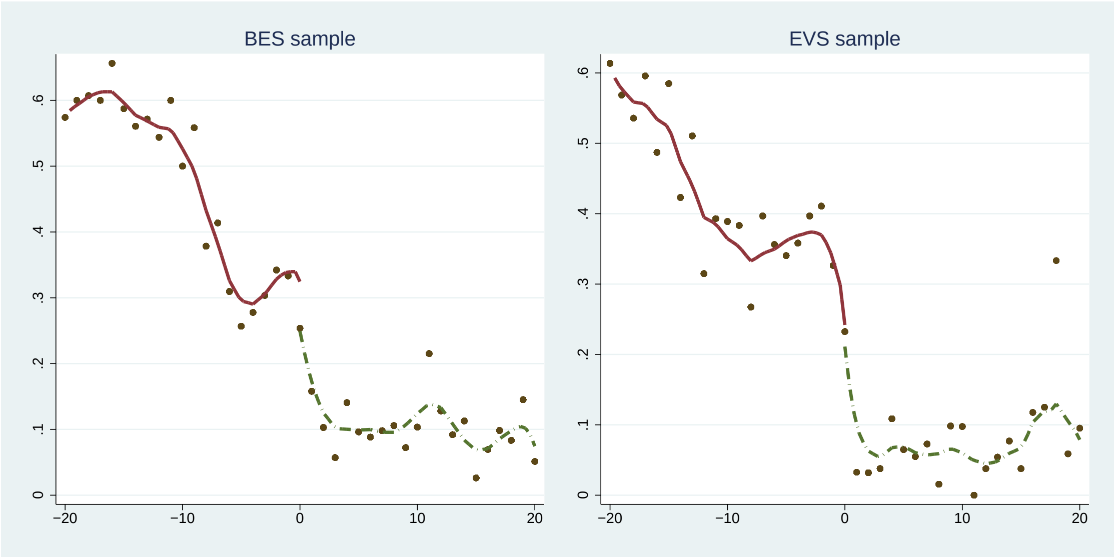

FIGURE 5.2.— Local linear regressions of education before and after the reform.

(p-value = 0.70). These results suggest a specification that includes interactions of 1972 reform with background variables such as social class.

I use a standard IV technique where the endogenous education variable is replaced by its fitted values from the first stage regression. The problem with this (and control function approach) is due to both the nonlinearity of the model and discreteness of the endogenous regressor. Although these are very important limitations, I still follow a standard (fitted value) IV technique.[5] The vector of exclusion restrictions (or instruments) is constructed from: (i) a dummy for the 1972 reform (= reform72), (ii) interactions of the 1972 reform with respondent's social class (= r72class$_i$).

First stage estimates are in line with the expectations for both samples. For the BES dataset, the reform dummy and interaction with the highest social class are significant: $\hat{\alpha}_{1,\text{reform72}} = 0.32$ (p-value = 0.00), $\hat{\alpha}_{1,\text{r72class1}} =$ -0.37 (p-value = 0.00), and $\hat{\alpha}_{1,\text{r72class}_i}$, for $i = 2, 3, 4$ are not statistically significant.[6] The instruments are not weak since the F-stat is very high (= 122.02). Also, for the EVS sample, I obtain equivalent results: the F-stat is again very high (= 108.59), and the instruments are relevant, with coefficients $\hat{\alpha}_{1,\text{reform72}} = 0.53$ (p-value = 0.00), $\hat{\alpha}_{1,\text{r72class1}} =$ -0.31 (p-value = 0.02), $\hat{\alpha}_{1,\text{r72class2}} = 0.05$ (p-value = 0.68) $\hat{\alpha}_{1,\text{r72class3}} = 0.21$ (p-value = 0.04). In short, for the two datasets the instruments are relevant and not weak. Moreover, the interactions show the correct signs that support the hypothesis of a differential

[5] All technical details (references about IV in nonlinear models, the chosen IV approach's equations, etc.) are contained in Section 4.2.

[6] The dummy socialclass5 (working class) is the base category.

impact of the reform by socioeconomic background.

5.3. RESULTS

I now present the results for the discrete choice models described in Chapter 3. In particular, Section 5.3 includes estimations for the OP, OPM and IV-OPM, alongside a sensitivity analysis for civic behaviours and parametric estimations by high and low educational levels. The models that incorporate misclassification are estimated by constrained maximum likelihood, since probabilities are positive and less than one by definition, and furthermore consistent standard errors for the IV-OPM are obtained by bootstrapping. I only briefly discuss the results of the other explanatory variables in this section as the key objective of the thesis is to investigate the estimated education coefficients and misclassification probabilities. As previously mentioned, I expect a positive bias on the estimated education coefficient as a result of misclassification and/or endogeneity across models. That is: $\hat{\beta}_{\text{ed,OP}} \ll \hat{\beta}_{\text{ed,IV-OP}} \lesseqgtr \hat{\beta}_{\text{ed,OPM}} \ll \hat{\beta}_{\text{ed,IV-OPM}}$.

5.3.1. *Parametric estimations for civic outcomes*

Estimates for the four civic opinions are displayed in Table 5.1. On the one hand, the first three outcomes, 'general interest in politics', 'attention to politics', and 'discuss politics', all measure the degree of engagement in politics as a whole. Being interested, paying attention to and discussing politics are clearly linked as shown by their correlations (≈ 0.50 between each other). These indicators are relevant because people who are interested in the political sphere are clearly more likely to want to participate in the electoral process. For the same dataset, Sanders et al. (2005) find that amongst those with relatively high levels of interest, 75% voted in the general election. On the other hand, the fourth civic opinion, 'active in a voluntary organisation', is not directly linked with political participation and belongs to the social participation dimension of social capital; which is why the average correlation is smaller (of ≈ 0.15 with the other three indicators).

I now discuss the results for the first three indicators jointly. The coefficient on age is statistically significant across models. In line with earlier findings (e.g., Algan and Cahuc (2006)), older people are more likely to be interested in, pay attention to and discuss politics.[7] Political engagement increases with age, but as indicated by the coefficient of age^2, at a decreasing rate. This is also suggested by most empirical studies that state that political activity rises in the early years, peaks in middle age, and falls in later years (Fahmy (2006)). As hypothesized by the civic voluntarism

[7]Indeed, the key finding of Sanders et al. (2005) is that, as in the BES 2001, age remains a crucial predictor of voting.

model (Verba et al. (1995), Verba et al. (2005)), people's economic situation is positively associated with higher levels of social capital. For any of the three indicators, individuals with higher incomes are more engaged in politics. Regarding gender, men are more likely to be engaged in politics, a result usually found in the literature (Burns et al. (2001)). Due to differences in taste (Dow (2009)) and resources, men score significantly higher in measures of interest in politics, knowledge of politics, consumption of news media, etc. Surprisingly, there is no impact of employment status or being married however having children, in general, is related to 'be interested in and discussing politics'. Similarly to existing research, some of the social class variables are significant predictors of political engagement. The negative sign of the social class dummies is due to the base category being the highest class, socialclass1 (salariat), and as it is shown by their estimated values, the lowest significant effect on political issues is the dummy socialclass5 (i.e., working class). With regards to country effects, there are no regular differences between countries. This is in line with Sanders et al. (2005) who find that there are no significant national variations in turnout patterns; Scottish and Welsh voters are virtually indistinguishable in this regard from voters in England.

Crucially, the estimated coefficient of education is statistically significant in the specification of the three measures of political engagement and it is also one of the highest.[8] This is consistent with most empirical studies that find that schooling is one of the strongest determinants of social capital in different countries (Delhey and Newton (2003), Bekkers (2007), van Oorschot and Finsveen (2009)), and with UK studies (e.g., Li et al. (2005), Fahmy (2006)). As earlier shown in the simulations of Chapter 3, if misclassification holds, the OP model yields biased estimates with higher RMSE. This is certainly the case for the estimations of Table 5.1 since misclassification not only introduces positive biases on most coefficients of more than 50%, but also an increase in all standard errors. The chi-bar squared ($\bar{\chi}^2$) test confirms that civic opinions are mostly misreported, with the OPM, which allows for misclassification errors, outperforming the OP.[9] For the civic opinions 'attention to politics' and 'discuss politics', the $\bar{\chi}^2$ statistics are 1.003 (p-value = 0.010) and 0.966 (p-value = 0.027) respectively, so that for both indicators the null hypothesis that the misclassification probabilities are equal to zero is rejected. The outcome 'general interest in politics', however, is not misclassified according to the IV-OPM results[10] of the $\bar{\chi}^2$ test, because the OPM yields a $\bar{\chi}^2 = 0.565$ (p-value = 0.000). In sum, as in the case of Italy, there is a tendency of self-reported civic opinions to be misreported

[8]This is true for any of the OP, OPM and IV-OPM models.
[9]See Appendix A for details on the test.
[10]Note that the IV-OPM is only accepted as the correct model at a p-value of 8.7%.

TABLE 5.1

Parametric estimates for civic opinions (UK)

	General interest in politics			Attention to politics		
Variables	OP	OPM	IV-OPM	OP	OPM	IV-OPM
Education	0.1833**	0.3289**	0.6272**	0.148**	0.2416**	0.6074**
	(0.0168)	(0.0867)	(0.1947)	(0.014)	(0.0509)	(0.182)
Age	0.0287**	0.0485**	0.0618**	0.0297**	0.0413**	0.065**
	(0.0068)	(0.0173)	(0.0163)	(0.0061)	(0.0128)	(0.0201)
$Age^2/100$	-0.0136**	-0.0221*	-0.0276**	-0.0135**	-0.0147	-0.0234
	(0.0065)	(0.0131)	(0.0113)	(0.0057)	(0.0112)	(0.0169)
Employed	0.0157	0.0193	0.0266	-0.1143**	-0.1493**	-0.1825**
	(0.051)	(0.0826)	(0.0678)	(0.0455)	(0.0689)	(0.0786)
Income	0.0387**	0.0622**	0.0067	0.0285**	0.0424**	0.0084
	(0.0085)	(0.0214)	(0.0229)	(0.0072)	(0.0149)	(0.0228)
Male	0.4**	0.6292**	0.552**	0.4405**	0.6673**	0.8039**
	(0.0446)	(0.1737)	(0.0882)	(0.0385)	(0.1136)	(0.1417)
Married	0.0785*	0.0605	0.093	-0.0253	-0.0601	-0.0689
	(0.0455)	(0.0766)	(0.0704)	(0.0398)	(0.0716)	(0.0872)
Number of children	-0.049**	-0.0608*	-0.0388	-0.0507**	-0.0516	-0.0406
	(0.0231)	(0.0323)	(0.0288)	(0.021)	(0.032)	(0.0357)
Socialclass2	-0.0837	-0.1647	-0.0581	-0.0796	-0.1283	-0.0534
	(0.0576)	(0.1048)	(0.0933)	(0.05)	(0.0849)	(0.1027)
Socialclass3	-0.1858*	-0.2525	-0.028	-0.1394	-0.2301	-0.1032
	(0.0998)	(0.2148)	(0.1885)	(0.0873)	(0.1802)	(0.2293)
Socialclass4	-0.1113	-0.2203	0.0713	-0.0717	-0.0844	0.129
	(0.0797)	(0.135)	(0.1498)	(0.069)	(0.106)	(0.1645)
Socialclass5	-0.2988**	-0.4795**	-0.1295	-0.2295**	-0.3622**	-0.1488
	(0.0576)	(0.1693)	(0.1344)	(0.0515)	(0.0947)	(0.1784)
Wales	-0.1732**	-0.2742**	-0.2671**	-0.0573	-0.0844	-0.1521*
	(0.0534)	(0.1059)	(0.0717)	(0.0474)	(0.0718)	(0.0852)
Scotland	-0.0911*	-0.1523*	-0.0996	-0.0035	-0.0065	-0.0087
	(0.0486)	(0.0826)	(0.0634)	(0.0427)	(0.0691)	(0.0862)
$\hat{c}_1$	-0.0459	0.056	1.6033	0.8602**	1.5121**	3.1319**
	(0.1906)	(0.7494)	(1.3024)	(0.1706)	(0.3926)	(0.9193)
$\hat{c}_2$	1.2047**	2.2722**	3.3586**	2.5394**	3.1647**	4.7479**
	(0.1911)	(0.8433)	(0.951)	(0.1736)	(0.6545)	(1.0643)
$\hat{\pi}_{1,2}$		0.0677	0.0572		0.0752*	0.0484**
		(0.0459)	(0.0488)		(0.0412)	(0.0085)
$\hat{\pi}_{1,3}$		0.041	0.0788**		0.022	0.0217
		(0.0476)	(0.0394)		(0.0245)	(0.0216)
$\hat{\pi}_{2,1}$		0.1264**	0.1286**		0.0537	0.1078**
		(0.0302)	(0.0452)		(0.0646)	(0.0275)
$\hat{\pi}_{2,3}$		0.1401	0.0551		0.0433	0.0471
		(0.1345)	(0.0477)		(0.0467)	(0.0416)
$\hat{\pi}_{3,1}$		0	0.0002		0.0696**	0.1006**
		(0)	(0.0006)		(0.03)	(0.0021)
$\hat{\pi}_{3,2}$		0.091**	0.096**		0.3242**	0.4271**
		(0.0235)	(0.0286)		(0.0987)	(0.0645)
Log-likelihood	-2865.5	-2852.84	-2908.78	-3850.89	-3833.42	-3887.91
$\bar{\chi}^2$ (P-value)		0.565 (0.000)	0.116 (0.148)		1.686 (0.026)	1.003 (0.010)
$\chi^2(1)$ (P-value)			2.928 (0.087)			4.382 (0.036)

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	Discuss politics			Active in a voluntary organisation		
Variables	OP	OPM	IV-OPM	OP	OPM	IV-OPM
Education	0.1586**	0.3615**	0.4832**	0.1298**	0.2201**	0.5318**
	(0.0139)	(0.1171)	(0.227)	(0.0143)	(0.0487)	(0.1562)
Age	0.0141**	0.0365*	0.0746**	0.0352**	0.056**	0.0749**
	(0.0061)	(0.0219)	(0.0372)	(0.0064)	(0.0144)	(0.0185)
$Age^2/100$	-0.0128**	-0.0369	-0.0742**	-0.0322**	-0.0512**	-0.0604**
	(0.0057)	(0.0231)	(0.0374)	(0.006)	(0.0129)	(0.0153)
Employed	-0.04	-0.0836	-0.17	-0.1176**	-0.1802**	-0.1668*
	(0.0453)	(0.126)	(0.1485)	(0.0472)	(0.0914)	(0.0927)
Income	0.0445**	0.0911**	0.0781**	0.0031	0.0069	-0.0332
	(0.0072)	(0.0243)	(0.0347)	(0.0075)	(0.0134)	(0.0207)
Male	0.1782**	0.4267**	0.3898**	-0.0372	-0.0702	-0.0613
	(0.0383)	(0.1298)	(0.1048)	(0.0399)	(0.0621)	(0.0577)
Married	0.0083	0.0054	-0.0684	0.0806*	0.1209	0.1283
	(0.0397)	(0.0949)	(0.104)	(0.0416)	(0.0774)	(0.0925)
Number of children	-0.056**	-0.1246**	-0.1094**	0.006	0.0154	0.0317
	(0.0208)	(0.0519)	(0.0522)	(0.0217)	(0.0396)	(0.0443)
Socialclass2	-0.0911*	-0.1901	-0.1035	-0.1244**	-0.2152**	-0.0485
	(0.0498)	(0.1424)	(0.1691)	(0.0516)	(0.0965)	(0.1138)
Socialclass3	-0.058	-0.2146	-0.3755	-0.008	-0.0029	0.2679
	(0.0873)	(0.2976)	(0.8206)	(0.0898)	(0.1596)	(0.2273)
Socialclass4	-0.1183*	-0.3282*	-0.4861	-0.3262**	-0.4941**	-0.1517
	(0.0682)	(0.1853)	(0.4088)	(0.0728)	(0.1551)	(0.1738)
Socialclass5	-0.2408**	-0.5838**	-0.5286**	-0.3719**	-0.5941**	-0.237
	(0.0513)	(0.1886)	(0.2661)	(0.0541)	(0.117)	(0.1604)
Wales	0.0077	0.0101	-0.0061	0.0645	0.0742	0.033
	(0.0473)	(0.1353)	(0.1257)	(0.0494)	(0.1089)	(0.0972)
Scotland	-0.0102	-0.0142	0.0259	-0.0491	-0.1195	-0.0864
	(0.0429)	(0.1217)	(0.1217)	(0.0451)	(0.1009)	(0.094)
$\hat{c}_1$	0.5065**	0.723	1.7469	1.0459**	1.6311**	3.0712**
	(0.1698)	(0.6243)	(1.3327)	(0.1765)	(0.4493)	(0.876)
$\hat{c}_2$	1.4039**	3.0066**	3.8727**	1.5275**	2.0709**	3.34**
	(0.1705)	(1.0482)	(1.3989)	(0.177)	(0.469)	(0.9631)
$\hat{\pi}_{1,2}$		0.0796**	0.0943**		0.0634*	0.0724*
		(0.0389)	(0.0227)		(0.0382)	(0.0401)
$\hat{\pi}_{1,3}$		0.1762	0.3566**		0.0752**	0.0351
		(0.1097)	(0.0888)		(0.036)	(0.0448)
$\hat{\pi}_{2,1}$		0.3618**	0.422**		0.1391	0.2156
		(0.1102)	(0.0982)		(0.1487)	(0.1313)
$\hat{\pi}_{2,3}$		0.1493	0.0924		0.2479**	0.1945
		(0.1085)	(0.0682)		(0.1076)	(0.1372)
$\hat{\pi}_{3,1}$		0.0098	0.0252		0.1524**	0.1471*
		(0.0272)	(0.0338)		(0.0685)	(0.0819)
$\hat{\pi}_{3,2}$		0.2121**	0.1986**		0.1598**	0.1927**
		(0.0695)	(0.0939)		(0.0563)	(0.0719)
Log-likelihood	-4345.31	-4327.89	-4385.15	-4062.68	-4054.45	-4087.76
$\bar{\chi}^2$ (P-value)		0.966 (0.027)	0.592 (0.001)		0.032 (0.582)	0.207 (0.194)
$\chi^2(1)$ (P-value)			0.392 (0.531)			4.411 (0.036)

** significant at 5 % and * significant at 10 %.
Standard errors are given in parentheses.
Bootstrapped OPM and IV-OPM, 100 number of repetitions.Log-likelihood is the average over 100 repetitions.

due to SD.

With regards to endogeneity, the null of exogeneity of education is rejected for two indicators (interest and attention to politics) at 10%; exogeneity of education is only accepted for 'discuss politics', with a $\chi^2(1)$ (p-value) = 0.392 (0.531). As the potential endogeneity of education is the main interest, I use a Hausman test only for this parameter.[11] As in other settings, a test on a subset of parameters can lead to a conclusion different from that of a test on all parameters. These results are nevertheless confirmed by additional IV-OP estimations, where the $\chi^2(1)$ statistics and probabilities are for interest in politics 5.34 (0.02), attention to politics 2.42 (0.10), and discuss politics, 0.64 (0.42). In short, unobserved factors (determination, intelligence, etc.) are likely to be driving both education decisions as well as political engagement. I therefore rely on the IV-OPM model to discuss the estimates of the misclassification probabilities and how they fit the misclassification assumptions of Chapter 3.

Estimates of the misclassification probabilities for the indicator 'general interest in politics' (in the IV-OPM model) satisfy the necessary stochastic condition of Eq. (3.10). Although this outcome is (statistically) misreported, the probabilities that individuals indeed reveal their truthful interest in politics are quite high: $\hat{\pi}_{j,j} > 0.81$ ($j = 1, 2, 3$), so that Assumption 3.1 holds.[12] The largest and statistically significant misclassification probabilities are $\hat{\pi}_{2,1}$ and $\hat{\pi}_{3,2}$. This agrees with Assumption 3.3(i) which is based on findings from political science that support over-reporting of civic opinion (Karp and Brockington (2005)). This over-reporting, in turn, leads to a large upper bias of the education's coefficient, increasing from 0.18 in the OP to 0.63 in the IV-OPM. Similar results are obtained for 'attention to politics'. First, misclassification plays a major role in the magnitude of the effect of schooling (i.e., its coefficient raises from 0.15 to 0.61) and, second, Assumption 3.3(i) holds too, with an important misclassification for the top answers ($\hat{\pi}_{3,3} = 0.47$), and $\hat{\pi}_{3,1}$ (=0.10) and $\hat{\pi}_{3,2}$ (=0.42) are statistically different from zero. In other words, individuals who apparently show the highest political engagement ($j = 3$) are more likely to misreport. Finally, estimations for 'discuss politics' also confirm the same results in terms of misreporting (big values for $\hat{\pi}_{j,k}$, for $j > k$) and on the estimated impact of education ($\triangle\hat{\beta}_{\text{ed}}$). Note that, if inference were carried out by calculating marginal effects based upon the OP estimates, it would be very misleading. This highlights the importance of accounting for misreporting.

Estimations for the fourth civic opinion, 'active in a voluntary organisation', are

[11]The Hausman test for the schooling variable is given by: $\mathrm{H} = \frac{(\hat{\beta}_{\text{ed,OPM}} - \hat{\beta}_{\text{ed,IV-OPM}})^2}{\mathrm{se}^2_{(\hat{\beta}_{\text{ed,IV-OPM}})} - \mathrm{se}^2_{(\hat{\beta}_{\text{ed,OPM}})}} \sim \chi^2(1)$.

[12]See estimated $\hat{\Pi}_j$ matrix in Table 5.6.

presented in the last part of Table 5.1. A higher level of participation in civic organisations is vital since it fosters habits of cooperation, solidarity and public-spiritedness (Putnam et al. (1993)). The main result for this civic opinion is that it is not misreported according to the misclassification test, as the $\bar{\chi}^2$ p-values for the OPM and IV-OPM are well above the critical 5%. Reported and true answers to this question, then, tend to agree as the impact of SD is weaker than for previous three civic opinions. Unlike measures of political engagement, factors such guilt and stigma are not likely to be operating. Perhaps this is because participation in civic organisations belongs to a different dimension of social capital (networks) and is more time consuming.

As before, the null of exogeneity of schooling is rejected, so the correct model here is the IV-OP (not shown in Table 5.1). Intuitively, unobservables impact simultaneously on the dependent variable and education, because parents who instil a spirit of cooperation and solidarity to their children, are also likely to to stress them the importance to carry on with further education. As for the other three civic opinions, education is also one of the strongest covariates of being 'active in a voluntary organisation'. The IV-OP coefficient is 0.34 (p-value = 0.00); hence, there is a large positive bias induced by endogeneity since $\hat{\beta}_{\text{ed}}$ of the OP is 0.13. The remaining covariates' results are as expected. The variable being in employment, for instance, is negative related to the indicator, due to the time consuming nature of volunteering activities.

Comparing the results for Italy and the UK thus far, namely the civic opinions set of estimations of Tables 4.1 and 5.1, reveals that the only difference between these two countries, principally consists of the endogeneity of education. Causality of schooling for the different measures of political engagement in the UK are mostly driven by unobservables, but not for 'interest in politics' in Italy, where the null of exogeneity of education is accepted. The transmission of interest in issues within the political sphere occurs in the UK, as suggested by the civic voluntarism model at the family level, but not in the case of Italy. The results are similar since education is a significant determinant and civic opinions are misreported in the two countries. At least for civic opinions, contextual factors of each country seem to be relevant at the micro-level, where endogeneity is often found to be an empirical issue that needs to be controlled for, whereas the impact of SD and misreporting are more related to the nature of the indicators.

Table 5.2 contains the results for civic behaviours. These three indicators for the UK are exactly the same as the ones for Italy: failing to report accidental damage to a parked vehicle (car damage), keeping money that you have found (keeping money), and avoiding a fare on public transport (avoiding fare). To begin with, I briefly mention some explanatory variables estimations.[13] Age and age^2 have similar signs as for civic opinions, with older people more likely to adhere more to social norms than younger people (van Oorschot and Arts (2005)), but at a decreasing rate. For the civic behaviour 'car damage' most covariates become statistically insignificant as a result of accounting for endogeneity and misreporting in the IV-OPM. For instance, income level, gender and social class dummies all change, from being significant in the OP model, to being insignificant in the IV-OPM formulation. Nonetheless, for the indicator 'keeping money', these individual and socioeconomic background variables are still significant in the IV-OPM model, albeit in some cases (e.g., for income) having the wrong sign. For the third civic behaviour 'avoiding fare', on the contrary, the chosen OP model shows an expected positive impact for covariates such as income, social class and marital status. That is, the higher the income or social status of an individual, the less likely it is that he judges avoiding the fare on public transport as acceptable. Marital status is an individual level variable which has an impact on this civic behaviour because it embodies certain personality types, in particular, a disposition to trust when selecting into marriage and/or divorce (Allum et al. (2010)). There is an overall tendency, however, for the effect of socioeconomic background variables to disappear when accounting for misclassification.[14]

Equally to civic opinions, misclassification tests indicates that civic behaviours in the UK also suffer from SDB (King and Bruner (2000)). This tendency for interviewees to lie, under-reporting socially undesirable behaviours, holds for the majority of indicators. That is, the null hypothesis of non-misreporting is rejected for both 'car damage' and 'keeping money' variables ($\bar{\chi}^2$ = 5.142 with p-value = 0.0132, and $\bar{\chi}^2$ = 3.203 with p-value = 0.0378, respectively), and regardless of which version of the OPM model one considers. Only for the third outcome, 'avoiding fare', does the OP outperform the misclassified version of the models ($\bar{\chi}^2$ = 0.161, p-value = 0.530).

As usual, misclassification leads to upward biases in all estimated coefficients as well as an increase in their standard errors. Controlling for the plausible endogeneity of education has an equivalent empirical effect. This is a common outcome when using a two-stage procedure, where there is always a trade-off between consistency and precision. The null of exogeneity of education is rejected for two indicators. More specifically, the civic behaviours which are misclassified according to the $\bar{\chi}^2$ test are also endogenous by the Hausman test. For 'car damage' $\chi^2(1) = 6.407$, with p-value = 0.011; and for 'keeping money', $\chi^2(1) = 14.039$, with p-value = 0.000. Schooling is

[13]According to the misclassification and endogeneity tests, the chosen models (columns) for the estimated covariates' impacts are given by IV-OPM model for 'car damage' and 'keeping money', and by the OP column for 'avoiding fare'.

[14]See OPM columns of Table 5.2.

TABLE 5.2.— Parametric estimates for civic behaviours (UK)

Variables	Car damage OP	Car damage OPM	Car damage IV-OPM	Keeping money OP	Keeping money OPM	Keeping money IV-OPM	Avoiding fare OP	Avoiding fare OPM	Avoiding fare IV-OPM
Education	0.1039**	0.2226	1.708**	0.0473**	0.0429	1.5516**	0.0235	0.049	-0.2204
	(0.0222)	(0.1586)	(0.6079)	(0.021)	(0.0932)	(0.4133)	(0.0202)	(0.0433)	(0.2107)
Age	0.0583**	0.1574	0.1873**	0.0589**	0.1355	0.1895**	0.0336**	0.0384*	0.0406
	(0.0088)	(0.1211)	(0.081)	(0.0087)	(0.0939)	(0.0433)	(0.0082)	(0.0232)	(0.0269)
$Age^2/100$	-0.043**	-0.0997	-0.105*	-0.0412**	-0.0798	-0.1093**	-0.0133	-0.0033	-0.0053
	(0.0092)	(0.0958)	(0.0581)	(0.0091)	(0.0716)	(0.0369)	(0.0086)	(0.0307)	(0.0334)
Employed	-0.0058	0.1573	-0.0008	-0.0554	-0.0704	-0.1197	0.0356	0.0657	0.0766
	(0.0619)	(0.3574)	(0.2871)	(0.061)	(0.2977)	(0.1769)	(0.057)	(0.0968)	(0.1236)
Income	-0.0655**	-0.3278	-0.3208	-0.0472**	-0.1743	-0.2205**	0.0387**	0.0668**	0.0944**
	(0.0134)	(0.3343)	(0.313)	(0.0131)	(0.1579)	(0.0781)	(0.0125)	(0.0237)	(0.041)
Male	-0.1451**	-0.3433	-0.2812	-0.3323**	-0.9877	-0.921**	-0.0761	-0.1592*	-0.2166
	(0.0511)	(0.297)	(0.1907)	(0.0497)	(0.6128)	(0.2563)	(0.0478)	(0.0963)	(0.1497)
Married	0.0732	-0.0345	0.3926	0.103*	0.2282	0.5783**	0.1258**	0.2397**	0.2283
	(0.0602)	(0.4775)	(0.5291)	(0.0585)	(0.3485)	(0.2234)	(0.0554)	(0.1187)	(0.148)
Number of children	-0.0197	-0.0747	0.0306	-0.0327	-0.0992	-0.005	-0.0165	-0.0244	-0.0484
	(0.0204)	(0.1321)	(0.1358)	(0.0201)	(0.111)	(0.0647)	(0.0188)	(0.0324)	(0.0436)
Socialclass1	0.2096**	1.1209	-1.4513	0.0912	0.3777	-2.0354**	0.3444**	0.5769**	1.0904
	(0.0933)	(1.4767)	(1.1163)	(0.0894)	(0.3601)	(0.7087)	(0.0904)	(0.2044)	(0.5015)
Socialclass2	0.167**	0.8007	-0.4676	0.1837**	0.7062	-0.4856	0.0879	0.1318	0.3703
	(0.0736)	(1.1271)	(1.0562)	(0.0727)	(0.5391)	(0.3898)	(0.0674)	(0.1126)	(0.2264)
Socialclass3	0.0726	0.4095	0.0688	0.0312	0.1269	-0.0953	0.0282	0.0456	0.0843
	(0.0681)	(0.4709)	(0.4156)	(0.067)	(0.2113)	(0.2295)	(0.0632)	(0.1176)	(0.1542)
Wales	-0.2259**	-0.5954*	-0.8586*	-0.4492**	-1.2421*	-1.443**	-0.0292	-0.0247	0.0123
	(0.084)	(0.3372)	(0.4778)	(0.0778)	(0.6597)	(0.396)	(0.0817)	(0.1309)	(0.1989)
Scotland	0.0255	0.4452	0.3947	0.091	0.2611	0.2429	-0.0276	0.0175	-0.0217
	(0.0873)	(0.7106)	(0.523)	(0.0873)	(0.3199)	(0.3112)	(0.0776)	(0.17880	(0.2065)
$\hat{c}_1$	-0.4989**	-0.9928	3.8739*	-0.4962**	-0.8292	4.6158**	-0.3179*	0.6612	0.4864
	(0.1948)	(1.2844)	(1.9801)	(0.1893)	(1.2259)	(1.9165)	(0.1809)	(0.7022)	(1.0105)
$\hat{c}_2$	0.393**	1.6768	6.0109**	0.3574*	1.6368	6.1627**	0.7138**	1.6353**	1.5041*
	(0.1941)	(1.2994)	(1.8538)	(0.1889)	(1.0486)	(1.4376)	(0.1806)	(0.4801)	(0.8006)
$\hat{\pi}_{1,2}$		0.1749	0.3239*		0.0866	0.2156		0.1962	0.2169
		(0.1919)	(0.1939)		(0.1182)	(0.1329)		(0.159)	(0.1436)
$\hat{\pi}_{1,3}$		0.1458	0.2653		0.2631	0.3605*		0.3272**	0.4278**
		(0.114)	(0.1894)		(0.2194)	(0.2051)		(0.152)	(0.1592)
$\hat{\pi}_{2,1}$		0.0956	0.0922		0.1346**	0.0931		0.0119	0.014
		(0.0614)	(0.0889)		(0.0408)	(0.0873)		(0.0283)	(0.0327)
$\hat{\pi}_{2,3}$		0.3979**	0.4474**		0.4768**	0.4826**		0.3775**	0.473**
		(0.1974)	(0.1506)		(0.0743)	(0.0713)		(0.0888)	(0.087)
$\hat{\pi}_{3,1}$		0.0153**	0.0129**		0.0078**	0.0079**		0.0027	0.0028
		(0.0049)	(0.0047)		(0.0038)	(0.0031)		(0.0038)	(0.0038)
$\hat{\pi}_{3,2}$		0.0602**	0.0538**		0.0643**	0.0607**		0.0402	0.04
		(0.0156)	(0.0152)		(0.0098)	(0.0093)		(0.0277)	(0.0298)
Log-likelihood	-1821.19	-1798.3	-1790.79	-1987.25	-1971.38	-1960.8	-2111.27	-2099.66	-2099.47
$\bar{\chi}^2$ (P-value)		6.065 (0.008)	5.142 (0.0132)		2.919 (0.045)	3.203 (0.0378)		0.161 (0.530)	0.318 (0.616)
$\chi^2(1)$ (P-value)			6.407 (0.011)			14.039 (0.000)			1.707 (0.191)

See references in Table 5.1.

exogenous only for the variable 'avoiding fare' ($\chi^2(1) = 1.707$, p-value $= 0.191$). One of the possible explanations of endogeneity is due to the unobservable intelligence, which is not controlled for in the civic behaviours' specifications. That is, more intelligent individuals are more accurate in their assessments of the consequences when 'damaging a car' or 'keeping money', but the same group of more intelligent individuals are also more probable to undertake further schooling.

The considerable positive bias induced by endogeneity is what makes schooling the strongest predictor across civic behaviours. While misclassification modifies the original relationship of education with civic behaviours in the OP from statistically significant to insignificant, endogeneity turns the lack of impact of education in the OPM to a meaningful one in the IV-OPM.[15] This is the key difference with estimations for Italy where the null of exogeneity of education is accepted, and $\hat{\beta}_{\text{ed}}$ is statistically equals to zero by their t-tests, in either the OPM or the IV-OPM for the three civic behaviours. Certainly, I believe that the way in which causality of schooling and civic behaviours varies in both Italy and the UK, is the core difference when comparing Chapter 4 and 5's empirical results. I finish this section by discussing the estimated misreporting probabilities below.

The estimated matrix $\hat{\Pi}_3$ for the first two civic behaviours are in line with each other, and follows the misclassification assumptions of Chapter 3. Assumption 3.1 does not hold for either 'car damage' and 'keeping money'. Observed answers taking values 1 and 2 do not contain enough information on true responses, and so individuals are more likely to lie than to tell the truth for $j = 1, 2$. That is, $\hat{\pi}_{1,1} < 0.50$ and $\hat{\pi}_{2,2} < 0.50$, while $\hat{\pi}_{3,3} \approx 0.93$ (see the first two matrices of Table 5.7). Furthermore, Assumption 3.2 (monotonicity of correct report) is valid too. Elements along the diagonal are increasing: $\hat{\pi}_{1,1} < \hat{\pi}_{2,2} < \hat{\pi}_{3,3}$, which means that the misclassification problem is decreasing the more civically behaved individuals are, according to their reported answers. Assumption 3.3(i) is also relevant. The estimated misclassification probabilities below the diagonal of $\hat{\Pi}_3$ are small ($\hat{\pi}_{j,k} < 0.10$), and above the diagonal are rather high ($\hat{\pi}_{j,k} < 0.21$). For both indicators, the largest misclassification probability is $\hat{\pi}_{2,3}$. This means that people whose reported answers show a middle degree of social trust ($j = 2$) are more concerned in presenting themselves in the best socially acceptable terms ($j = 3$) and, consequently, they are the most likely to lie about how they react to this hypothetical situation. Taken as a whole, the results show, equally to the Italian case, that measures of civic behaviours are more likely to suffer from misreporting to a larger extent than indicators on civic engagement.

[15] For the variable 'avoiding fare', schooling is not associated with civic behaviour in any of the OP, OPM or IV-OPM models.

5.3.2. *Additional results related to politics, voting and trust*

This section contains further results for the UK. Four extra indicators related to politics and voting, as well as two concerning social trust are analysed. Namely, whether respondents believe that 'political activity takes too much time and effort', 'family and friends think that voting is a waste of time', 'feel very guilty if not vote', 'neglect my duty as a citizen if not vote', as well as two outcomes concerning trust: whether 'most people can be trusted' and whether they 'trust the local government'. The last two indicators, according to the framework by van Oorschot et al. (2006), add another dimension of social capital to the UK analysis which is not captured by the previous Italian indicators. They are: generalised trust (interpersonal trust, trust in people) and trust in institutions (state institutions such as the health care system, the justice system or the government).

Estimations for the four additional dependent variables associated with politics and voting are presented in Table 5.3. For the first two, I am able to examine whether the lower levels of political engagement in the UK may be explained, by either the time constraint of participation in politics or the lack of belief in politics. Recall that recently there has been a decline in social capital in the UK, also including trust in politics and politicians (Halpern (2009)). Research in the economics field (e.g., Gibson (2001), Dee (2004)) suggest alternative mechanisms by which additional schooling might actually reduce civic engagement. For example, by raising the opportunity cost of an individual's time, increased schooling could reduce the amount of time and attention allocated to civic activities. Education could also reduce voter participation by promoting an awareness of voting as an essentially expressive act with an infinitesimally small probability of influencing actual policy. Similarly to the earlier civic outcomes, misreporting can also have an influence on how these variables are reported, because respondents may be reluctant to reveal that they are too busy to participate in politics or that their votes are worthless.

The indicator 'political activity takes too much time and effort' is not misreported and education is not endogenous by the corresponding statistical tests, and so the OP is then the chosen model. Education has a negative impact on the dependent variable ($\hat{\beta}_{\text{ed}}$ = -0.0572 , p-value = 0.0139), meaning that the more educated an individual is, the less likely he would be to judge the time aspect of political activity as a reason for his lack of participation. This implies that, at least when applied to political activities in the UK, the opportunity cost of time is not higher for more educated individuals.

Schooling is also exogenous for the indicator 'voting is a waste of time', but it is misreported ($\bar{\chi}^2$ = 1.693, p-value = 0.018), so the correct model is the OPM. This

TABLE 5.3

Parametric estimates for outcomes related to politics and voting (UK)

Variables	Political activity takes too much time and effort			Voting is a waste of time		
	OP	OPM	IV-OPM	OP	OPM	IV-OPM
Education	-0.0572**	-0.1122**	-0.2633	-0.1539**	-0.3125**	-0.484
	(0.0139)	(0.0533)	(0.2151)	(0.0161)	(0.0586)	(0.4237)
$\hat{\pi}_{1,2}$		0.0794	0.1453		0.0538**	0.0322
		(0.114)	(0.1492)		(0.0202)	(0.0349)
$\hat{\pi}_{1,3}$		0.1301	0.158		0.0816**	0.0714*
		(0.1166)	(0.1185)		(0.0174)	(0.0407)
$\hat{\pi}_{2,1}$		0.119	0.1948**		0.1979**	0.1976**
		(0.095)	(0.0297)		(0.0201)	(0.0203)
$\hat{\pi}_{2,3}$		0.2068	0.1507		0.0861	0.0924
		(0.1366)	(0.2035)		(0.1617)	(0.1704)
$\hat{\pi}_{3,1}$		0.1453*	0.1784**		0.1792**	0.1921**
		(0.0812)	(0.0606)		(0.0556)	(0.0381)
$\hat{\pi}_{3,2}$		0.1437*	0.0748		0.0418	0.0367
		(0.0835)	(0.091)		(0.0698)	(0.0663)
Log-likelihood	-4470.92	-4457.77	-4463.71	-3359.04	-3350.94	-3397.97
$\bar{\chi}^2$ (P-value)		0.015 (0.935)	0.163 (0.220)		1.693 (0.018)	0.396 (0.044)
$\chi^2(1)$ (P-value)			0.526 (0.468)			0.167 (0.683)
	Feel very guilty if not vote			Neglect my duty as a citizen if not vote		
Variables	OP	OPM	IV-OPM	OP	OPM	IV-OPM
Education	0.104**	0.2028**	0.2829	0.1069**	0.1868**	0.6025**
	(0.0156)	(0.0554)	(0.2786)	(0.0166)	(0.0459)	(0.2241)
$\hat{\pi}_{1,2}$		0.141**	0.1283*		0.2352**	0.2456**
		(0.0701)	(0.078)		(0.1147)	(0.048)
$\hat{\pi}_{1,3}$		0.0051	0.0657		0.0537	0.2108*
		(0.0286)	(0.1107)		(0.1083)	(0.1194)
$\hat{\pi}_{2,1}$		0.1485	0.1324		0.1907	0.1479
		(0.1853)	(0.1765)		(0.2288)	(0.1429)
$\hat{\pi}_{2,3}$		0.2924*	0.3577**		0.1666**	0.2476**
		(0.176)	(0.1166)		(0.0693)	(0.109)
$\hat{\pi}_{3,1}$		0.0932**	0.0923**		0.0446**	0.0447**
		(0.0144)	(0.02)		(0.0137)	(0.0148)
$\hat{\pi}_{3,2}$		0.0517**	0.0485**		0.0335**	0.0346**
		(0.0122)	(0.0164)		(0.0127)	(0.0116)
Log-likelihood	-3433.76	-3404.07	-3432.76	-2986.71	-2964.54	-2984.91
$\bar{\chi}^2$ (P-value)		4.148 (0.000)	2.922 (0.000)		5.091 (0.002)	2.804 (0.004)
$\chi^2(1)$ (P-value)			0.086 (0.769)			3.591 (0.058)

See references in Table 5.1.

variable might suffer from misreporting as one may feel embarrassed to judge politics as ineffective and appear as an egoistic and self-interested voter. Measures of political engagement are also misreported due to similar reasons, which is why the estimated misclassification probabilities follow Assumption 3.3(i) for civic opinions.[16] Note that the education coefficient is negative and statistically significant; voting is not considered a waste of time for more educated people. The negative link of schooling with the two indicators challenges the alternative mechanisms proposed by some studies in the economics field. Time constraint is not an issue for more educated individuals, who also do not consider the voting process futile.

The variables 'feel very guilty if not vote' and 'neglect my duty as a citizen if not vote' are linked to over-reporting of voting behaviour found in the literature (Karp and Brockington (2005)). There are diverse hypotheses for over-reporting. Alternatively, theories place emphasis on either feelings of guilt (Bernstein et al. (2001)), a desire to look good before the interviewer, or see over-reporting as an expression of satisfaction with the status quo (Silver et al. (1986)) The indicators allow me to investigate the extent in which feelings of guilt and duty in the participation of the political process, might vary by schooling levels.

As can be seen in the second part of Table 5.3, these feelings vary by schooling levels. The coefficient $\hat{\beta}_{\text{ed}}$ is statistically significant and positive for both outcomes, which are misreported by the $\bar{\chi}^2$ test. More educated persons are more likely to have stronger feelings of guilt, or believe that they are neglecting their duty as citizens, if they do not vote. This positive association between education and the indicators, validates the hypotheses of over-reporting and therefore supports Assumption 3.4(i). In short, more educated individuals would tend to misreport civic opinions as they are under the most pressure from these factors.

Table 5.4 contains estimations for the two aspects of the trust dimension of social capital: generalised trust (interpersonal trust, trust in people) and trust in institutions (state institutions such as the health care system, the justice system or the government). For the first indicator, 'trust people', I am able to replicate the positive impact of education on generalised trust found in the literature. For the UK, Sturgis and Smith (2010), for instance, also find a significant and direct effect of having a degree on generalised and particularised (i.e., in the neighborhood, in the local area) forms of trust. As stated by Allum et al. (2010), education is without doubt the most consistent as well as the strongest predictor of generalised trust. Indeed, this is reflected by the estimations of the first three columns of the table, where education is still significant whether or not I control for misreporting and endogeneity. By the

[16] That is, $\hat{\pi}_{j,k}$ are small on the upper part of $\hat{\Pi}_J (j < k)$.

TABLE 5.4

Parametric estimates for outcomes related to trust (UK)

Variables	Trust people			Trust local government		
	OP	OPM	IV-OPM	OP	OPM	IV-OPM
Education	0.1008**	0.3791**	0.3049*	0.026*	0.0444**	-0.4613
	(0.0142)	(0.1606)	(0.1629)	(0.0149)	(0.0138)	(0.3768)
$\hat{\pi}_{1,2}$		0.2735	0.0841**		0.1999**	0.4354**
		(0.2296)	(0.0359)		(0.0000)	(0.1545)
$\hat{\pi}_{1,3}$		0.1999	0.076*		0.0999**	0.2208**
		(0.2021)	(0.0398)		(0.0001)	(0.0977)
$\hat{\pi}_{2,1}$		0.1609**	0.1402**		0.0026	0.1007**
		(0.0749)	(0.0617)		(0.0072)	(0.0466)
$\hat{\pi}_{2,3}$		0.0627	0.0803**		0.061**	0
		(0.0748)	(0.0361)		(0.0030)	(0.0001)
$\hat{\pi}_{3,1}$		0.0353*	0.0129		0.2973**	0.2071
		(0.0181)	(0.0227)		(0.0100)	(0.2354)
$\hat{\pi}_{3,2}$		0.4834**	0.3805**		0.3999**	0.3901**
		(0.0393)	(0.0704)		(0.0000)	(0.1983)
Log-likelihood	-3605.18	-3586.59	-3617.43	-3022.25	-2998.65	-2977.53
$\bar{\chi}^2$ (P-value)		1.542 (0.098)	1.251 (0.045)		0.154 (0.033)	0.337 (0.030)
$\chi^2(1)$ (P-value)			7.399 (0.007)			1.720 (0.190)

See references in Table 5.1.

$\bar{\chi}^2$ and Hausman tests, the chosen model is the IV-OPM. Thus, this self-reported data on generalised trust for the UK is, as the majority of the earlier indicators, subject to SD and misreported. Unobservable traits, too, are driving the reported answers of this variable. These unobservables could be either specific to the individuals (e.g., intelligence) and the families or communities in which they were raised.[17] The second aspect of the trust dimension, trust in institutions, is directly affected by education as well. Yet the magnitude of the impact, as expected, is much smaller ($0.04 < 0.31$), and the null of exogeneity of education is accepted ($\chi^2(1) = 1.720$, p-value $= 0.190$). As interpersonal trust, the variable 'trust local government' is misclassified. In summary, SD affects both types of trust, but unobservables only affect interpersonal trust.

5.3.3. *Sensitivity analysis for civic behaviours*

In this section, I examine if the recoding of civic behaviours into three categories affects the main conclusions drawn from the estimates of Table 5.2. Recall that these results were obtained by changing a 1 to 10 scale to a 1 to 3 scale, and by grouping and recoding 1 to 3 (=1), 4 to 7 (=2) and 8 to 10 (=3). To provide further support to the civic behaviours estimations, I also carry out the same analysis using a five point scale, with observations recoded as follows: (1,2)=1, (3,4)=2,..., (9,10)=5.

Estimations for $J = 5$, using a full misclassification matrix Π_5, are displayed in

[17] The different levels at which unobservables operate could be explained by the socialisation process at an early stage of the life-course, which creates family social capital (e.g., Coleman (1988)); and, moreover, there is new evidence suggesting that trust may also have a genetic basis (Hatemi et al. (2009)).

TABLE 5.5

SENSITIVITY ANALYSIS FOR CIVIC BEHAVIOURS (UK): Π_5

	Car damage		Keeping money		Avoiding fare	
Variables	OP	OPM	OP	OPM	OP	OPM
Education	0.0982**	0.3723	0.0481**	0.0674	0.0092	0.0107
	(0.0195)	(0.3987)	(0.0188)	(0.0517)	(0.0179)	(0.0311)
$\hat{\pi}_{1,2}$		0.0509		0.0875**		0.0187
		(0.0491)		(0.0299)		(0.039)
$\hat{\pi}_{1,3}$		0.0752*		0.0712*		0.0218
		(0.0426)		(0.0409)		(0.0412)
$\hat{\pi}_{1,4}$		0.0654		0.0659		0.063
		(0.0468)		(0.0425)		(0.0477)
$\hat{\pi}_{1,5}$		0.0405		0.0421		0.0708
		(0.0488)		(0.0446)		(0.0447)
$\hat{\pi}_{2,1}$		0.077		0.1191		0.0613
		(0.0916)		(0.1159)		(0.072)
$\hat{\pi}_{2,3}$		0.1601		0.0975		0.0674
		(0.1386)		(0.1079)		(0.094)
$\hat{\pi}_{2,4}$		0.3362**		0.1857		0.2556**
		(0.1463)		(0.1421)		(0.0882)
$\hat{\pi}_{2,5}$		0.1767		0.2115		0.2847**
		(0.1916)		(0.1639)		(0.0554)
$\hat{\pi}_{3,1}$		0.036		0.1861**		0.0095
		(0.0298)		(0.0635)		(0.0377)
$\hat{\pi}_{3,2}$		0.0449		0.0445		0.0158
		(0.0489)		(0.0332)		(0.0532)
$\hat{\pi}_{3,4}$		0.0862		0.1601**		0.254**
		(0.0789)		(0.0742)		(0.0914)
$\hat{\pi}_{3,5}$		0.4811**		0.3244**		0.2995**
		(0.0538)		(0.0993)		(0.0042)
$\hat{\pi}_{4,1}$		0.0179		0.0149		0.0404
		(0.0261)		(0.0123)		(0.0749)
$\hat{\pi}_{4,2}$		0.0614		0.0935**		0.0058
		(0.0554)		(0.0254)		(0.0329)
$\hat{\pi}_{4,3}$		0.0795		0.1897**		0.2017
		(0.0768)		(0.0427)		(0.1263)
$\hat{\pi}_{4,5}$		0.4898**		0.4832**		0.2999**
		(0.0599)		(0.0371)		(0.0000)
$\hat{\pi}_{5,1}$		0.0056**		0.0039**		0.0012
		(0.002)		(0.0017)		(0.0022)
$\hat{\pi}_{5,2}$		0.0107**		0.0052**		0.0021
		(0.0032)		(0.0023)		(0.0025)
$\hat{\pi}_{5,3}$		0.0564**		0.0445**		0.0085
		(0.0086)		(0.0055)		(0.0147)
$\hat{\pi}_{5,4}$		0.063**		0.0772**		0.0551**
		(0.019)		(0.0067)		(0.0228)
Log-likelihood	-2836.16	-2803.49	-3025.66	-3001.49	-3289.68	-3276.13
$\bar{\chi}^2$ (P-value)		6.416 (0.021)		5.605 (0.032)		1.018 (0.417)

The 1 to 10 scale is changed to a 1 to 5 scale, with (1,2)=1, (3,4)=2,..., (9,10)=5, and Π_5.
** significant at 5 % and * significant at 10 %.
Standard errors are given in parentheses.
Bootstrapped OPM, 100 number of repetitions. Log-likelihood is the average over 100 repetitions.

Table 5.5. Only the OP and OPM models are included, since the central aim of this exercise is to check whether the recoding into a J=3 scale qualitatively influences the estimated education coefficient as well as the outcome of the misclassification test. The results confirm the previous estimations. On the one hand, for the same two civic behaviours ('car damage' and 'keeping money') the OPM outperforms the OP (both $\bar{\chi}^2$ p-values are less than 5%). This is explained by SDB, with respondents providing biased answers so as to gain social approval. On the other hand, the OPM's estimated impact of education is not significant for any of the three civic behaviours. Misclassification increases the standard errors relatively more than $\hat{\beta}_{\text{ed,OPM}}$, which renders the relationship of education to be non-statistically significant.

The misreporting patterns of 'car damage' and 'keeping money' given by the misclassification probabilities matrices $\hat{\Pi}_5$ are qualitatively similar to the ones from $\hat{\Pi}_3$. The probability of telling the truth is less than a half for answers taking values j = 2, 3, 4, so that Assumption 3.1 fails for J = 5 too. Although the monotonicity of correct report assumption fails, Assumption 3.3(i) remains valid for the two outcomes. That is, $\hat{\pi}_{j,k}$ are small on the lower part of $\hat{\Pi}_J(j > k)$. The largest misreporting probabilities are in the last column of matrix $\hat{\Pi}_5$, so that individuals mainly lie by reporting answers at the top the civic behaviour scale. In summary, misreporting behaviours are not affected by the J = 3 recoding.

5.3.4. *Parametric estimations for civic outcomes by education level*

I now briefly investigate how the earlier whole sample misclassification results are explained by educational levels. When comparing the estimated misclassification probabilities of Tables 5.1 and 5.2, it can be seen that the probabilities of correct report are much lower for civic behaviours than for civic opinions. That is, whereas Assumption 3.1 does not hold for either 'car damage' and 'keeping money', it does hold for 'general interest in politics', 'attention to politics', and 'discuss politics'. Can this higher misreporting of civic behaviours be explained by a significant misreporting from the group of less (or more) educated individuals? Additionally, do only more educated people over-report civic opinions because, for example, they are more influenced by factors such as stigma, feelings of guilt or are more concerned with their class interests? This section offers answers to these questions for the UK data. The main hypothesis I rely on is contained in Assumption 3.4. I estimate OPM models for two sub-samples: low education (left full-time education at 15 or younger), and medium/high education level (left full-time education at 16 or older). Results for these two sub-samples are shown in Tables 5.6 and 5.7.

To begin with, consider the civic opinions estimates of Table 5.6. Unlike the three measures of political engagement, the outcome 'active in a voluntary orga-

TABLE 5.6

PARAMETRIC ESTIMATES FOR CIVIC OPINIONS BY EDUCATION LEVEL (UK): Π_3

General interest in politics			Attention to politics		
a) Whole sample (N = 4161)					
0.864	0.0572	0.0788**	0.9299	0.0484**	0.0217
0.1268**	0.8163	0.0551	0.1078**	0.8451	0.0471
0.0002	0.096**	0.9038	0.1006**	0.4271**	0.4723
$\bar{\chi}^2$ (P-value): 0.116 (0.148)			$\bar{\chi}^2$ (P-value): 1.003 (0.010)		
b) Left full-time education at 15 or younger (N = 1399)					
0.9026	0.0516	0.0458	0.8783	0.0929**	0.0288
0.0229	0.8188	0.1583**	0.024	0.8319	0.1441**
0.0149	0.0627	0.9224	0.2255*	0.1905	0.584
$\bar{\chi}^2$ (P-value): 0.378 (0.451)			$\bar{\chi}^2$ (P-value): 0.669 (0.151)		
c) Left full-time education at 16 or older (N = 2762)					
0.8302	0.0819**	0.0879**	0.8785	0.0889**	0.0326
0.2001**	0.7346	0.0653	0.2153**	0.7062	0.0785*
0.0008	0.1089**	0.8903	0.061**	0.4579**	0.4811
$\bar{\chi}^2$ (P-value): 0.278 (0.004)			$\bar{\chi}^2$ (P-value): 0.801 (0.054)		
Discuss politics			Active in voluntary organisation		
a) Whole sample (N = 4161)					
0.7442	0.0796**	0.1762	0.8925	0.0724*	0.0351
0.3618**	0.4889	0.1493	0.2156	0.5899	0.1945
0.0098	0.2121**	0.7781	0.1471*	0.1927**	0.6602
$\bar{\chi}^2$ (P-value): 0.966 (0.027)			$\bar{\chi}^2$ (P-value): 0.207 (0.194)		
b) Left full-time education at 15 or younger (N = 1399)					
0.9425	0.0304	0.0271	0.9299	0.0431	0.027
0.4666**	0.3338	0.1996**	0.1528	0.7873	0.0599
0.0903	0.2056*	0.7041	0.2462**	0.2805**	0.4733
$\bar{\chi}^2$ (P-value): 0.275 (0.052)			$\bar{\chi}^2$ (P-value): 0.158 (0.126)		
c) Left full-time education at 16 or older (N = 2762)					
0.6059	0.241**	0.1531**	0.8677	0.0564	0.0759*
0.3069**	0.3693	0.3238**	0.17	0.7588	0.0712
0.1169**	0.2576**	0.6255	0.2393	0.0441	0.7166
$\bar{\chi}^2$ (P-value): 0.237 (0.092)			$\bar{\chi}^2$ (P-value): 0.164 (0.265)		

Bootstrapped OPM estimates, 100 number of repetitions.
Whole sample estimates are from Table 5.1.
Sub-samples results control for the same covariates of Table 5.1 apart from education.
Diagonal elements of $\hat{\Pi}_3$ are 1 minus the sum of $\hat{\pi}_{j,k}$ across rows.
** significant at 5 % and * significant at 10 %.

TABLE 5.7

PARAMETRIC ESTIMATES FOR CIVIC BEHAVIOURS BY EDUCATION LEVEL (UK): Π_3

Car damage			Keeping money			Avoiding fare		
a) Whole sample (N = 3651)								
0.4108	0.3239*	0.2653	0.4239	0.2156	0.3605*	0.4766	0.1962	0.3272**
0.0922	0.4604	0.4474**	0.0931	0.4243	0.4826**	0.0119	0.6106	0.3775**
0.0129**	0.0538**	0.9333	0.0079**	0.0607**	0.9314	0.0027	0.0402	0.9571
$\bar{\chi}^2$ (P-value): 5.142 (0.0132)			$\bar{\chi}^2$ (P-value): 3.203 (0.0378)			$\bar{\chi}^2$ (P-value): 0.161 (0.530)		
b) Left full-time education at 15 or younger (N = 2240)								
0.5108	0.133	0.3562**	0.3013	0.2988**	0.3999**	0.6605	0.1009	0.2386**
0.0345	0.6133	0.3522**	0.0998**	0.5247	0.3755**	0.0508	0.6233	0.3259**
0.0228**	0.0665**	0.9107	0.0136**	0.0534**	0.933	0.0106	0.0728**	0.9166
$\bar{\chi}^2$ (P-value): 1.763 (0.059)			$\bar{\chi}^2$ (P-value): 1.035 (0.108)			$\bar{\chi}^2$ (P-value): 0.055 (0.803)		
c) Left full-time education at 16 or older (N = 1411)								
0.6416	0.1866	0.1718	0.4717	0.2007**	0.3276**	0.6769	0.0992	0.2239
0.0924	0.5144	0.3932**	0.0833**	0.614	0.3027**	0.001	0.6213	0.3777**
0.0133**	0.0424**	0.9443	0.0007	0.0595**	0.9398	0.0028	0.0363	0.9609
$\bar{\chi}^2$ (P-value): 3.597 (0.036)			$\bar{\chi}^2$ (P-value): 0.984 (0.013)			$\bar{\chi}^2$ (P-value): 0.219 (0.457)		

See references in Table 5.6.

nization' is not misreported for the whole sample. Futhermore, as expected, it is neither misreported by the lower educated nor the higher educated groups of individuals (both $\bar{\chi}^2$ statistics p-values $\geq$ 12.6%). On the contrary, the other civic opinions are misclassified for at least one of these groups. Consider, for example, the indicator 'general interest in politics', which is not statistically misreported for the whole sample ($\bar{\chi}^2 \approx 0.15$). This lack of misreporting is driven by the group of lower educated individuals ($\bar{\chi}^2 = 0.378$, p-value = 0.451), as factors such as stigma, feelings of guilt or class interests (e.g., Bernstein et al. (2001)) are indeed operating for the higher educated group of individuals ($\bar{\chi}^2 = 0.278$, p-value = 0.004), which make them over-report their interest in political issues. These factors are also influencing the higher educated group when answering the question on whether they 'pay attention to politics' (for p-values < 0.054), but have no influence on the less educated group of people, for whom the variable 'pay attention to politics' is not statistically misclassified ($\bar{\chi}^2$ p-value = 0.151). The two indicators' misclassification patterns follow Assumption 3.4(i). Only the outcome 'discuss politics' is misclassified in spite of the education level considered (both $\bar{\chi}^2$ statistics are less then 5%). In general, misreporting for civic opinions are attributable to individuals with higher levels of schooling.

Table 5.7 replicates the same analysis for civic behaviours. Apart from 'avoiding fare', which is not misreported by either education level (or in the whole sample), results for the other two civic behaviours suggest that there is fairly strong evidence to conclude that civic behaviours are misreported despite the schooling attainment considered.[18] Misreporting is equally likely to hold for different education levels and, therefore, the misclassification probabilities agree with the hypothesis outlined in Assumption 3.4(ii). The main argument I believe may explain this result, is drawn from empirical research in social psychology which tends to find a strong effect of descriptive social norms (see, e.g., Cialdini et al. (2006)). Elements above the diagonal of $\hat{\Pi}_3$ are the highest, particularly the significant (by their t-values) elements $\hat{\pi}_{1,3}$ and $\hat{\pi}_{2,3}$ (≥ 0.35). In other words, Assumption 3.2 is still valid for either less or more educated individuals. Taken as a whole, estimations indicate homogenous misreporting patterns across the whole sample and schooling levels for the majority of civic behaviours. This result for the UK is in line with the lower and higher educated sub-samples of individuals for the Italian case.

5.4. CONCLUSIONS

In this Chapter, I investigated how misreporting impacts on the causality of schooling on various measures of social capital in the UK. Social desirability bias (SDB) may produce systematic unreliable responses by interviewees and therefore an invalid relationship between education and social capital. As in the previous Chapter, I rely on results from parametric discrete choice models which account for misclassification (OPM) and also for the probable endogeneity of schooling (IV-OPM). An issue also studied in this Chapter was to discern whether the misclassification bias was mainly explained by the sub-group defined of lower or higher educated individuals. Besides, by comparing the analysis of Chapter 4 for Italy and the current Chapter 5 for the UK, I am able to provide a cross-national perspective on whether the relationship of education to civic outcomes might vary, when accounting for issues of endogeneity and misreporting. Because there is mixed evidence on how social capital is distributed across Europe, it is then important to know whether unobservables behind education choices and social desirability (SD) are local to social structures or are country specific.

In line with previous studies that use other types of self-reported dependent variables, the analysis in this Chapter shows that most civic outcomes are misclassified and, consequently, misreporting is an important empirical issue for the UK too. On the one hand, the three different measures of political engagement are over-reported; specifically, individuals who apparently show the highest political engagement are more likely to misreport due to factors such as stigma and feelings of guilt. This

[18] Only for the sub-sample of lower schooling for the variable 'keeping money', $\bar{\chi}^2$ p-value is ≈ 0.11.

over-reporting, in turn, plays a major role in the magnitude of the estimated effect of schooling. The fourth civic opinion, 'active in a voluntary organisation', is not misreported according to the misclassification test, because unlike measures of political engagement, the impact of SD is not as strong. The group of civic behaviours, on the other hand, suffer from misreporting to a larger extent than indicators on civic engagement. The extent of misclassification is such that, for certain values, individuals are more likely to lie than to tell the truth. Also, the assumption of monotonicity of correct report holds, which means that the problem is decreasing, the more civically behaved individuals are, according to their reported answers.

With regards to the additional indicators related to politics and voting, the negative link of schooling with the first two indicators 'political activity takes too much time and effort' and 'voting is a waste of time', challenges the alternative mechanisms proposed by some studies in the economics field. This implies that, at least when applied to political activities in the UK, the opportunity cost of time is not higher for more educated individuals, who also do not consider the voting process futile. In fact, estimations suggest that the more educated an individual is, the less likely he would judge the time aspect of political activity as a reason for his lack of participation and also the less likely he would consider voting a waste of time. The other indicators 'feel very guilty if not vote' and 'neglect my duty as a citizen if not vote' allow me to investigate the extent to which, feelings of guilt and duty in the participation of the political process, vary by educational levels. Indeed, these feelings vary by schooling levels as, even after controlling for misclassification, the coefficient of education is statistically significant and positive for both outcomes. This offers a direct and additional support to the hypothesis of SD driving misclassification of civic outcomes. Moreover, self-reported data on generalised trust (trust people) and trust in institutions (trust local government) are, as the majority of the earlier indicators, subject to SD and misreported. Unobservable traits are driving reported answers only for the measure of interpersonal trust, 'trust people'. Education has a positive and significant effect on both types of trust, with a lower magnitude for the impact on trust in institutions.

A common empirical issue across the array of civic outcomes is endogeneity since the null hypothesis of exogeneity of education is rejected for most indicators. The direction of the bias introduced by endogeneity follows the same direction as the one introduced by endogeneity, with upward biases in both cases. In other words, unobserved factors which lead individuals to develop a taste for education, are also positively correlated with civic opinions and civic behaviours. In fact, results appear to suggest that the extent of this correlation is such, that the impact of education on civic behaviours becomes statistically significant when accounting for endogeneity. This is the main difference with the Italian case: schooling has significant positive effects on all civic outcomes in the UK. Chapter 5's main finding is that educational achievement emerges as a strong predictor across different dimensions of social capital.

Additionally, estimations by educational levels show significant misreporting of civic behaviours regardless of the schooling level considered, but, for civic opinions, misreporting only holds for the group of more educated individuals. This lack of misreporting, principally for measures of political engagement, is driven by the group of lower educated individuals. Factors such as stigma, feelings of guilt or class interests only operate within the higher educated group of individuals, which cause the group to over-report their interest in political issues. Estimations for civic behaviours, however, indicate homogenous misreporting patterns across the whole sample and schooling levels. This result for the UK, as well as the one from civic opinions, are in line with the the lower and higher educated sub-samples of individuals for the Italian case.

The core difference, when comparing Chapter 4 and 5's empirical results, is how causality of schooling and civic behaviours varies in Italy and the UK. As far as civic opinions are concerned, the only difference between these two countries, principally consists of the endogeneity of education. Causality of schooling for the different measures of political engagement in the UK is mostly driven by unobservables, but not for 'interest in politics' in Italy, where the null of exogeneity of education is accepted. As suggested by the civic voluntarism model, the transmission of interest in politics in the UK occurs at the family level, but this is not the case in Italy.

Chapter 6

A hurdle ordered probit with misclassification

6.1. Introduction

A large body of social science research shows that sensitive questions are misreported in surveys. A question could be regarded as sensitive because respondents perceive it as intrusive, believing that by giving a truthful answer they may disclose important information triggering potential repercussions (Tourangeau and Yan (2007)). In this Chapter, however, the focus is mainly on questions that triggers social desirability concerns, which naturally arises when respondents are asked questions on social behaviours and illegal activities. Because respondents are apparently reluctant to admit to an interviewer that they lack civic awareness or have engaged in illegal activity, they would tend to choose answers which are viewed as more socially acceptable. This tendency to present themselves in the most favourable manner relative to prevailing social norms is known as social desirability (SD) or social desirability bias (SDB) (see, e.g., King and Bruner (2000) and Tourangeau et al. (2001)). Typically, individuals would tend to under-report socially undesirable behaviours and over-report socially desirable ones (Paulhus (1991)).

A systematic misreporting would result in a large amount of observations at one end of the outcome variable distribution. Standard parametric procedures, such as the ordered probit (OP), are commonly used to analyse ordered categorical dependent variables but are unable to explain the prevalence of answers taking certain values. Because they ignore the issue of SD and misreporting, this leads to inconsistent estimates for the parameters of interest (Ramalho (2002)).[1] This could obscure crucial causal links and yields ambiguous relationships.

In Chapter 6, I propose an alternative framework to deal with a skewed and misclassified distribution of observed answers. The model can be applied to questions on sensitive issues whose answers are given into an ordered 1 to J scale. The model is particularly appropriate for discrete and ordered scales where $J = 10$, as in the case of most civic behaviours, or for data on satisfaction or happiness, where generally $J = 7$. The main assumption of the model is that individuals approach the question as a two step process. Firstly, they decide whether they belong to either the low

[1] For a misclassification review, see Section 3.2.

or high group as measured by reporting their answers below or above the median of the 1 to J scale, respectively. This is in line with the two-part model assumption found in the literature as well as sequential models based on conditional probabilities. Secondly, answers in the top half (where most observations are located) are subject to misclassification.

These two assumptions characterise a hurdle and binary ordered probit with misclassification (HOPM and BOPM, respectively), which depends on whether or not one allows for the correlation of the latent equations as defined by the two-part hypothesis. Ignoring misclassification defines their non-misclassified versions of the former models: a hurdle ordered probit (HOP) and binary ordered probit (BOP).

I carry out extensive Monte Carlo simulations under different true models or data generation processes (d.g.p.) to evaluate the models in terms of biases, precision of estimates, and marginal effects (MEs). Various tests and information criteria are used to compare the performance of the different models. I then apply the models to a civic behaviour based on Italian data, measuring the willingness to leave the name when scraping a car, which is likely to be misreported. By comparing observed probabilities for the ordered categories to the estimated true answers, it is possible to describe individuals patterns of misreporting.

Chapter 6 is organised as follows. I introduce the different econometrics models in Section 6.2. In Section 6.3, I discuss the tests used to compare the parametric models. Section 6.4 presents extensive Monte Carlo evidence on the finite sample performance of the proposed models. The empirical application to civic behaviours is contained in Section 6.5, and Section 6.6 concludes. Full expressions for the MEs are included in Appendix B.

6.2. ECONOMETRIC MODELS

6.2.1. *A hurdle OP*

When the outcome variable has a substantial proportion of values at one end of its distribution, some kind of mixture model is required to provide a good fit of the data. A hurdle (or two-part) model is commonly used in this situation as it introduces flexibility by modeling different types of d.g.p. using two latent equations. Thus, combining a binary choice model and a OP model is a standard practice in the empirical literature. This modeling approach is well established within the field of health economics in the analysis of smoking, drinking and health expenditures (Jones (2000)). For example, when modeling cigarette consumption with microdata, it is typically assumed that consumption is subject to two decisions: whether to smoke and how much to smoke (see, e.g.,Yen (2005), Kasteridis et al. (2010), Madden (2008)).

There are also applications of hurdle models from a Bayesian perspective. Deb et al. (2006) study the effect of managed care on medical expenditure using a model in which the insurance status is assumed to be endogenous and managed this by using a hurdle and multinomial probit model, as the variable of interest has a significant amount of zeros.

This section relies on some ideas recently advanced by Harris and Zhao (2007). Their approach, however, is conceptually different, as they study a zero-inflated ordered probit (ZIOP) model to take into account the possibility that the presence of zeros in tobacco consumption can arise from two latent equations. Although this Chapter also deals with a skewed outcome, it is additionally misclassified. This is the first assumption. The hypothesis of SDB from social psychology makes the analysis conceptually different. I rely on a two-part model because of its flexibility to allow covariates to have a different impact upon the division of an ordered scale. The second crucial assumption is that, when individuals are asked a question on a sensitive topic involving a social behaviour, they take their decisions in two steps. First, they decide to which group they belong: the low or high civically behaved. Second, having decided they belong to the high civically behaved group, they choose their ranking in this group by answering an integer $j \in [(J/2)+1, ..., J]$, where the response variable is coded $j = 1, ..., J$. The two step answering process is also related to sequential models (e.g., Tutz (1991)) based on conditional transitional probabilities: $\Pr(y_i = j|y_i \geq j)$.

I now introduce the model. Let y be the *observed* (or reported) response. Because the OP model assumes that there is not misclassification, *observed* responses coincide with *true* responses. Thus, y also denotes the true outcome under this model. Variable y takes discrete ordered values 1, 2,...,J, with a large proportion of observations at the top half of its distribution. Mapping an underlying latent variable y^* to the outcome y via the cut points c_j (j = 1,2,...,J) consists of a standard OP model; however, due to the large proportion of values at the end of y distribution, proceeding in this way would be inefficient. Instead, as it has been suggested in the literature, I rely on a hurdle OP model which consists of two latent processes.

The first latent process is a probit selection equation that explains whether y values are above or below the median of y and the second latent equation is an OP for values of y above the median. Let J be even,[2] and divide the whole sample N by the median of y; that is, low values y_l if $y \in [y_{min}, y_{median})$, and high values y_h if $y \in (y_{median}, y_{max}]$. Low and high values of y have their associated latent variable representations y_l^* and y_h^*. The first crucial point is that, to account for the negative

[2]I assume that J is even for practical reasons, i.e., the notation fits the empirical application in Section 6.5.

skewness of the distribution of y, I formulate a probit for whether individuals' answers are either in the bottom half or top half of the distribution.[3] The whole sample latent equation is

$$d^* = \mathbf{x}'\beta + \varepsilon, \tag{6.1}$$

where $\mathbf{x}$ is a vector of explanatory variables, β a vector of unknown coefficients, and ε a normally distributed error term. Instead of d^*, the researcher observes an indicator variable d, where $d = 1$ if $y \in y_h$ and $d = 0$ if $y \in y_l$. Then, the probability of answers being above the median is,

$$\Pr(d = 1|\mathbf{x}) = \Pr(d^* > 0|x) = \Phi(\mathbf{x}'\beta), \tag{6.2}$$

where $\Phi(.)$ is a univariate normal cumulative distribution function (c.d.f.). Conditional on $d = 1$, answers to y are represented by the discrete variable y_h that is generated by a second latent equation,

$$y_h^* = \mathbf{z}'\gamma + u, \tag{6.3}$$

where $\mathbf{z}$ is a vector of covariates, γ a vector of regression coefficients, u a normal idiosyncratic term, and there is no requirement that $\mathbf{x}$ is equal to $\mathbf{z}$. The relationship between y_h and y_h^* is given by a standard OP model,

$$y_h = \begin{cases} \frac{J}{2} + 1, & \text{if } y_h^* \leq c_{(J/2)+1}; \\ j, & \text{if } \mathrm{c}_{j-1} < y_h^* \leq c_j \text{ for } j = \frac{J}{2} + 2, ..., J - 1; \\ J, & \text{if } c_{J-1} < y_h^*. \end{cases} \tag{6.4}$$

If the two decisions are not independent, the latent equations (6.1) and (6.3) are linked. It could be probable that high civically behaved people are not randomly selected from the population. Hence, I assume that the two disturbance terms are jointly bivariate normally distributed,

$$\begin{bmatrix} \varepsilon \\ u \end{bmatrix} \sim \mathcal{N}_2 \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right), \tag{6.5}$$

where the variances have been normalised to one. However, since these two decisions could also be independent, I also experiment with models where $\rho = 0$.

[3]Although one could consider other distributions for y such as the negative binomial, I assume that y follows a truncated normal distribution as it is standard in the literature. For a discussion about the normality assumption, see Greene (2003) (p. 789).

The HOP model, given by Eqs. (6.1)-(6.5), implies a recoding of the outcome y equal to zero for values below the median. Formally, the researcher would observe the following transformation of y,

$$\tilde{y} = d \times y_h = \begin{cases} 0, & \text{if } (d^* \leq 0); \\ (J/2)+1, & \text{if } (d^* > 0 \text{ and } y_h^* \leq c_{(J/2)+1}); \\ j, & \text{if } (d^* > 0 \text{ and } c_{j-1} < y_h^* \leq c_j) \text{ for } j = \frac{J}{2}+2, ..., J-1; \\ J, & \text{if } (d^* > 0 \text{ and } c_{J-1} < y_h^*). \end{cases} \tag{6.6}$$

The corresponding probabilities are given by the following expressions,

$$\Pr(\tilde{y}) = \begin{cases} \Pr(\tilde{y} = 0|\mathbf{z}, \mathbf{x}) = \Pr(d = 0|\mathbf{x}) = [1 - \Phi(\mathbf{x}'\beta)]; \\ \Pr(\tilde{y} = (J/2)+1|\mathbf{z}, \mathbf{x}) = \Phi_2(\mathbf{x}'\beta, c_{(J/2)+1} - \mathbf{z}'\gamma; -\rho); \\ \Pr(\tilde{y} = j|\mathbf{z}, \mathbf{x}) = \Phi_2(\mathbf{x}'\beta, c_j - \mathbf{z}'\gamma; -\rho) - \Phi_2(\mathbf{x}'\beta, c_{j-1} - \mathbf{z}'\gamma; -\rho) \\ \text{for } j = \frac{J}{2}+2, ..., J-1; \\ \Pr(\tilde{y} = J|\mathbf{z}, \mathbf{x}) = \Phi_2(\mathbf{x}'\beta, \mathbf{z}'\gamma - c_{J-1}; \rho), \end{cases} \tag{6.7}$$

where $\Phi_2(.)$ denotes the bivariate *c.d.f.* The parameter vector $\theta = (\beta', \gamma', c', \rho)'$ of the HOP model can be straightforwardly estimated by maximum likelihood (ML). The log-likelihood function to be maximized is

$$\ell(\theta) = \sum_{i=1}^{N} \sum_{j=0}^{J} \mathbf{1}(\tilde{y}_i = j) \ln[\Pr(\tilde{y}_i = j|\mathbf{x}_i, \mathbf{z}_i, \theta)], \tag{6.8}$$

where $j \notin (1, 2, ..., \frac{J}{2})$. As mentioned earlier, all these models assume that true answers are reported because misreporting is not present. Moreover, a hypothesis test on the independence of the error terms ε and u can be performed by a Wald test or a t-test on ρ. Note that the HOP becomes a BOP if there is no correlation between the error terms.[4]

6.2.2. *A hurdle OPM*

Because the dependent variable y measures a sensitive topic, it is likely to be misclassified. This bias arises since respondents will tend to answer, though unconsciously, according to what is considered to be socially acceptable in order to gain approval of others, and will result in an under-report of undesirable behaviours and

[4]The probabilities for the BOP model are: $\Pr(\tilde{y} = 0|\mathbf{z}, \mathbf{x}) = [1 - \Phi(\mathbf{x}'\beta)], \Pr(\tilde{y} = (J/2)+1|\mathbf{z}, \mathbf{x}) = \Phi(\mathbf{x}'\beta)[\Phi(c_{(J/2)+1} - \mathbf{z}'\gamma)], \Pr(\tilde{y} = j|\mathbf{z}, \mathbf{x}) = \Phi(\mathbf{x}'\beta)[\Phi(c_j - \mathbf{z}'\gamma) - \Phi(c_{j-1} - \mathbf{z}'\gamma)]$ for $j = \frac{J}{2}+2, ..., J-1$, and $\Pr(\tilde{y} = J|\mathbf{z}, \mathbf{x}) = \Phi(\mathbf{x}'\beta)[1 - \Phi(c_{J-1} - \mathbf{z}'\gamma)]$.

an over-report of desirable ones. There is a long tradition within social psychology in the research of SDB (see, for instance, Hattie et al. (2006); Tourangeau and Yan (2007)). Typically, this bias would vary by the format of the question, its context, and privacy in the data-collection mode and may be a very important property to reduce it (Ong and Weiss (2000)). But the current framework does not involve responses under anonymity. Hence, I employ an ordered response model with misclassification probabilities to account for SDB.

I follow Abrevaya and Hausman (1999) and Dustmann and van Soest (2004) to introduce a parametric misclassification model. Under misclassification, the wrong outcome is reported, in other words, true and reported answers do not coincide any longer. As stated before, I assume misreporting on the top half part of the distribution of y. Thus, instead of observing the 'true' response y_h, I observe a 'misclassified' version of it which is denoted as ω_h. As I suppose that there is no error in the underlying latent variable y_h^*, the reported dependent variable ω_h is still generated by the latent variable model of Eq. (6.3).

I now define the misclassification probabilities that link true and reported responses. Let the probability that observations belonging to category j are classified in category k as,

$$\pi_{j,k} = \Pr(\omega_h = k | y_h = j, \mathbf{z}) \text{ for } j, k \in [(J/2) + 1, ..., J] \text{ and } j \neq k. \tag{6.9}$$

In the top half of the scale for answers of y there are $(J/2)$ outcomes subject to mismeasurement, which entails $[(J/2) \times ((J/2) - 1)]$ misclassification probabilities. However, as the dependent variable represents a civic behaviour subject to SDB, individuals will clearly have no incentive to lie, reporting a lower civic awareness than the one given by their true answers.[5] This means that misclassification probabilities $\pi_{j,k}$ for $j > k$ should tend to zero. Therefore, the misreporting pattern can be depicted by an upper triangular matrix of misclassification probabilities,

$$\Pi_{(J/2)} = \begin{bmatrix} \pi_{(J/2)+1,(J/2)+1} & \pi_{(J/2)+1,(J/2)+2} & \cdots & \pi_{(J/2)+1,J} \\ 0 & \pi_{(J/2)+2,(J/2)+2} & \cdots & \pi_{(J/2)+2,J} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \pi_{J,J} \end{bmatrix}, \tag{6.10}$$

where the diagonal elements are the probabilities that observations are correctly classified, and by definition each matrix row adds up to one.

[5]Recall that higher values of the dependent variable indicates a higher sense of civic duty according to observed (or reported) answers on the original 1 to J scale.

For the whole sample, let $\tilde{\omega}$ $(= d \times \omega_h)$ be the transformation of y that accounts for both the skewness on the distribution of y as well as the misclassification of y_h. These two assumptions define the HOPM model, with the following probabilities for the 'reported' (or misclassified) dependent variable $\tilde{\omega}$,

$$\Pr(\tilde{\omega}) = \begin{cases} \Pr(\tilde{\omega} = 0|\mathbf{z}, \mathbf{x}) = \Pr(\tilde{y} = 0|\mathbf{x}) = \Pr(d = 0|\mathbf{x}) = [1 - \Phi(\mathbf{x}'\beta]; \\ \Pr(\tilde{\omega} = (J/2) + 1|\mathbf{z}, \mathbf{x}) = \pi_{(J/2)+1,(J/2)+1}\Pr(\tilde{y} = (J/2) + 1|\mathbf{z}, \mathbf{x}); \\ \Pr(\tilde{\omega} = (J/2) + 2|\mathbf{z}, \mathbf{x}) = \pi_{(J/2)+1,(J/2)+2}\Pr(\tilde{y} = (J/2) + 1|\mathbf{z}, \mathbf{x}) \\ \qquad\qquad + \pi_{(J/2)+2,(J/2)+2}\Pr(\tilde{y} = (J/2) + 2|\mathbf{z}, \mathbf{x}); \\ \vdots \\ \Pr(\tilde{\omega} = J|\mathbf{z}, \mathbf{x}) = \sum_{j=(J/2)+1}^{J} \pi_{j,J}\Pr(\tilde{y} = j|\mathbf{z}, \mathbf{x}) \text{ for } j = \frac{J}{2} + 1, ..., J; \end{cases} \tag{6.11}$$

with $\Pr(\tilde{y} = j|\mathbf{z}, \mathbf{x})$ defined in Eq. (6.7) and subject to $\sum_k \pi_{j,k} = 1$.

The misclassification process assumed in (6.10) implies that there is an under-reporting for the lowest value above the median ($\tilde{\omega} = (J/2) + 1$)) and over-reporting for the highest value ($\tilde{\omega} = J$). This can easily be seen in Eq. (6.11) because $\pi_{(J/2)+1,(J/2)+1} < 1$ and $\pi_{J,J} = 1$, respectively. The hypothesis that individuals tend to under-report socially undesirable behaviours and over-report socially desirable ones is a well known phenomena in social psychology (e.g., King and Bruner (2000)). For the remaining categories, however, either under-reporting or over-reporting can hold. Formally,

PROPOSITION 6.1: *Suppose that the misclassification process is given by $\Pi_{(J/2)}$ in (6.10). Then, for values of $\tilde{\omega} = k \in [(J/2) + 2, ..., J - 1]$, there is either: (i) Under-reporting of category k: $Pr(\tilde{\omega} = k) < Pr(\tilde{y} = k) \iff \sum_{j<k}^{k-1} \pi_{j,k} Pr(\tilde{y} = j) < Pr(\tilde{y} = k) \sum_{j>k}^{J} \pi_{k,j}$; (ii) Over-reporting of category k: $Pr(\tilde{\omega} = k) > Pr(\tilde{y} = k) \iff \sum_{j<k}^{k-1} \pi_{j,k} Pr(\tilde{y} = j) > Pr(\tilde{y} = k) \sum_{j>k}^{J} \pi_{k,j}$.*

PROOF. This is shown by letting $\Pr(\tilde{\omega} = k) = \sum_{j<k}^{k-1} \pi_{j,k}\Pr(\tilde{y} = j) + \pi_{k,k}\Pr(\tilde{y} = k)$ and replacing $\pi_{k,k} = 1 - \sum_{j>k}^{J} \pi_{k,j}$. *Q.E.D.*

Although, in general, one would expect under-reporting when category j is near $(J/2) + 1$ and over-reporting when j tends to J.

The HOPM model[6] includes l additional parameters to be estimated given by the elements of the matrix $\Pi_{(J/2)}$ $[l = (J/2) \times ((J/2) - 1) - J]$. Let $\tilde{\theta} = (\beta', \gamma', c', \rho, \pi')'$.

[6]As before, a binary version of this model (BOPM) is obtained by setting $\rho = 0$ and replacing $\Pr(\tilde{y}|.)$ accordingly.

The HOPM log-likelihood is,

$$\ell(\tilde{\theta}) = \sum_{i=1}^{N}\sum_{j=0}^{J} \mathbf{1}(\tilde{\omega}_i = j)\ \ln[\Pr(\tilde{\omega}_i = j|\mathbf{x}_i, \mathbf{z}_i, \tilde{\theta})], \tag{6.12}$$

for $j \notin (1, 2, ..., \frac{J}{2})$. There are two conditions for the HOPM to be valid. On the one hand, the misclassification process must be correctly specified. In other words, the probabilities of misclassification must be a function only of the subset (defined by the cutpoints in Eq. (6.4)) to which y_h^* belongs and not of the level of y_h^*. Otherwise maximum likelihood (ML) estimates would yield inconsistent estimates. Thus, the main identification assumption is that $\pi_{j,k}$ are not a function of the covariates. On the other hand, a stochastic condition on the behaviour of the misclassification probabilities which guarantees that $\mathbb{E}(\omega_h|\mathbf{z})$ increases with $\mathbf{z}'\gamma$ and thus γ is identified. In terms of the matrix $\Pi_{(J/2)}$ this condition implies that the elements of the first column must be weakly decreasing as you go down row-by-row, the sum of the elements of the first two columns must be weakly decreasing as you go down row-by-row, and so on. Hence, the implicit assumption is that observational units with larger true values for their dependent variable are more likely to report larger values than observational units with smaller true values (see Abrevaya and Hausman (1999), p. 252, for details).

6.2.3. *Marginal effects*

Researchers are often interested in MEs rather than estimates of the parameter vector itself. The HOPM model contains two sets of MEs which warrant examination. Firstly, the ME of a covariate on the probability of answers belonging to the top half part of the distribution, $\Pr(d = 1)$. Secondly, the impact of an explanatory variable on the probability of the misclassified outcome $\tilde{\omega}$ conditional on d be equal to 1, that is, $\Pr(\tilde{\omega} = j|d = 1)$.

In the remaining of this section I concentrate on the MEs for a continuous variable (i.e., $\mathbf{x}_k$) instead of dummy variable. The ME on the probability that $y \in y_h$ is given by taking derivatives w.r.t. $\mathbf{x}_k$ in Eq. (6.2),

$$\underset{\Pr(d=1)}{ME} = \frac{\partial \Pr(d = 1)}{\partial \mathbf{x}_k} = \phi(\mathbf{x}'\beta)\beta_k, \tag{6.13}$$

where $\phi(.)$ is the p.d.f. of a standard normal univariate distribution.

To analyse the partial effect of an infinitesimal change of $\mathbf{x}_k$ on the probability of the dependent variable $\tilde{\omega}$, I need to partition the covariates and related coefficients.[7]

[7] I use the same approach and notation as in Harris and Zhao (2007), p. 1077-1079.

Let $\mathbf{w}$ denotes common covariates that appear in both $\mathbf{x}$ and $\mathbf{z}$ with associated coefficients β_w and γ_w, and let the unique variables of the latent equations be $\tilde{\mathbf{x}}$ and $\tilde{\mathbf{z}}$ with coefficients $\tilde{\beta}$ and $\tilde{\gamma}$, respectively. That is,

$$\mathbf{x} = \begin{bmatrix} \mathbf{w} \\ \tilde{\mathbf{x}} \end{bmatrix}, \ \beta = \begin{bmatrix} \beta_w \\ \tilde{\beta} \end{bmatrix}, \ \mathbf{z} = \begin{bmatrix} \mathbf{w} \\ \tilde{\mathbf{z}} \end{bmatrix} \text{ and } \gamma = \begin{bmatrix} \gamma_w \\ \tilde{\gamma} \end{bmatrix}. \tag{6.14}$$

For the whole model denote the full group of unique covariates as $\mathbf{x}^* = (\mathbf{w}', \tilde{\mathbf{x}'}, \tilde{\mathbf{z}'})'$, and set the associated coefficient vectors for $\mathbf{x}^*$ as $\beta^* = (\beta_w', \tilde{\beta}', 0')'$ and $\gamma^* = (\gamma_w', 0', \tilde{\gamma}')'$. The MEs of covariate $\mathbf{x}^*$ on the probabilities of the reported dependent variable $\tilde{\omega}$ of Eq. (6.11) are,

$$\begin{aligned}
\underset{\Pr(\tilde{\omega}=0)}{ME} &= \frac{\partial \Pr(\tilde{\omega}=0|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*} = \frac{\partial \Pr(\tilde{y}=0|\mathbf{x})}{\partial \mathbf{x}^*}; \\
\underset{\Pr(\tilde{\omega}=(J/2)+1)}{ME} &= \frac{\partial \Pr(\tilde{\omega}=(J/2)+1|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*} = \pi_{(J/2)+1,(J/2)+1} \frac{\partial \Pr(\tilde{y}=(J/2)+1|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*}; \\
\underset{\Pr(\tilde{\omega}=(J/2)+2)}{ME} &= \frac{\partial \Pr(\tilde{\omega}=(J/2)+2|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*} = \pi_{(J/2)+1,(J/2)+2} \frac{\partial \Pr(\tilde{y}=(J/2)+1|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*} \\
&\quad + \pi_{(J/2)+2,(J/2)+2} \frac{\partial \Pr(\tilde{y}=(J/2)+2|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*}; \\
&\ \vdots \\
\underset{\Pr(\tilde{\omega}=J)}{ME} &= \frac{\partial \Pr(\tilde{\omega}=J|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*} = \sum_{j=(J/2)+1}^{J} \pi_{j,J} \frac{\partial \Pr(\tilde{y}=j|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*}.
\end{aligned} \tag{6.15}$$

Since it is supposed that the outcome variable is not affected by misreporting when it takes values in the lower half of the distribution, true and reported outcomes (as well as MEs) are the same for the model which accounts for misclassification and also for the hurdle (or binary) model. MEs differ, however, for true and reported outcomes whose answers are in the top half of the distribution. Suppose that all elements of the coefficient vectors β^* and γ^* are positive. Then, Eq. (6.15) shows an under-estimation of the MEs for the reported outcome $\tilde{\omega}$ when $j = (J/2) + 1$ and an over-estimation for $j = J$ which is due to $\pi_{(J/2)+1,(J/2)+1} < 1$ and $\pi_{J,J} = 1$, respectively. For other values of $\tilde{\omega}$, probabilities and HOPM (BOPM) MEs could be either under or over-estimated compared to the HOP (BOP) model. This would depend on two factors. Firstly, whether condition (i) or (ii) of Proposition 6.1 holds and, secondly, on the downward bias of estimated γ coefficients which are affected by misreporting. Full expressions for the MEs can be found in Appendix B.

6.3. TESTING THE DIFFERENT MODELS

Considering the econometrics models described in Section 6.2, there are three types of tests that the researcher might be interested in. Namely, whether sample selection is present, the validity of the hurdle and binary modeling assumptions and, finally, if the dependent variable suffers from misclassification. I discuss each of them in turn below.

Statistical comparisons of the correlated and uncorrelated versions of the models can be straightforwardly tested, by comparing the t-ratio of the estimate of ρ and its standard error to the appropriate critical value of the standard normal distribution. In the present framework, a t-test on $\rho = 0$ would imply a test between hurdle and binary models, that is, the HOPM (or HOP) against the BOPM (or BOP). Yet, there are some doubts about the power of t-test in this context unless the sample size is large. For example, Nawata and McAleer (2001) find that the t-test performs poorly as it rejects the correct null hypothesis far too frequently, especially when $\mathbf{x} = \mathbf{z}$. Although the simulations in Section 6.4 use a large N to avoid this problem, t-test for ρ should still be interpreted cautiously when it rejects the null hypothesis of lack of sample selection.

Because researchers typically are more likely to fit an OP when faced with the discrete ordered dependent variable y, a natural test would be to compare the OP model with the remaining models. The OP model discards latent equation (6.1) as well as the probit selection rule of Eq. (6.2), and thus no splitting process of the observed dependent variable y is assumed according to low and high values. In other words, $(\mathbf{x}'\beta) \to +\infty \Rightarrow \Phi(\mathbf{x}'\beta) \to 1$ and then $\Pr(d = 1|\mathbf{x}) \to 1$. Note that testing these sort of models entails comparing the non-nested models. Specifically, hurdle and binary models propose a recoding where the outcome variable $y \in (0, \frac{J}{2} + 1, ..., J)$, whereas in the OP model $y \in (1, 2, ..., J)$. From a conceptual point of view, they belong to a class of non-nested models that represent conflicting theories of economic behaviour at micro level (e.g., Szroeter (1999)) as their random utility models, which generate them, assume different choice sets. Nevertheless, one can still rely on some standard statistics to compare them. In particular, the LR statistic is employed.[8]

In addition, I use a well established test on the literature due to Vuong (1989), which is based on the Kullback-Leibler information criterion (KLIC) that measures the distance between the given and the true distribution. The OP model and the hurdle (and binary) models are strictly non-nested as their parameters intersection is

[8]This test is used by Harris and Zhao (2007) in a similar context and they find a good performance in their Monte Carlo simulations. The LR test has good properties in non-standard conditions such as non-i.i.d observations and lower rates of convergence. See, for instance, Vu and Zhou (1997) and Banerjee (2005).

$$\begin{tikzcd}
\mathrm{HOPM}(\tilde{\omega}) \arrow[r, "\rho=0"] \arrow[d, "\Pi_{(J/2)}=I_{(J/2)}"'] & \mathrm{BOPM}(\tilde{\omega}) \arrow[d, "\Pi_{(J/2)}=I_{(J/2)}"] \\
\mathrm{HOP}(\tilde{y}) \arrow[r, "\rho=0"] \arrow[d, squiggly, "\nexists d"'] & \mathrm{BOP}(\tilde{y}) \arrow[dl, squiggly, "\nexists d"'] \\
\mathrm{OP}(y) & \mathrm{OPM}(\tilde{\nu}) \arrow[l, "\Pi_{(J)}=I_{(J)}"]
\end{tikzcd}$$

FIGURE 6.1.— Alternative econometrics models.

the null set (see, Vuong (1989), Definition 2). Formally, the conditional distributions of the competing models are for the OP model: $F_\xi \equiv \{F_{y|\mathbf{x}}(.|.;\xi); \xi \in \Xi \subset \Re^p\}$, and for the HOP model $G_\theta \equiv \{F_{\tilde{y}|\mathbf{z},\mathbf{x}}(.|.;\theta); \theta \in \Theta \subset \Re^q\}$, where $\xi = (c^*, \gamma)$ and $\theta = (\beta, \gamma, c, \rho)$, and these models are strictly non-nested because $F_\xi \cap G_\theta = \emptyset$. For the HOPM model redefine θ as $\tilde{\theta}$ so as to include the misclassification parameter π and for the binary (or without correlated error terms) representation of these models, set $\rho = 0$. Moreover, for the OPM model which accounts for misreporting along the whole original scale of y, let j vary from $1, ..., J$ in Eq. (6.11) to obtain the appropriate dependent variable (denoted by $\tilde{\nu}$) with misclassification matrix Π_J. Figure 6.1 presents the whole range of models, along with their corresponding dependent variables and parameters' constraints under which are obtained.

Suppose one is testing the OP model against the HOP model, and let $f(.|.)$ and $g(.|.)$ be their corresponding predicted probabilities. The null hypothesis of the Vuong test states that the two models are equally close to the true specification,

$$\mathrm{H}_0: \ \mathbb{E}_0\left[\ln \frac{f(y_i|\mathbf{x}_i, \xi)}{g(\tilde{y}_i|\mathbf{z}_i, \mathbf{x}_i, \theta)}\right] = 0. \tag{6.16}$$

Let $m_i = \ln[f(.|.)/g(.|.)]$ denote the ratio of the previous expression; the Vuong test statistic is given by,

$$\upsilon = \frac{\sqrt{N}(1/N\sum_{i=1}^{N} m_i)}{\sqrt{1/N\sum_{i=1}^{N}(m_i - \bar{m})^2}} \xrightarrow{\mathcal{D}} \mathcal{N}[0, 1]. \tag{6.17}$$

For a critical value c, discrimination between the two models is not possible if $|\upsilon| < c$, the test favours the HOP model if $\upsilon < -c$ and the OP if $\upsilon > c$. When testing the OP against the other models, one should replace the denominator of Eq. (6.16) by their appropriate predicted probabilities.

I also compare all models by using the Akaike information criterion (AIC), Bayesian information criterion (BIC), and consistent Akaike information criterion (CAIC). For more details about information criteria statistics and non-nested model testing in general, see, Cameron and Trivedi (2005), p. 278-284.

Finally, I briefly describe how to test for misclassification. Note that I am examining whether $\Pi_{(J/2)} \equiv I_{(J/2)}$ and thus I am testing the HOPM (BOPM) against the HOP (BOP). The main problem when testing misclassification is that one cannot use a standard test because the null hypothesis places the parameters on the boundary of the parameter space. Instead of using a likelihood ratio/Wald test with a χ^2 distribution, one needs to use a chi-bar-squared distribution ($\bar{\chi}^2$), which is distributed as a mixture of χ^2 distributions (Shapiro (1985)). The $\bar{\chi}^2$ statistic is normally simulated, given that finding the weights is a difficult numerical problem as well as that there is not a closed expression form for the weights when the number of restrictions tested is higher than 4. Reasonably accurate estimates of the weights can be easily obtained by Monte Carlo simulation (i.e., Andrews (2001) and Liu and Wang (2003)).

A formal definition of the test procedure is included in Appendix A of Chapter 3. Only redefine the parameters' vectors to fit the models proposed in this Chapter. For instance, for the hurdle models, recall that the parameter vector of the HOPM is $\tilde{\theta} = (\beta, \gamma, c, \rho, \pi)$ and $\theta = (\beta, \gamma, c, \rho)$ for the HOP. Suppose that one would like to test that the l estimated misclassification probabilities $[l = (J/2) \times ((J/2) - 1) - J]$ are zero, against the alternative that they are higher than zero. Stack these l estimated misclassification probabilities $\hat{\pi}_{j,k}$ (for $j < k$) in a row vector $\hat{\Psi}_l$. Then proceed as in Appendix A.

6.4. SIMULATIONS

In this section, I evaluate the performance of the above models by Monte Carlo simulation. The main interest concerns the comparisons of the hurdle versions (where there is a correlation in the error terms of the latent equations) with the OP model, although I also set up experiments with $\rho = 0$ as a way to contrast the performance of binary specifications. I choose $J = 10$ in the simulation's designs as most attitudinal questions have a 1 to 10 scale, which also motivates the empirical application I examine later in Section 6.5. This choice, however, has empirical disadvantages because, given the great number of alternatives, identification of the misclassification probabilities on the OPM model becomes very difficult, even more so if the dependent variable has few observations for values below the median. Thus, I do not estimate the OPM model. The main evaluation is across hurdle and non-hurdle versions of the models of Figure 6.1, and the principal cases I consider are those when the true d.g.p. is the HOPM, BOPM and OP models.

6.4.1. *Models 1: HOPM d.g.p.*

In the group of Models 1 the true d.g.p. is given by the HOPM model. In Model 1A there is no overlap of $\mathbf{x}$ and $\mathbf{z}$ variables and in Model 1B there is partial overlap. I set $J = 10$ for the dependent variable, a sample size $N = 2000$ and use a number of repetitions $M = 100$ for all experiments. The Monte Carlo design is aimed at mimicking the observed and true distributions of civic behavioural questions/variables.

Model 1A covariates are: $\mathbf{x} = (\mathbf{x}_0, \mathbf{x}_1)$, $\mathbf{z} = (\mathbf{z}_1, \mathbf{z}_2)$, where $\mathbf{x}_0$ is a vector of ones, $\mathbf{x}_1$ = Lognormal(0, 1), $\mathbf{z}_1$ = Binomial(p = 0.6), and $\mathbf{z}_2$ = Normal(10, 3). The parameter vector for the probit selection in Eq. (6.2) is $\beta = (\beta_0, \beta_1) = (1, 0.3)$. The values for β are chosen so that the probability of answers above the median ($j \geq 6$) is ≈ 0.90, which coincides with the sample values of civic behaviours.[9] I select $\gamma_2 = 0.8$ and γ_2 = -0.2, as well as cutpoints values (i.e., c_j in Eq. (6.4)) $c_6 = -1.8$, $c_7 = -0.8$, $c_8 = 0.1$ and $c_9 = 1$. As mentioned above, the design attempt to match a hypothetical $\tilde{y}$ civic behaviour, with 'true' answers concentrated around values of $j \in (6, 7, 8)$.

Because the d.g.p. is given by the HOPM model, the next step is to generate[10] the misclassified 'observed' outcome $\tilde{\omega}$ which is used in the log-likelihood of Eq. (6.12). I assume the following misclassification probabilities,

$$\Pi_{(5)} = \begin{bmatrix} \pi_{6,6} & \pi_{6,7} & \pi_{6,8} & \pi_{6,9} & \pi_{6,10} \\ 0 & \pi_{7,7} & \pi_{7,8} & \pi_{7,9} & \pi_{7,10} \\ 0 & 0 & \pi_{8,8} & \pi_{8,9} & \pi_{8,10} \\ 0 & 0 & 0 & \pi_{9,9} & \pi_{9,10} \\ 0 & 0 & 0 & 0 & \pi_{10,10} \end{bmatrix} = \begin{bmatrix} 0.46 & 0.03 & 0.06 & 0.20 & 0.25 \\ 0 & 0.30 & 0.15 & 0.25 & 0.30 \\ 0 & 0 & 0.30 & 0.30 & 0.40 \\ 0 & 0 & 0 & 0.55 & 0.45 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

which yields underreporting for categories $j = 6, 7, 8$ and over-reporting for categories $j = 9, 10$. Hence, Proposition 6.1 holds. The misreporting process mirrors SD (e.g., Paulhus (1991)). In fact, the misclassification pattern is very significant and the probability of reporting the truth is less than lying/misreporting for answers close to the median: $\pi_{j,j} < 0.5$ for $j \in (6, 7, 8)$.

Monte Carlo results for the first model are in Table 6.1 and Table 6.2. They contain the MEs at the mean of covariates, but I also include the estimated coefficients to show why average MEs across models differ, as well as several statistical tests to guide model selection. Specifically, for each model I present the true MEs, the estimated MEs averaged over the M repetitions and their root mean squared errors. I also display the value of the overall root mean squared errors of the coefficients,

[9] The distribution of $\mathbf{x}_1$ may mimic a variable such as income, $\mathbf{z}_1$ a qualitative variable that represents, for instance, marital status or a regional dummy, and $\mathbf{z}_2$ could be years of education.

[10] See Chapter 3 (Section 3.4) for details on the simulation algorithm.

TABLE 6.1

Simulations results (marginal effects) for Model 1A: HOPM d.g.p. with no overlap ($z \neq x$)

Covariates	TRUE	HOPM	BOPM	HOP	BOP	OP
	J=0					
x_1	-0.039	-0.039	-0.039	-0.038	-0.039	
		0.005	0.005	0.006	0.005	
z_1						
z_2						
	J=6					
x_1	0.013	0.013	0.007	0.021	0.007	
		0.003	0.006	0.009	0.006	
z_1	-0.133	-0.138	-0.138	-0.072	-0.067	-0.072
		0.020	0.020	0.063	0.067	0.063
z_2	0.033	0.034	0.034	0.017	0.016	0.018
		0.004	0.004	0.016	0.017	0.016
	J=7					
x_1	0.004	0.004	0.005	0.006	0.004	
		0.001	0.002	0.002	0.001	
z_1	0.006	0.008	0.006	-0.022	-0.022	-0.024
		0.011	0.012	0.029	0.029	0.031
z_2	-0.002	-0.002	-0.001	0.005	0.005	0.006
		0.003	0.003	0.007	0.007	0.008
	J=8					
x_1	0.004	0.004	0.005	0.004	0.005	
		0.001	0.002	0.001	0.002	
z_1	0.037	0.039	0.041	-0.012	-0.014	-0.015
		0.012	0.013	0.049	0.051	0.052
z_2	-0.009	-0.009	-0.010	0.003	0.003	0.004
		0.003	0.003	0.012	0.013	0.013
	J=9					
x_1	0.009	0.009	0.010	0.005	0.010	
		0.001	0.002	0.005	0.002	
z_1	0.040	0.043	0.046	0.012	0.009	0.009
		0.019	0.018	0.029	0.032	0.031
z_2	-0.010	-0.011	-0.011	-0.003	-0.002	-0.002
		0.004	0.004	0.007	0.008	0.008
	J=10					
x_1	0.011	0.010	0.012	0.002	0.013	
		0.002	0.002	0.009	0.003	
z_1	0.050	0.048	0.049	0.094	0.095	0.102
		0.019	0.018	0.047	0.048	0.055
z_2	-0.012	-0.012	-0.012	-0.023	-0.023	-0.025
		0.005	0.004	0.011	0.011	0.013

that is, $\text{RMSE}_{\text{all}} = \left[\text{tr } \mathbb{E}\big([\hat{\theta}-\theta][\hat{\theta}-\theta]'\big)\right]^{\frac{1}{2}}$, which gives an overall performance of the model. Tests results are shown as the proportion of times that the statistic supports each model out of 100 M repetitions using a 5% significance level.

As expected, Table 6.1 shows that Model 1A's estimated MEs differ with respect to the true ones across models. The amount of bias in the MEs is a function of two components. First, $\hat{\pi}_{j,k}$ and, second, the bias in the $\hat{\gamma}$ coefficients due to misreporting (Eq. (6.15)). As it can be seen at the bottom of Table 6.2, whereas the estimated coefficients for the models that account for misclassification (i.e., HOPM and BOPM) tend to the true values, but this is not the case for the other models. There is significant downward bias in $\hat{\gamma}$ coefficients and cutpoints that lead to a poor performance in

TABLE 6.2

Simulation results (tests and estimates) for Model 1A: HOPM d.g.p. with no overlap ($z \neq x$)

Tests	HOPM	BOPM	HOP	BOP	OP						
t-test (ρ)	0.51	0.49									
$\bar{\chi}^2$ test hurdle	1.00		0.00								
$\bar{\chi}^2$ test binary		1.00		0.00							
LR1	1.00				0.00						
LR2		1.00			0.00						
Vuong1	1.00				0.00						
Vuong2		1.00			0.00						
Vuong3			1.00		0.00						
Vuong4				1.00	0.00						
AIC hurdle	1.00		0.00		0.00						
AIC binary		1.00		0.00	0.00						
AIC all	0.21	0.79	0.00	0.00	0.00						
BIC hurdle	0.53		0.47		0.00						
BIC binary		0.57		0.43	0.00						
BIC all	0.00	0.57	0.06	0.37	0.00						
CAIC hurdle	0.35		0.65		0.00						
CAIC binary		0.39		0.61	0.00						
CAIC all	0.00	0.39	0.07	0.54	0.00						
Parameters	TRUE	HOPM	Rmse	BOPM	Rmse	HOP	Rmse	BOP	Rmse	OP	Rmse
β_0	1	0.999	0.063	1.000	0.063	1.019	0.066	1.000	0.063		
β_1	0.3	0.300	0.048	0.299	0.048	0.283	0.050	0.299	0.048		
c_6	-1.8	-1.816	0.223	-1.971	0.287	-1.309	0.500	-1.478	0.336	-1.478	0.336
c_7	-0.8	-0.869	0.308	-0.968	0.367	-0.955	0.178	-1.100	0.314	-1.100	0.314
c_8	0.1	0.101	0.344	0.032	0.452	-0.611	0.717	-0.736	0.842	-0.736	0.842
c_9	1	0.824	0.356	0.779	0.454	0.039	0.966	-0.057	1.062	-0.057	1.062
γ_1	0.8	0.856	0.166	0.899	0.189	0.277	0.525	0.285	0.518	0.285	0.518
γ_2	-0.2	-0.210	0.034	-0.220	0.040	-0.066	0.134	-0.069	0.131	-0.069	0.131
ρ	0.5	0.487	0.170			0.590	0.199				
$\pi_{6,7}$	0.03	0.030	0.028	0.032	0.029						
$\pi_{6,8}$	0.06	0.062	0.030	0.063	0.030						
$\pi_{6,9}$	0.2	0.209	0.042	0.209	0.043						
$\pi_{6,10}$	0.25	0.249	0.045	0.250	0.044						
$\pi_{7,8}$	0.15	0.145	0.108	0.145	0.105						
$\pi_{7,9}$	0.25	0.207	0.138	0.211	0.137						
$\pi_{7,10}$	0.3	0.288	0.130	0.288	0.137						
$\pi_{8,9}$	0.3	0.307	0.162	0.296	0.173						
$\pi_{8,10}$	0.4	0.380	0.148	0.384	0.152						
$\pi_{9,10}$	0.45	0.379	0.145	0.332	0.217						
RMSE-all			0.216		0.370		1.413		1.514		1.514

terms of the RMSE_{all} and, accordingly, to differences in the estimated MEs. Instead, predictions for $\hat{\beta}$ coefficients for all models are similar because this parameter is not affected by misclassification at the bottom of the scale. As a result, the MEs for x_1 (for all j) do not vary.

But they do indeed vary for covariates $\mathbf{z}$ in two groups. On the one hand, although the BOPM assumes that $\rho = 0$, it performs very well and its MEs are practically the same as the HOPM model and very close to the true ones. For the HOP, BOP and OP models on the other hand, in some cases MEs are of the opposite sign to the true MEs and are in general underestimated; moreover, they are imprecisely estimated as it is shown by their higher root mean squared errors (RMES). In summary, based upon predicted MEs, this latter group of models does not perform very well.

In terms of model selection, the OP is never chosen. The misclassification hy-

TABLE 6.3

Simulation results (marginal effects) for Model 1B: HOPM d.g.p. with partial overlap ($x_1 = z_1$)

Covariates	TRUE	HOPM	BOPM	HOP	BOP	OP
	J=0					
$x_1 = z_1$	-0.060	-0.058	-0.058	-0.051	-0.058	
		0.015	0.015	0.018	0.015	
z_2						
	J=6					
$x_1 = z_1$	-0.107	-0.106	-0.106	-0.049	-0.047	-0.064
		0.020	0.020	0.059	0.061	0.095
z_2	0.031	0.032	0.032	0.017	0.016	0.018
		0.004	0.004	0.014	0.015	0.125
	J=7					
$x_1 = z_1$	0.008	0.009	0.010	-0.016	-0.014	-0.023
		0.010	0.011	0.025	0.022	0.024
z_2	0.000	-0.001	-0.001	0.006	0.006	0.007
		0.003	0.003	0.006	0.006	0.001
	J=8					
$x_1 = z_1$	0.040	0.040	0.039	-0.008	-0.005	-0.015
		0.012	0.010	0.048	0.045	0.007
z_2	-0.009	-0.009	-0.009	0.003	0.004	0.004
		0.004	0.003	0.012	0.012	0.036
	J=9					
$x_1 = z_1$	0.053	0.054	0.051	0.018	0.022	0.007
		0.013	0.013	0.035	0.031	0.017
z_2	-0.010	-0.011	-0.011	-0.003	-0.002	-0.002
		0.004	0.004	0.007	0.008	0.055
	J=10					
$x_1 = z_1$	0.066	0.061	0.062	0.105	0.102	0.094
		0.016	0.017	0.043	0.040	0.108
z_2	-0.012	-0.012	-0.013	-0.023	-0.023	-0.027
		0.004	0.004	0.011	0.011	0.092

pothesis is fully supported with both the HOPM and BOPM correctly selected over the HOP and BOP for all M repetitions. (See $\bar{\chi}^2$ test hurdle and binary in Table 6.2). The likelihood ratio tests also select these two models over the OP in all cases. Neither is the OP preferred to the other four models according to the Vuong test. Yet, there seems to be an identification problem with the correlation coefficient, since according to the t-test on ρ the HOPM is only chosen in 51% of cases over the BOPM.[11] Information criteria further confirms this problem, with the binary versions of the models more likely to be chosen by the AIC, BIC and CAIC when comparing the five models. Overall, the BOPM performs slightly better than the HOPM.

Table 6.3 and Table 6.4 contain the results for Model 1B under partial overlap of covariates. The MEs for the models that do not include misreporting are far way from their true values with high RMSE and, for some j, have different signs than the true MEs. Once more, the OP is never selected by any test and the HOPM performs similarly to the previous experiment, although it is chosen by information criteria fewer times now. It should be noted that in this design there is only one exclusion restriction, $\mathbf{z}_2$, and the percentage of observations below the median is still small ($\bar{d}$ = 0.88). Together, these two reasons, may explain why ρ is not easily identified. This agrees with studies comparing the sample selection and two-part models, which find that the power of the t-test for selectivity is limited by collinearity and by the degree of censoring (Leung and Yu (1996) and Norton et al. (2008)).

To investigate this issue further, I re-run the models under full overlap of covariates (Model 1C) and increase the proportion of answers in the bottom half of the scale by lowering β_1 (Model 1D). Table 6.5 shows the tests result for these models. As before, the OP is never chosen. When the set of explanatory variables is the same, ρ is very poorly estimated because there is not enough nonlinearity to identify it. Results for the hurdle version of the misclassification test are affected too, only choosing the true HOPM model 32% of the times, but not for the binary misclassified version of this test. On the contrary, the quality of true HOPM model is enhanced by decreasing the probability of $d = 1 (\approx 0.55)$. Now both the t-test and $\bar{\chi}^2$ test fully support the HOPM. Information criteria further validate this. In summary, the model which accounts for misreporting but ignores correlation, provides the better results based on the range of tests and predicted MEs and, for the HOPM, the degree of censoring and exclusion restrictions are crucial to its performance.

[11] I examine this issue by modifying the simulation design and inspect how this affects the t-test's outcome.

TABLE 6.4

SIMULATION RESULTS (TESTS AND ESTIMATES) FOR MODEL 1B: HOPM D.G.P. WITH PARTIAL OVERLAP ($x_1 = z_1$)

Tests	HOPM	BOPM	HOP	BOP	OP						
t-test (ρ)	0.53	0.47									
$\bar{\chi}^2$ test hurdle	1.00		0.00								
$\bar{\chi}^2$ test binary		1.00		0.00							
LR1	1.00				0.00						
LR2		1.00			0.00						
Vuong1	1.00				0.00						
Vuong2		1.00			0.00						
Vuong3			1.00		0.00						
Vuong4				1.00	0.00						
AIC hurdle	1.00		0.00		0.00						
AIC binary		1.00		0.00	0.00						
AIC all	0.00	1.00	0.00	0.00	0.00						
BIC hurdle	0.33		0.67		0.00						
BIC binary		0.41		0.59	0.00						
BIC all	0.00	0.41	0.00	0.59	0.00						
CAIC hurdle	0.19		0.81		0.00						
CAIC binary		0.24		0.76	0.00						
CAIC all	0.00	0.24	0.00	0.76	0.00						
Parameters	TRUE	HOPM	Rmse	BOPM	Rmse	HOP	Rmse	BOP	Rmse	OP	Rmse
β_0	1	1.003	0.055	1.003	0.055	1.022	0.061	1.003	0.055		
β_1	0.3	0.292	0.076	0.291	0.076	0.253	0.092	0.291	0.076		
c_6	-1.8	-1.899	0.255	-2.142	0.422	-1.267	0.541	-1.573	0.252	-1.573	0.252
c_7	-0.8	-0.879	0.330	-1.032	0.429	-0.918	0.147	-1.182	0.398	-1.182	0.398
c_8	0.1	0.066	0.353	-0.075	0.456	-0.580	0.685	-0.809	0.915	-0.809	0.915
c_9	1	0.780	0.378	0.672	0.508	0.057	0.947	-0.124	1.129	-0.124	1.129
γ_1	0.8	0.820	0.168	0.820	0.184	0.310	0.493	0.262	0.541	0.262	0.541
γ_2	-0.2	-0.215	0.036	-0.228	0.045	-0.070	0.131	-0.074	0.126	-0.074	0.126
ρ	0.5	0.496	0.170			0.688	0.200				
$\pi_{6,7}$	0.03	0.035	0.030	0.037	0.031						
$\pi_{6,8}$	0.06	0.061	0.034	0.061	0.033						
$\pi_{6,9}$	0.2	0.207	0.046	0.207	0.046						
$\pi_{6,10}$	0.25	0.249	0.050	0.249	0.050						
$\pi_{7,8}$	0.15	0.155	0.090	0.159	0.089						
$\pi_{7,9}$	0.25	0.221	0.120	0.226	0.119						
$\pi_{7,10}$	0.3	0.302	0.124	0.308	0.119						
$\pi_{8,9}$	0.3	0.341	0.143	0.331	0.156						
$\pi_{8,10}$	0.4	0.379	0.141	0.384	0.149						
$\pi_{9,10}$	0.45	0.409	0.143	0.379	0.176						
RMSE-all			0.266		0.563		1.395		1.611		1.611

TABLE 6.5

SIMULATION RESULTS (TESTS) FOR MODEL 1C AND MODEL 1D: HOPM D.G.P.

A) MODEL 1C: FULL OVERLAP IN COVARIATES

Tests	HOPM	BOPM	HOP	BOP	OP
t-test (ρ)	0.35	0.65			
$\bar{\chi}^2$ test hurdle	0.32		0.68		
$\bar{\chi}^2$ test binary		0.94		0.06	
LR1	1.00				0.00
LR2		1.00			0.00
Vuong1	1.00				0.00
Vuong2		1.00			0.00
Vuong3			1.00		0.00
Vuong4				1.00	0.00
AIC hurdle	0.56		0.44		0.00
AIC binary		0.89		0.11	0.00
AIC all	0.03	0.62	0.34	0.01	0.00
BIC hurdle	0.00		1.00		0.00
BIC binary		0.01		0.99	0.00
BIC all	0.00	0.01	0.92	0.07	0.00
CAIC hurdle	0.00		1.00		0.00
CAIC binary		0.01		0.99	0.00
CAIC all	0.00	0.01	0.89	0.10	0.00

B) MODEL 1D: NO OVERLAP IN COVARIATES WITH LOWER $\Pr(d = 1|\mathbf{x})$

Tests	HOPM	BOPM	HOP	BOP	OP
t-test (ρ)	0.88	0.12			
$\bar{\chi}^2$ test hurdle	1.00		0.00		
$\bar{\chi}^2$ test binary		1.00		0.00	
LR1	1.00				0.00
LR2		1.00			0.00
Vuong1	1.00				0.00
Vuong2		1.00			0.00
Vuong3			1.00		0.00
Vuong4				1.00	0.00
AIC hurdle	1.00		0.00		0.00
AIC binary	1.00			0.00	0.00
AIC all	0.72	0.28	0.00	0.00	0.00
BIC hurdle	0.11		0.89		0.00
BIC binary		0.04		0.96	0.00
BIC all	0.02	0.02	0.15	0.81	0.00
CAIC hurdle	0.02		0.98		0.00
CAIC binary		0.00		1.00	0.00
CAIC all	0.01	0.00	0.11	0.88	0.00

TABLE 6.6

Simulation results (marginal effects) for Model 2: BOPM d.g.p. with partial overlap ($x_1 = z_1$)

Covariates	TRUE	HOPM	BOPM	HOP	BOP	OP
	J=0					
$x_1 = z_1$	-0.060	-0.060	-0.058	-0.058	-0.058	
		0.013	0.015	0.015	0.015	
z_2						
	J=6					
$x_1 = z_1$	-0.113	-0.111	-0.113	-0.054	-0.050	-0.069
		0.015	0.019	0.060	0.064	0.101
z_2	0.031	0.032	0.032	0.014	0.016	0.018
		0.003	0.004	0.017	0.015	0.131
	J=7					
$x_1 = z_1$	0.014	0.014	0.015	-0.013	-0.012	-0.021
		0.010	0.011	0.028	0.027	0.020
z_2	-0.002	-0.002	-0.002	0.004	0.005	0.006
		0.002	0.003	0.006	0.007	0.009
	J=8					
$x_1 = z_1$	0.042	0.042	0.042	-0.004	-0.004	-0.013
		0.009	0.012	0.046	0.046	0.005
z_2	-0.008	-0.009	-0.009	0.003	0.003	0.003
		0.002	0.003	0.011	0.011	0.039
	J=9					
$x_1 = z_1$	0.052	0.052	0.052	0.024	0.023	0.009
		0.012	0.013	0.029	0.030	0.018
z_2	-0.009	-0.010	-0.009	-0.002	-0.002	-0.002
		0.003	0.003	0.007	0.007	0.055
	J=10					
$x_1 = z_1$	0.065	0.063	0.064	0.107	0.102	0.094
		0.013	0.016	0.045	0.041	0.107
z_2	-0.011	-0.011	-0.012	-0.019	-0.022	-0.025
		0.003	0.004	0.008	0.011	0.089

6.4.2. *Model 2: BOPM d.g.p.*

Due to the lack of identification of ρ in the previous experiments, one would expect Model 2 (with zero correlation for the error terms) to perform extremely well. Table 6.6 and Table 6.7 indicate that this is the case when the true d.g.p is given by the BOPM model.

Note first that the BOPM RMSE_{all} is smaller and closer to the HOPM. Now, the t-test for ρ mostly support the BOPM over the HOPM (in 71% of cases). The mean estimate of ρ over the M replications are relatively small for the hurdle models, between 0.11-0.18, approaching to the zero true value but with a high RMSE. Second, the estimated MEs follow the pattern of the former models in Section 6.4.1: for the BOPM and HOPM they tend to be the true ones, but diverge significantly for the other three models. This difference is due to the HOP, BOP and OP models ignoring the misclassification probabilities and the downward bias in $\hat{\gamma}_1$ and $\hat{\gamma}_2$ coefficients.

With regard to tests, except from the one for ρ, all results are very similar to Model 1B which also assumes partial overlapping. Binary models are preferred by model selection criteria. For example, the AIC chooses the BOPM in all cases amongst the five models and there is nearly an equal split with the BOP by the BIC. Although

TABLE 6.7

Simulation results (tests and estimates) for Model 2: BOPM d.g.p. with partial overlap ($x_1 = z_1$)

Tests	HOPM	BOPM	HOP	BOP	OP						
t-test (ρ)	0.29	0.71									
$\bar{\chi}^2$ test hurdle	1.00		0.00								
$\bar{\chi}^2$ test binary		1.00		0.00							
LR1	1.00				0.00						
LR2		1.00			0.00						
Vuong1	1.00				0.00						
Vuong2		1.00			0.00						
Vuong3			1.00		0.00						
Vuong4				1.00	0.00						
AIC hurdle	1.00		0.00		0.00						
AIC binary		1.00		0.00	0.00						
AIC all	0.00	1.00	0.00	0.00	0.00						
BIC hurdle	0.34		0.66		0.00						
BIC binary		0.35		0.65	0.00						
BIC all	0.00	0.35	0.00	0.65	0.00						
CAIC hurdle	0.19		0.81		0.00						
CAIC binary		0.22		0.78	0.00						
CAIC all	0.00	0.22	0.00	0.78	0.00						
Parameters	TRUE	HOPM	Rmse	BOPM	Rmse	HOP	Rmse	BOP	Rmse	OP	Rmse
β_0	1	0.997	0.044	1.003	0.055	1.002	0.054	1.003	0.055		
β_1	0.3	0.299	0.064	0.291	0.076	0.292	0.076	0.291	0.076		
c_6	-1.8	-1.855	0.189	-1.873	0.274	-1.295	0.512	-1.455	0.361	-1.455	0.361
c_7	-0.8	-0.850	0.282	-0.871	0.383	-0.936	0.156	-1.092	0.312	-1.092	0.312
c_8	0.1	0.112	0.293	0.064	0.428	-0.586	0.690	-0.739	0.846	-0.739	0.846
c_9	1	0.864	0.332	0.821	0.492	0.083	0.919	-0.065	1.071	-0.065	1.071
γ_1	0.8	0.806	0.125	0.828	0.165	0.295	0.507	0.264	0.538	0.264	0.538
γ_2	-0.2	-0.210	0.030	-0.213	0.037	-0.061	0.139	-0.070	0.131	-0.070	0.131
ρ	0	0.117	0.201			0.180	0.212				
$\pi_{6,7}$	0.03	0.029	0.024	0.031	0.029						
$\pi_{6,8}$	0.06	0.060	0.028	0.062	0.032						
$\pi_{6,9}$	0.2	0.202	0.035	0.203	0.040						
$\pi_{6,10}$	0.25	0.246	0.042	0.250	0.047						
$\pi_{7,8}$	0.15	0.147	0.082	0.141	0.104						
$\pi_{7,9}$	0.25	0.229	0.112	0.225	0.135						
$\pi_{7,10}$	0.3	0.297	0.121	0.291	0.150						
$\pi_{8,9}$	0.3	0.312	0.144	0.304	0.172						
$\pi_{8,10}$	0.4	0.389	0.126	0.369	0.173						
$\pi_{9,10}$	0.45	0.418	0.124	0.348	0.209						
RMSE-all			0.200		0.239		1.375		1.532		1.532

the correct comparison, the $\bar{\chi}^2$ test, selects the BOPM for all repetitions. Vuong and LR tests also support these models against the misspecified OP, which is never selected. I believe that all this evidence is enough to support that the true d.g.p. in this experiment is the BOPM model.

6.4.3. *Models 3: OP d.g.p.*

I now consider situations when the true d.g.p. is given by the standard OP model (Tables 6.8 and 6.9). In Model 3A, I assume the same misclassification matrix as before and, in Model 3B, no misclassification ($\Pi_{(5)} \equiv I_{(5)}$). For the usual OP there is no split process by low and high observations due to $(\mathbf{x}'\beta) \rightarrow +\infty$. Thus, the dependent variable now takes values $j \in (1, ..., 10)$ and the MEs for the HOPM are

TABLE 6.8

SIMULATION RESULTS FOR MODEL 3A: OP D.G.P. WITH MISCLASSIFICATION

Marginal effects	J=6			J=7			J=8		
	TRUE	OP	BOPM	TRUE	OP	BOPM	TRUE	OP	BOPM
z_1	-0.060	-0.048	-0.139	0.013	-0.027	0.006	0.049	-0.009	0.037
		0.014	0.084		0.040	0.017		0.058	0.022
z_2	0.015	0.012	0.035	-0.003	0.007	-0.001	-0.012	0.002	-0.009
		0.004	0.021		0.010	0.004		0.014	0.005
	J=9			J=10					
	TRUE	OP	BOPM	TRUE	OP	BOPM			
z_1	0.077	0.043	0.048	0.096	0.174	0.050			
		0.035	0.039		0.080	0.054			
z_2	-0.019	-0.010	-0.012	-0.024	-0.042	-0.013			
		0.009	0.010		0.019	0.013			
Tests	OP	BOPM							
$\bar{\chi}^2$ test	0.00	1.00							
LR	0.00	1.00							
AIC	0.00	1.00							
BIC	0.00	1.00							
CAIC	0.04	0.96							
Parameters	TRUE	OP	Rmse	BOPM	Rmse				
c_1	-4	-3.310	0.699	-4.049	0.156				
c_2	-3.6	-2.937	0.671	-3.654	0.149				
c_3	-3.2	-2.550	0.657	-3.244	0.140				
c_4	-2.9	-2.264	0.642	-2.942	0.132				
c_5	-2.6	-1.974	0.632	-2.637	0.125				
c_6	-1.8	-1.589	0.228	-1.783	0.173				
c_7	-0.8	-1.276	0.484	-0.776	0.321				
c_8	0.1	-0.950	1.054	0.057	0.397				
c_9	1	-0.328	1.330	0.835	0.438				
γ_1	0.8	0.545	0.260	0.815	0.072				
γ_2	-0.2	-0.133	0.068	-0.204	0.012				
$\pi_{6,7}$	0.03			0.045	0.059				
$\pi_{6,8}$	0.06			0.074	0.064				
$\pi_{6,9}$	0.2			0.184	0.103				
$\pi_{6,10}$	0.25			0.243	0.102				
$\pi_{7,8}$	0.15			0.135	0.101				
$\pi_{7,9}$	0.25			0.258	0.146				
$\pi_{7,10}$	0.3			0.294	0.135				
$\pi_{8,9}$	0.3			0.272	0.184				
$\pi_{8,10}$	0.4			0.388	0.152				
$\pi_{9,10}$	0.45			0.364	0.203				
RMSE-all			2.311		0.223				

Under OP d.g.p. the misreported dependent variable ω takes values $j \in (1, ..., 10)$. Only MEs for the top half are shown. For $j \in (1, ..., 5)$ MEs are similar and only differ by the downward bias of $\hat{\gamma}_{\text{OP}}$.
But for $j \in (6, ..., 10)$, the MEs of the BOPM are also function of $\hat{\pi}_{j,k}$.
Moreover, when the true d.g.p. is the OP model, only MEs of the BOPM are defined.
This can be seen by setting $(\mathbf{x}'\beta) \to +\infty$ (or $\beta^* = 0$) in Appendix B.

TABLE 6.9

SIMULATION RESULTS FOR MODEL 3B: OP D.G.P. WITHOUT MISCLASSIFICATION

Marginal effects	J=6			J=7			J=8		
	TRUE	OP	BOPM	TRUE	OP	BOPM	TRUE	OP	BOPM
z_1	-0.130	-0.131	-0.293	0.057	0.058	0.052	0.161	0.160	0.156
		0.011	0.165		0.008	0.023		0.012	0.016
z_2	0.033	0.033	0.073	-0.014	-0.015	-0.013	-0.040	-0.040	-0.039
		0.002	0.041		0.002	0.006		0.002	0.004
	J=9			J=10					
	TRUE	OP	BOPM	TRUE	OP	BOPM			
z_1	0.074	0.074	0.071	0.014	0.014	0.014			
		0.006	0.007		0.003	0.003			
z_2	-0.019	-0.019	-0.018	-0.003	-0.004	-0.003			
		0.001	0.002		0.001	0.001			
Tests	OP	BOPM							
$\bar{\chi}^2$ test	0.99	0.01							
LR	1.00	0.00							
AIC	1.00	0.00							
BIC	1.00	0.00							
CAIC	1.00	0.00							
Parameters	TRUE	OP	Rmse	BOPM	Rmse				
c_1	-4	-4.028	0.119	-4.073	0.122				
c_2	-3.6	-3.624	0.107	-3.667	0.109				
c_3	-3.2	-3.221	0.098	-3.264	0.096				
c_4	-2.9	-2.927	0.103	-2.970	0.102				
c_5	-2.6	-2.621	0.098	-2.663	0.096				
c_6	-1.8	-1.819	0.093	-1.787	0.095				
c_7	-0.8	-0.814	0.081	-0.758	0.099				
c_8	0.1	0.079	0.080	0.170	0.123				
c_9	1	0.980	0.099	1.117	0.171				
γ_1	0.8	0.801	0.046	0.827	0.055				
γ_2	-0.2	-0.202	0.008	-0.207	0.009				
$\pi_{6,7}$	0			0.072	0.083				
$\pi_{6,8}$	0			0.010	0.054				
$\pi_{6,9}$	0			0.002	0.198				
$\pi_{6,10}$	0			0.000	0.250				
$\pi_{7,8}$	0			0.053	0.110				
$\pi_{7,9}$	0			0.001	0.249				
$\pi_{7,10}$	0			0.001	0.299				
$\pi_{8,9}$	0			0.060	0.246				
$\pi_{8,10}$	0			0.004	0.396				
$\pi_{9,10}$	0			0.054	0.400				
RMSE-all			0.066		0.826				

When the true d.g.p. is an OP without misclassification, the dependent variable is $y = 1, ..., 10$, and $\Pi_5 = I_{(5)}$.
The MEs for $j \in (1, ..., 5)$ are exactly the same for the OP and BOPM.
Though for answers in the top half, they differ by $\hat{\pi}_{j,k}$ of the BOPM MEs .
Again, only MEs of the BOPM are defined. See explanation in Table **??**.

equivalent to the BOPM as well as the HOP (and BOP) to the MEs of the OP.[12]

Table 6.8 reports the simulations for Model 3A.[13] Not surprisingly, the OP model in this scenario, performs very poorly with very significant biases in the estimated c_j and γ parameters: whereas the RMSE_{all} for the BOPM is 0.22, for the OP is 2.31. In fact, the true d.g.p. is closer to the BOPM and, consequently, true MEs (except for $j = 6$) are much better approximated by this model. All tests lead to the same conclusion.[14] The misclassification test, LR test and information criteria statistics choose the BOPM for all M repetitions.

On the other hand, when I assume lack of misreporting in Model 3B (see Table 6.9), results clearly change towards supporting the OP model. The $\bar{\chi}^2$ test accepts the null of non-misreporting for all instances, and the LR tests, AIC, BIC and CAIC support the OP model for all cases too. Although here the true model is strictly the OP because all $\pi_{j,k}$ are set to zero, the BOPM actually performs extremely well considering its estimated MEs which are close to the OP and true ones. This is a very favourable result. It means that when the reported outcome is in fact not misreported or misclassified, fitting a BOPM would still produce predictions close to the true model. This shows the capability of the BOPM to detect the lack of misclassification as all $\hat{\pi}_{j,k}$ tend to zero.

Figure 6.2 and Figure 6.3 show how the MEs for covariates $\mathbf{z}_1$ and $\mathbf{z}_2$ vary by the amount of misclassification. I multiply the off-diagonal elements of the $\Pi_{(5)}$ matrix by a constant $k = 0, 0.1, 0.2, ..., 1$ to generate different degrees of misreporting. Then, when $k = 0$ the misclassification matrix is identity matrix $I_{(5)}$ (Model 3B) and for $k = 1$ the one displayed previously (Model 3A). Both figures shows that BOPM model yields, regardless of the level of misclassification, MEs that are closer to the true MEs as compared to the MEs under the OP model. All MEs coincide when $k = 0$ but, when k increases, the MEs for the OP monotonically depart from the true ones. The BOPM is also accepted by the misclassification test as the true model in all instances for most values of k (i.e, $k \geq 0.3$). Once more, these figures support the BOPM even though misclassification may not be present.

I can conclude for the Monte Carlo results in this Chapter the following. First, when the true d.g.p. is given by the HOPM and the BOPM, both models perform well and the remaining HOP, BOP and OP models MEs are far away from their true values and imprecisely estimated. Second, based on the t-test on ρ, the performance of the

[12]This can be seen by replacing $(\mathbf{x}'\beta)$ by $+\infty$ in the full expressions for MEs in Appendix B.

[13]MEs for the bottom half answers are not shown because misclassification is only assumed for observed answers in the top half of the distribution. Hence, MEs for $j \in (1, ..., 5)$ are similar for the two models, and mainly explained by a downward bias of OP $\hat{\gamma}$ coefficients as they are not function of misclassification probabilities.

[14]I do not include the Vuong test as the two models are strictly nested by setting $\pi_{j,k} = 0$.

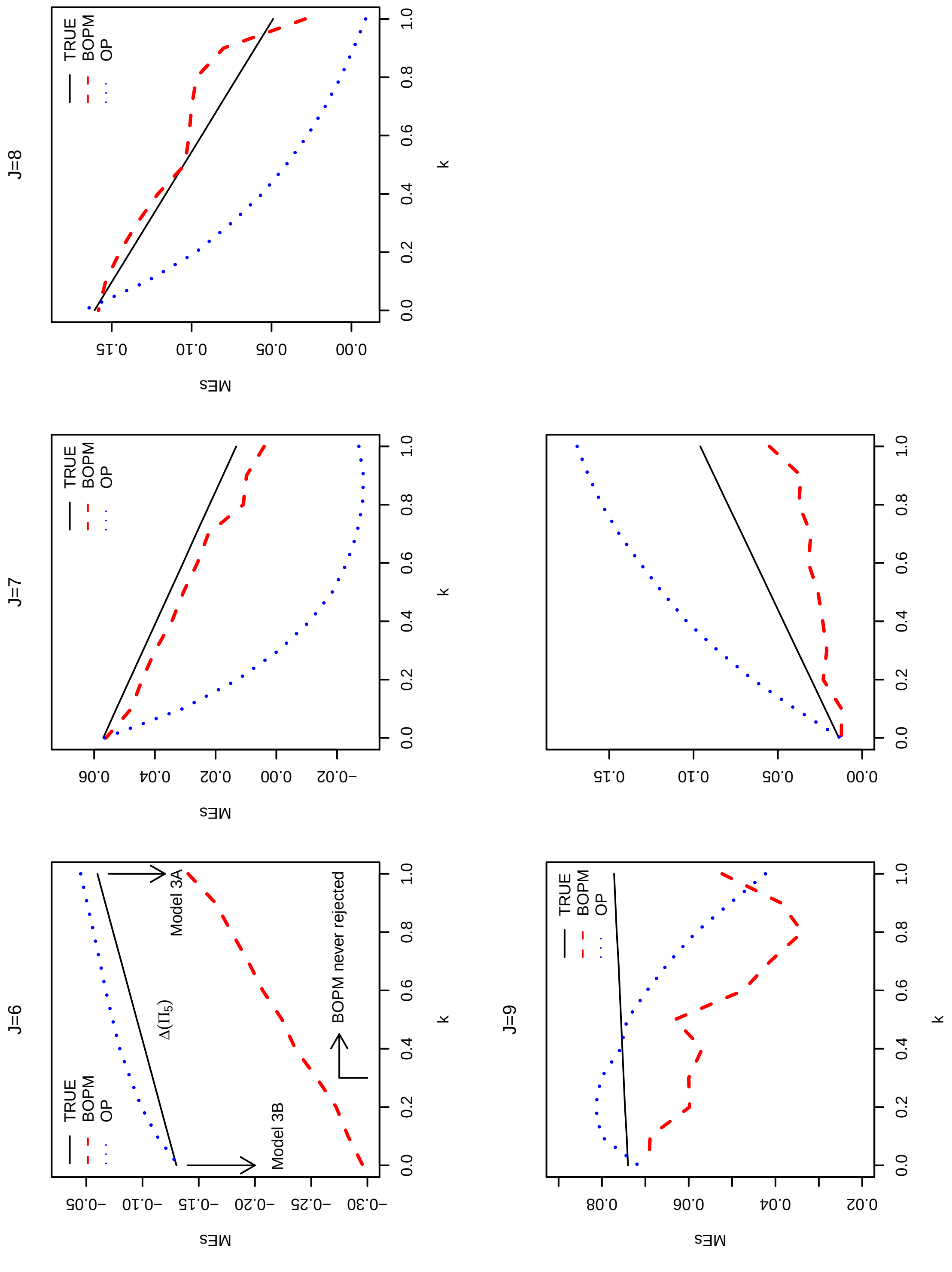

FIGURE 6.2.— Marginal effects for covariate z_1 by amount of misclassification.

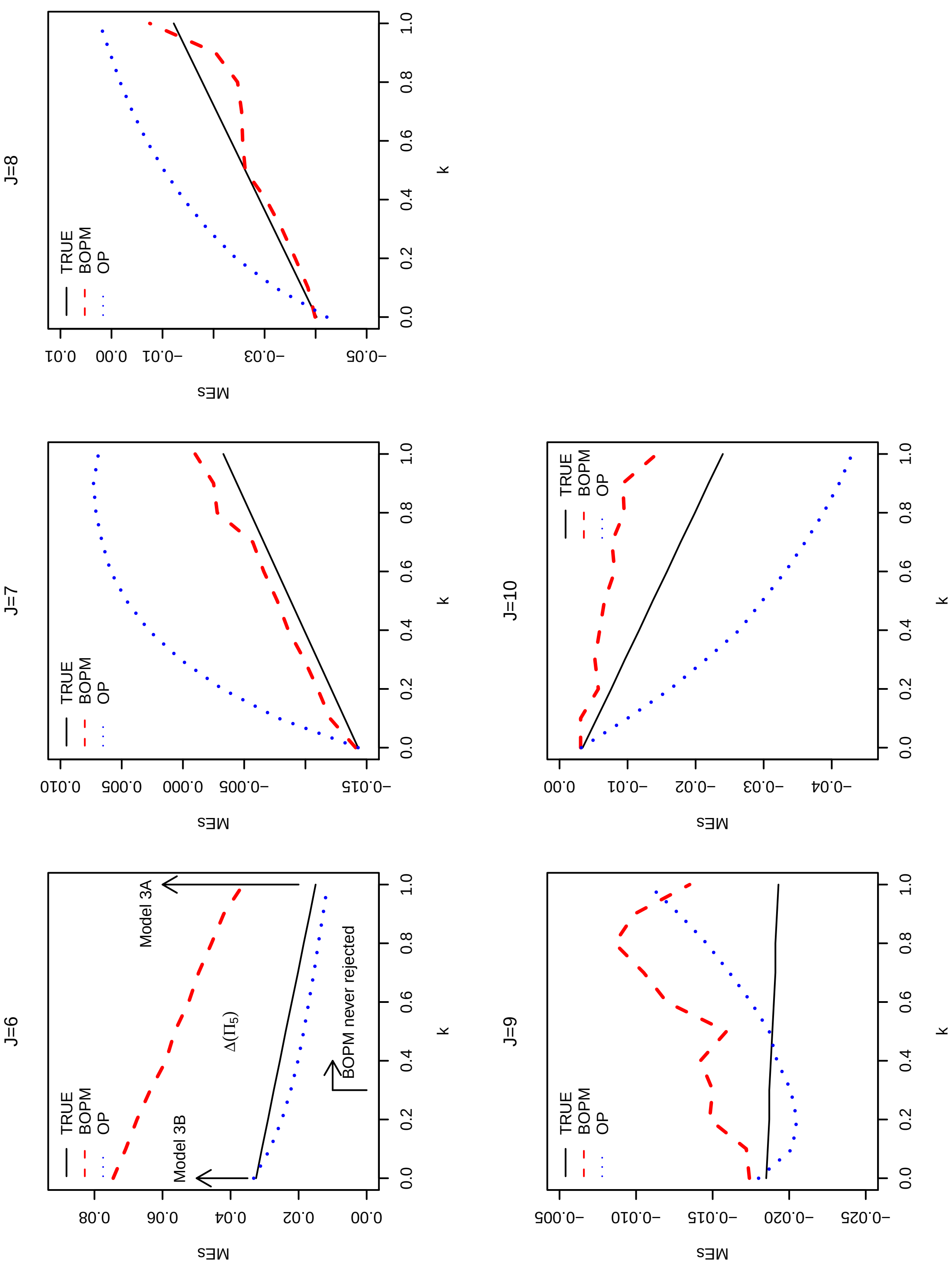

FIGURE 6.3.— Marginal effects for covariate z_2 by amount of misclassification.

HOPM model compared to the BOPM model is mainly enhanced the less skew the distribution of dependent variable is. Instead, as I assume a very skew outcome, the BOPM model performs the best across the different experiments. Third, a positive result is that the BOPM yields accurate estimates and MEs even when the true d.g.p. is the usual OP model and, unless this is true model, the OP is never chosen by any test or information criteria. Furthermore, when choosing amongst the models, the $\bar{\chi}^2$ test always picks the correct model, as well as the LR and Vuong tests. Yet, for the information criteria statistics, only the AIC select the correct true model, with the BIC and CAIC more likely to choose the smaller models (i.e., HOP and BOP) as they penalise the more parameterised models. All information criteria, however, do not fail to choose the correct model when d.g.p. is given by the OP. The crucial and encouraging result is the BOPM's good performance, regardless of the d.g.p. assumed.

6.5. EMPIRICAL APPLICATION TO CIVIC BEHAVIOURS

I now turn to an empirical application of the econometric models. It is based on one of the civic behaviours' variables I introduced earlier in the data Section 2.3 of Chapter 2. This dependent variable is convenient to apply to the previous models since: (i) it contains a significant amount of skewness, and (ii) because it is a measurement of a sensitive topic (question), it is very likely to be misreported due to SD.

In particular, the civic behaviour chosen is a question regarding the willingness to leave the name when scraping a car (for Italy). Recall that individuals were asked to report the extent to which *not leaving your name for the owner of a car you accidentally scraped* was acceptable, with responses given in an ordered scale from 1 'never justified' to 10 'always justified'. The order to the answers of this question is reversed so that a higher value indicates a higher sense of civic duty. Table 6.10 presents the proportions of each answers $j = (1, ..., 10)$. Clearly, the distribution of the dependent variable is highly skewed (skewness = -2.24), with a small fraction of answers below the median of $\approx$ 7%. Covariates included in the analysis are displayed in Table 2.1 of Chapter 2.

6.5.1. *Results*

In this section I present the array of tests and MEs for the group of models previously discussed. (See Figure 6.1). I select the covariates so as to explain whether individuals' answers are in the bottom or top half of the distribution of the dependent variable 'not leaving name' the following socioeconomic proxies: years of education

TABLE 6.10

Civic behaviour ('not leaving name') frequencies

Not leaving name: $\Pr(\omega = j)$, for $j = 1, ..., 10$	
always justifiable = 1	0.88
2	0.78
3	1.86
4	1.34
5	1.47
6	4.45
7	4.32
8	7.91
9	15.04
never justifiable = 10	61.95
Number of observations	3,059

and household income. That is, the vector of explanatory variables for the probit selection rule of Eq. (6.2) is $\mathbf{x} = (\mathbf{x}_0, \mathbf{x}_1, \mathbf{x}_2)$, where $\mathbf{x}_0$ is a vector of ones, $\mathbf{x}_1 =$ education, and $\mathbf{x}_2 =$ income. For answers above the median ($j \geq 6$), the covariates $\mathbf{z}$ are a subset of the whole range of variables of Table 2.1. Thus, the scenario is one of partial overlap with extra variables only in $\mathbf{z}$.

I purposely choose this set up for two reasons. First, individuals from privileged backgrounds are more likely to be more civically responsible, with their 'observed' responses located in the top half. Indeed, there is consensus in the empirical literature that education is positively associated with civic outcomes (e.g., Dee (2004)). Second, to facilitate identification of ρ through nonlinearities by a scenario of partial overlap between covariates $\mathbf{x}$ and $\mathbf{z}$.

Tests and information criteria for the five alternative econometric models[15] are contained in Table 6.11. The misclassification test confirms that, both the HOPM and BOPM models which allow for misclassification errors, outperform the the HOP and BOP models. The $\bar{\chi}^2$ statistics are 0.2129 and 0.1418, with probability values less than 5%, so one would reject the null hypothesis that the misclassification probabilities are equal to zero in either case. As expected, the civic behaviour 'not leaving name' suffers from SDB and is therefore misreported. This is particularly relevant for Italy which has often been characterised as a low trust society with a higher tolerance of self-interest acts, such as the one measured by the dependent variable in the current application (Halpern (2005)). When comparing the hurdle and binary versions of the models, binary representations are superior according to the t-test in

[15]Recall that for the hurdle and binary models a 6 point scale is used, with j taking values (1,2,...,5)=0, (6=6),..., (10=10), whereas for the OP the dependent variable takes values $j \in (1, ..., 10)$.

TABLE 6.11

MODELS' TESTS AND INFORMATION CRITERIA FOR 'NOT LEAVING NAME'

	HOPM	BOPM	HOP	BOP	OP
$\ell(\hat{\theta})$	-3688.96	-3689.29	-3755.68	-3702.17	-3989.19
$\hat{\rho}$	-0.0309		-0.0395		
(std error)	(0.8622)		(0.2643)		
$\bar{\chi}^2$	0.2129**	0.1418**			
(p-value)	(0.0225)	(0.0390)			
LR test versus OP	600.46**	599.78**			
AIC	7435.91	**7434.59**	7549.35	7440.34	8018.37
BIC	7610.66	7603.31	7663.84	**7548.80**	8138.89
CAIC	7639.66	7631.31	7682.84	**7566.80**	8158.89
Vuong test versus OP	-13.48	-13.45	-8.12	-11.94	

** significant at 5 % and * significant at 10 %.
The preferred model, with the lowest information criteria, is indicated in bold.
The OP dependent variable takes values $j \in (1, ..., 10)$. For the hurdle and binary models a 6 point scale is used, with (1,2,...,5)=0, (6=6),..., (10=10).

$\hat{\rho}$, and for the two hurdle models the correlation is statistically insignificant. Uncorrelated versions of the models are additionally supported by the information criteria statistics. The AIC suggests superiority of the BOPM, whereas the BIC and CAIC statistics which penalise more parameterised models, favour the BOP. Moreover, the OP performs poorly with the LR statistics rejecting the OP model, as well as the Vuong test. In summary, the BOPM is the most preferred model and the OP is never selected by any test and information criteria. The better performance of the BOPM across the five models is in line with the simulations results.

Nevertheless, one needs to evaluate the potential endogeneity of education to obtain a credible link between schooling and civic behaviour. Hence, I employ an educational reform as an instrument for schooling that provides a source of exogenous variation in individuals' level of schooling that is otherwise unrelated to the dependent variable.[16] Because the BOPM offers the best performance, I carry out a Hausman test to check for endogeneity for this model as well as for the OP. For this latter model, education only appears once as covariate in $\mathbf{z}$, thus I use a Hausman test only for this parameter.[17] The $\chi^2(1)$ statistic is 0.013 (p-value = 0.910), so that the null of exogeneity of education is accepted. I also arrive at the same conclusion in the BOPM framework. Here, education is included in the two groups of $\mathbf{x}$ and $\mathbf{z}$ covariates and one needs to apply a different version of the test. Specifically, the Hausman test statistic is H $= \left(\hat{\theta} - \tilde{\theta}\right)'\left(\hat{V}[\tilde{\theta}] - \hat{V}[\hat{\theta}]\right)^{-1}\left(\hat{\theta} - \tilde{\theta}\right) \sim \chi^2(\text{q})$, where $\hat{\theta}$ is the BOPM estimator, and $\tilde{\theta}$ the IV-BOPM estimator.[18] The $\chi^2(24)$ statistic is 18.80

[16] A detailed explanation of the IV strategy can be found in Section 4.2.

[17] The statistic is given by: H $= \frac{(\hat{\gamma}_{\text{ed,OP}} - \hat{\gamma}_{\text{ed,IV-OP}})^2}{\text{se}^2_{(\hat{\gamma}_{\text{ed,IV-OP}})} - \text{se}^2_{(\hat{\gamma}_{\text{ed,OP}})}} \sim \chi^2(1)$.

[18] Since $\left(\hat{V}[\tilde{\theta}] - \hat{V}[\hat{\theta}]\right)$ is of less than full rank (q= 24 < 28), then the generalised inverse is used and

with a p-value of 0.24. The standard MEs, without accounting for endogeneity, are then appropriate.

The estimated misclassification matrix for the preferred model, the BOPM, is

$$\hat{\Pi}_{(5)} = \begin{bmatrix} \hat{\pi}_{6,6} & \hat{\pi}_{6,7} & \hat{\pi}_{6,8} & \hat{\pi}_{6,9} & \hat{\pi}_{6,10} \\ 0 & \hat{\pi}_{7,7} & \hat{\pi}_{7,8} & \hat{\pi}_{7,9} & \hat{\pi}_{7,10} \\ 0 & 0 & \hat{\pi}_{8,8} & \hat{\pi}_{8,9} & \hat{\pi}_{8,10} \\ 0 & 0 & 0 & \hat{\pi}_{9,9} & \hat{\pi}_{9,10} \\ 0 & 0 & 0 & 0 & \hat{\pi}_{10,10} \end{bmatrix} = \begin{bmatrix} 0.4312 & 0.1960 & 0.1887 & 0.0000 & 0.1841 \\ 0.0000 & 0.6556 & 0.0821 & 0.0000 & 0.2623 \\ 0.0000 & 0.0000 & 0.4875 & 0.0126 & 0.4999 \\ 0.0000 & 0.0000 & 0.0000 & 0.5250 & 0.4750 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000 & 1.0000 \end{bmatrix}.$$

Note that the amount of misclassification is significant. The probabilities of answering the truth (the diagonal elements of $\hat{\Pi}_{(5)}$) are less than 52% (expect from $\hat{\pi}_{7,7}$). Overall, it is equally likely that individuals would either tell the truth or lie when answering the question on the civic behaviour 'not leaving name'. In particular, most misreporting is due to the elements $\hat{\pi}_{j,10}$. This means that people whose reported answers show a lower degree of civic awareness are more concerned in presenting themselves in the most socially acceptable terms (reporting $j = 10$) and, consequently, they tend to lie on how they would react to this hypothetical situation. This is consistent with findings from social psychology that support over-reporting of civic behaviours.

What is the impact of misclassification matrix in terms of 'true' answers? One can recover the vector of 'true' answers by an equation system (see, e.g., Molinari (2008)) that relates reported and true outcomes by the estimated misclassification matrix. Specifically, I only need to transpose the matrix and take its inverse to obtain a solution for the vector of true responses: $\hat{P}^{\tilde{y}} = \left(\hat{\Pi}'_{(5)}\right)^{-1} \times P^{\tilde{\omega}}$, where $P^{\tilde{\omega}}$ is given by the sample, that is, the vector of observed frequencies which is misclassified. Results of $\hat{P}^{\tilde{y}}_j$ for $j \in (6, ..., 10)$ are contained in Figure 6.4. Clearly, there is a very important under-reporting for $j = 6$ with true answers twice as large as observed values $\left(\hat{P}^{\tilde{y}}_6 = 0.10 > P^{\tilde{\omega}}_6 = 0.04\right)$, as well as over-reporting for the highest value $j = 10$ $\left(P^{\tilde{\omega}}_{10} = 0.62 > \hat{P}^{\tilde{y}}_6 = 0.40\right)$. The remaining categories $(j = 8, 9)$ are under-reported, with $P^{\tilde{\omega}}_7 \approx \hat{P}^{\tilde{y}}_7$. Predicted true probabilities follow Proposition 6.1(i) and there are significant differences between observed and true responses. This shows that some of the skewness of the distribution of the dependent variable is explained by misclassification, with most answers being under-reported, apart from $j = 10$.

I now discuss the estimated MEs for the different models. Table 6.12 presents the MEs for the binary and the OP models. The main comparison is between the chosen model, the BOPM, against the OP, which would be commonly used in this

the chi-square test has degrees of freedom equal to the rank of $\left(\hat{V}[\tilde{\theta}] - \hat{V}[\hat{\theta}]\right)$.

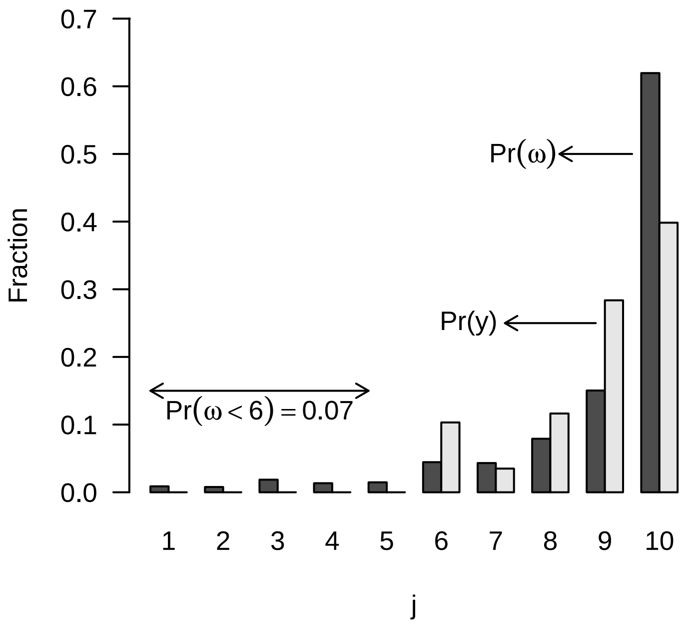

FIGURE 6.4.— Observed and true probabilities for 'not leaving name'.

type of application. Predictions for the explanatory variable family income underlines important differences between the two models. Results based on the BOPM model show a logical positive impact of income for all answers, with the effect rising along j. An increase of household income of a thousand results in a 0.0063 rise in the 'true' probability of answering $j = 6$, whereas the increase in the probability for $j = 10$ is significantly higher, of 9.67%. For the OP, however, this impact is not only constant but also negative for $j = 6, 7, 8$; even for category $j = 10$ is very small $(= 0.0012)$. Using the OP model, without accounting for misreporting, one would incorrectly conclude that income only increases the probability on the highest value of the scale.[19]

A similar example of significant MEs with opposite signs is given by the covariate age. Empirical evidence suggests that older individuals are likely to exhibit a higher concern for civic values compared to younger individuals (Algan and Cahuc (2006)). This is mostly predicted by the BOPM MEs but, for the OP, an increase of age reduces the effect on nearly all probabilities. Additionally, note that the MEs for the BOPM for overlapping covariates (education and income) are composed of two

[19]This might be caused by the smaller variation between 'observed' frequencies for $j = 6, ..., 9$.

elements: MEs on answers being above the median and MEs on the probability of the 'true' outcome conditional on this. For example, the ME of income of 0.0245 (for $j = 9$) is the result of the MEs of $\Pr(d = 1) = 0.1462$ and $\Pr(\tilde{\omega} = 9|d = 1) = 0.1679$.

Moreover, even if some MEs are in line with each other in term of signs, the OP model produces substantially biased results. For instance, the average bias of the significant MEs for the variable education, is around 800%. In some cases the upper bias in the MEs of the OP model leads to qualitatively different conclusions. Covariates such as number of children in the household and being married do not have a statistically significant impact (for all j) in the BOPM (p-values ≈ 0.40), but they are significant according to the OP model (p-values ≈ 0.02).

In summary, there are crucial discrepancies in the MEs according to the signs and statistical significance of these two models. This reflects the relevance of the two-part and misclassification assumptions in the estimated MEs. In contrast, MEs predictions for binary models are more alike in relation to their signs, but there are still important differences which are due to misclassification. Most BOPM's MEs are larger than the ones from the BOP.

I still present the results for the hurdle models although $\hat{\rho}$ is not significant. As can be seen in Table 6.13, the MEs of the HOPM are very similar to the BOPM and the HOP and BOP estimates are quite close as well, which additionally provide evidence on the independence of the two-part decisions. In other words, the MEs of the HOPM and HOP confirm earlier binary predictions. There are further disparities in the MEs significance levels between the HOPM and OP, with only two covariates agreeing completely (for all j) with regards to statistical significance.

6.6. CONCLUSIONS

In this Chapter, I propose a hurdle (and binary) OPM to deal with the skewness and misclassification of the distribution of a self-reported outcome. As the outcome variable has a substantial proportion of values at one end of its distribution, I account for this via a hurdle (or two-part) assumption which divides the distribution into two regimes, by the median of the dependent variable, using a split probit. I also allow for the possible correlation of the two latent equations in the HOPM model. In addition, as the framework is of a dependent variable which measures a sensitive topic, it is likely to be misclassified due to SDB, with individuals under-reporting undesirable behaviours and over-reporting desirable ones. I handle this by using an OPM to deal with misreporting of observed answers in the top half of the scale.

The Monte Carlo simulations provide a good performance. If the d.g.p. includes misclassification, both the HOPM and BOPM perform well with estimates and MEs

TABLE 6.12

Binary models and OP marginal effects for 'not leaving name'

Variables	BOPM Pr($\tilde{\omega}$=0)	BOP Pr($\tilde{y}$=0)		BOPM Pr($\tilde{\omega}$=6)	BOP Pr($\tilde{y}$=6)	OP Pr(y=6)
Education	-0.0008**	-0.0012**		-0.0001**	-0.0002**	-0.0018**
	(0.0002)	(0.0003)		(0.0000)	(0.0001)	(0.0004)
Income	-0.1462**	-0.1119**		0.0066**	0.0048**	-0.0002**
	(0.0115)	(0.0115)		(0.0034)	(0.0006)	(0.0001)
Age				0.0006	-0.0007	-0.0001
				(0.0009)	(0.0009)	(0.0006)
Age2/100				-0.0013*	-0.0003	-0.0005
				(0.0009)	(0.0008)	(0.0005)
Male				0.0015	0.0008	0.0005
				(0.0042)	(0.0045)	(0.0027)
Father's education				-0.0002	-0.0002	0.0000
				(0.0007)	(0.0008)	(0.0005)
Mother's education				-0.0006	-0.0007	-0.0000
				(0.0008)	(0.0009)	(0.0006)
Number of children				-0.0015	-0.0015	-0.0034**
				(0.0022)	(0.0024)	(0.0016)
Married				0.0008	0.0033	0.0065**
				(0.0049)	(0.0049)	(0.0033)
Center				-0.0308**	-0.0279**	-0.0201**
				(0.0145)	(0.0058)	(0.0040)
North				-0.0290**	-0.0237**	-0.0236**
				(0.0134)	(0.0049)	(0.0037)

Variables	BOPM Pr($\tilde{\omega}$=7)	BOP Pr($\tilde{y}$=7)	OP Pr(y=7)	BOPM Pr($\tilde{\omega}$=8)	BOP Pr($\tilde{y}$=8)	OP Pr(y=8)
Education	-0.0002*	-0.0001*	-0.0015**	-0.0002**	-0.0001*	-0.0021**
	(0.0001)	(0.0001)	(0.0004)	(0.0001)	(0.0001)	(0.0005)
Income	0.0059**	0.0050**	-0.0002**	0.0124**	0.0095**	-0.0002**
	(0.0008)	(0.0007)	(0.0001)	(0.0038)	(0.0011)	(0.0001)
Age	0.0007	-0.0005	-0.0001	0.0009	-0.0007	-0.0001
	(0.0009)	(0.0006)	(0.0005)	(0.0012)	(0.0009)	(0.0007)
Age2/100	-0.0015**	-0.0002	-0.0004	-0.0018**	-0.0003	-0.0006
	(0.0008)	(0.0006)	(0.0004)	(0.0010)	(0.0008)	(0.0006)
Male	0.0018	0.0006	0.0004	0.0021	0.0009	0.0006
	(0.0048)	(0.0033)	(0.0022)	(0.0058)	(0.0048)	(0.0033)
Father's education	-0.0003	-0.0001	0.0000	-0.0003	-0.0002	0.0000
	(0.0008)	(0.0006)	(0.0004)	(0.0010)	(0.0008)	(0.0006)
Mother's education	-0.0007	-0.0005	-0.0000	-0.0008	-0.0007	-0.0000
	(0.0009)	(0.0006)	(0.0005)	(0.0011)	(0.0009)	(0.0007)
Number of children	-0.0018	-0.0011	-0.0028**	-0.0021	-0.0016	-0.0041**
	(0.0029)	(0.0018)	(0.0013)	(0.0033)	(0.0026)	(0.0020)
Married	0.0009	0.0025	0.0054**	0.0011	0.0035	0.0079**
	(0.0060)	(0.0037)	(0.0027)	(0.0070)	(0.0053)	(0.0040)
Center	-0.0367**	-0.0208**	-0.0167**	-0.0437**	-0.0297**	-0.0244**
	(0.0097)	(0.0045)	(0.0034)	(0.0100)	(0.0063)	(0.0048)
North	-0.0346**	-0.0177**	-0.0195**	-0.0412**	-0.0253**	-0.0287**
	(0.0094)	(0.0038)	(0.0031)	(0.0089)	(0.0053)	(0.0043)

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Variables	BOPM Pr($\tilde{\omega}$=9)	BOP Pr($\tilde{y}$=9)	OP Pr(y=9)	BOPM Pr($\tilde{\omega}$=10)	BOP Pr($\tilde{y}$=10)	OP Pr(y=10)
Education	0.0001	-0.0001	-0.0024**	0.0012**	0.0017**	0.0110**
	(0.0001)	(0.0001)	(0.0006)	(0.0003)	(0.0004)	(0.0026)
Income	0.0249**	0.0184**	-0.0003**	0.0963**	0.0742**	0.0012**
	(0.0001)	(0.0020)	(0.0001)	(0.0074)	(0.0077)	(0.0004)
Age	0.0002	-0.0009	-0.0002	-0.0024	0.0028	0.0007
	(0.0005)	(0.0010)	(0.0008)	(0.0031)	(0.0035)	(0.0036)
Age2/100	-0.0004	-0.0004	-0.0006	0.0049**	0.0012	0.0030
	(0.0009)	(0.0009)	(0.0007)	(0.0027)	(0.0031)	(0.0033)
Male	0.0004	0.0010	0.0007	-0.0057	-0.0032	-0.0032
	(0.0015)	(0.0054)	(0.0037)	(0.0158)	(0.0180)	(0.0169)
Father's education	-0.0001	-0.0002	0.0000	0.0009	0.0007	-0.0002
	(0.0003)	(0.0010)	(0.0007)	(0.0027)	(0.0032)	(0.0033)
Mother's education	-0.0002	-0.0008	-0.0000	0.0022	0.0028	0.0002
	(0.0005)	(0.0010)	(0.0008)	(0.0030)	(0.0035)	(0.0036)
Number of children	-0.0004	-0.0018	-0.0046**	0.0058	0.0060	0.0212**
	(0.0013)	(0.0029)	(0.0022)	(0.0090)	(0.0096)	(0.0100)
Married	0.0002	0.0040	0.0088**	-0.0031	-0.0134	-0.0406**
	(0.0016)	(0.0060)	(0.0045)	(0.0193)	(0.0198)	(0.0204)
Center	-0.0087	-0.0338**	-0.0273**	0.1199**	0.1122**	0.1260**
	(0.0228)	(0.0070)	(0.0053)	(0.0212)	(0.0225)	(0.0231)
North	-0.0082	-0.0287**	-0.0320**	0.1129**	0.0953**	0.1479**
	(0.0214)	(0.0059)	(0.0047)	(0.0174)	(0.0189)	(0.0197)

** significant at 5 % and * significant at 10 %.
Standard errors are given in parentheses.
For the OP, only MEs for $j \in (6, ..., 10)$ are shown because they are comparable to the ones from the BOPM and BOP models.

close to the true values, and the $\bar{\chi}^2$ misclassification test always picks the correct model as well as the LR and Vuong tests. As regsards to information criteria statistics, only the AIC selects the correct true model, with the BIC and CAIC more likely to choose the smaller models (i.e., HOP and BOP) as they penalise the more parameterised models. When comparing the performance of the HOPM to the BOPM based on the t-test on ρ, the power of this test is enhanced, the less skewed the distribution of the dependent variable is, but since the framework is of a very skew outcome, the BOPM model provides the best performance. Under the scenario of misclassification, the remaining models, the HOP, BOP and OP, have MEs which are far away from their true values and imprecisely estimated. A positive result is that, even in the case of a d.g.p. given by the OP, the BOPM will still yield accurate estimates and MEs.

I then apply the models to a discrete civic behaviour (for Italy) outcome measuring the willingness to leave the name when scraping a car ('not leaving name') which is prone to suffer from SDB and, consequently, is likely to be misreported. In fact, I found a significant amount of misclassification, being equally likely that individuals would either tell the truth or lie. This demonstrates the superiority of the models which incorporate misreporting. An equation system that relates reported and true answers by the estimated misclassification matrix, shows that categories depicting low degree of civic behaviour are clearly under-reported and, in particular, the highest

TABLE 6.13

Hurdle models marginal effects for 'not leaving name'

Variables	HOPM Pr($\tilde{\omega}$=0)	HOP Pr($\tilde{y}$=0)	HOPM Pr($\tilde{\omega}$=6)	HOP Pr($\tilde{y}$=6)	HOPM Pr($\tilde{\omega}$=7)	HOP Pr($\tilde{y}$=7)
Education	-0.0008**	-0.0021**	-0.0002**	-0.0001*	-0.0002**	-0.0001
	(0.0003)	(0.0003)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Income	-0.1451**	-0.0386**	0.0061	0.0014	0.0055	0.0015
	(0.0120)	(0.0106)	(0.0141)	(0.0016)	(0.0137)	(0.0013)
Age			0.0008*	-0.0010**	0.0007**	-0.0007**
			(0.0006)	(0.0004)	(0.0004)	(0.0003)
Age^2/100			-0.0015**	-0.0001	-0.0014**	-0.0001
			(0.0007)	(0.0004)	(0.0003)	(0.0003)
Male			0.0009**	0.0006	0.0009**	0.0005
			(0.0001)	(0.0047)	(0.0001)	(0.0035)
Father's education			-0.0002	-0.0002	-0.0002	-0.0001
			(0.0007)	(0.0008)	(0.0007)	(0.0006)
Mother's education			-0.0005	-0.0007	-0.0005	-0.0005
			(0.0007)	(0.0009)	(0.0007)	(0.0006)
Number of children			-0.0018	-0.0015	-0.0017	-0.0011
			(0.0024)	(0.0024)	(0.0022)	(0.0018)
Married			0.0024	0.0037	0.0023	0.0027
			(0.0045)	(0.0050)	(0.0042)	(0.0037)
Center			-0.0298**	-0.0283**	-0.0291**	-0.0210**
			(0.0122)	(0.0059)	(0.0073)	(0.0045)
North			-0.0272**	-0.0241**	-0.0266**	-0.0179**
			(0.0115)	(0.0050)	(0.0069)	(0.0038)

Variables	HOPM Pr($\tilde{\omega}$=8)	HOP Pr($\tilde{y}$=8)	HOPM Pr($\tilde{\omega}$=9)	HOP Pr($\tilde{y}$=9)	HOPM Pr($\tilde{\omega}$=10)	HOP Pr($\tilde{y}$=10)
Education	-0.0002*	-0.0001	-0.0000	0.0001	0.0013**	0.0023**
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0004)	(0.0005)
Income	0.0116	0.0030*	0.0241**	0.0061**	0.0978**	0.0265**
	(0.0193)	(0.0020)	(0.0121)	(0.0028)	(0.0564)	(0.0088)
Age	0.0010**	-0.0010**	0.0006	-0.0012**	-0.0031**	0.0039**
	(0.0006)	(0.0004)	(0.0005)	(0.0005)	(0.0016)	(0.0015)
Age^2/100	-0.0020**	-0.0001	-0.0011	-0.0001	0.0060**	0.0003
	(0.0007)	(0.0004)	(0.0010)	(0.0005)	(0.0017)	(0.0017)
Male	0.0013**	0.0007	0.0007**	0.0008	-0.0038**	-0.0026
	(0.0001)	(0.0050)	(0.0001)	(0.0057)	(0.0001)	(0.0188)
Father's education	-0.0003	-0.0002	-0.0001	-0.0002	0.0008	0.0007
	(0.0010)	(0.0008)	(0.0005)	(0.0010)	(0.0029)	(0.0032)
Mother's education	-0.0007	-0.0008	-0.0004	-0.0009	0.0020	0.0029
	(0.0010)	(0.0009)	(0.0007)	(0.0010)	(0.0029)	(0.0034)
Number of children	-0.0024	-0.0016	-0.0013	-0.0019	0.0072	0.0062
	(0.0032)	(0.0026)	(0.0022)	(0.0029)	(0.0097)	(0.0097)
Married	0.0032	0.0039	0.0018	0.0044	-0.0098	-0.0147
	(0.0060)	(0.0053)	(0.0036)	(0.0060)	(0.0179)	(0.0200)
Center	-0.0403**	-0.0302**	-0.0226	-0.0344**	0.1218**	0.1138**
	(0.0086)	(0.0063)	(0.0193)	(0.0070)	(0.0218)	(0.0226)
North	-0.0367**	-0.0257**	-0.0206	-0.0293**	0.1110**	0.0969**
	(0.0079)	(0.0053)	(0.0171)	(0.0059)	(0.0189)	(0.0190)

** significant at 5 % and * significant at 10 %.
Standard errors are given in parentheses.

degree of civic behaviour is largely over-reported. In turn, this leads to considerable discrepancies in the estimated MEs between the chosen BOPM model and the OP, often yielding different qualitative conclusions.

The models introduced in Chapter 6 can be used to analyse diverse outcomes in the social sciences where one believes that individuals' answering is a two stage process, which is also subject to misclassification. Besides being applicable to several sensitive questions (e.g., civic behaviours, illegal activities, drug consumption, etc.) whose answers are either provided or can be recoded into 1 to J scale, the models are also useful to studies using satisfaction or happiness data.

B. APPENDIX: HOPM MARGINAL EFFECTS

In this appendix, I present the full MEs for the reported (misclassified) dependent variable $\tilde{\omega}$. For $\tilde{\omega} = \tilde{y} = 0$ the ME is,

$$\underset{\Pr(\tilde{\omega}=0)}{ME} = \frac{\partial \Pr(\tilde{y}=0|\mathbf{x})}{\partial \mathbf{x}^*} = \frac{\partial \Pr(d=0|\mathbf{x})}{\partial \mathbf{x}^*} = -\phi(\mathbf{x}'\beta)\beta^*. \tag{B.1}$$

When $\tilde{\omega} = \frac{J}{2} + 1$,

$$\underset{\Pr(\tilde{\omega}=(J/2)+1)}{ME} = \pi_{(J/2)+1,(J/2)+1} \frac{\partial \Pr(\tilde{y}=(J/2)+1|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*}, \tag{B.2}$$

where

$$\begin{aligned}\frac{\partial \Pr(\tilde{y}=(J/2)+1|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*} &= \frac{\partial \Phi_2(\mathbf{x}'\beta, c_{(J/2)+1} - \mathbf{z}'\gamma; -\rho)}{\partial \mathbf{x}^*} \\ &= \phi(\mathbf{x}'\beta)\Phi\left(\frac{c_{(J/2)+1} - \mathbf{z}'\gamma + \rho\mathbf{x}'\beta}{\sqrt{1-\rho^2}}\right)\beta^* \\ &- \phi(c_{(J/2)+1} - \mathbf{z}'\gamma)\Phi\left(\frac{\mathbf{x}'\beta + \rho(c_{(J/2)+1} - \mathbf{z}'\gamma)}{\sqrt{1-\rho^2}}\right)\gamma^*.\end{aligned}$$

The ME when $\tilde{\omega} = \frac{J}{2} + 2$ is,

$$\begin{aligned}\underset{\Pr(\tilde{\omega}=(J/2)+2)}{ME} &= \pi_{(J/2)+1,(J/2)+1} \frac{\partial \Pr(\tilde{y}=(J/2)+1|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*} \\ &+ \pi_{(J/2)+2,(J/2)+2} \frac{\partial \Pr(\tilde{y}=(J/2)+2|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*},\end{aligned} \tag{B.3}$$

where

$$\begin{aligned}\frac{\partial \Pr(\tilde{y}=(J/2)+2|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*} &= \frac{\partial \Phi_2(\mathbf{x}'\beta, c_{(J/2)+2} - \mathbf{z}'\gamma; -\rho)}{\partial \mathbf{x}^*} - \frac{\partial \Phi_2(\mathbf{x}'\beta, c_{(J/2)+1} - \mathbf{z}'\gamma; -\rho)}{\partial \mathbf{x}^*} \\ &= \left[\phi(\mathbf{x}'\beta)\Phi\left(\frac{c_{(J/2)+2} - \mathbf{z}'\gamma + \rho\mathbf{x}'\beta}{\sqrt{1-\rho^2}}\right) - \phi(\mathbf{x}'\beta)\Phi\left(\frac{c_{(J/2)+1} - \mathbf{z}'\gamma + \rho\mathbf{x}'\beta}{\sqrt{1-\rho^2}}\right)\right]\beta^* \\ &+ \left[\phi(c_{(J/2)+1} - \mathbf{z}'\gamma)\Phi\left(\frac{\mathbf{x}'\beta + \rho(c_{(J/2)+1} - \mathbf{z}'\gamma)}{\sqrt{1-\rho^2}}\right)\right. \\ &\left. - \phi(c_{(J/2)+2} - \mathbf{z}'\gamma)\Phi\left(\frac{\mathbf{x}'\beta + \rho(c_{(J/2)+2} - \mathbf{z}'\gamma)}{\sqrt{1-\rho^2}}\right)\right]\gamma^*.\end{aligned}$$

And similarly for $\frac{J}{2} + 3 \leq \tilde{\omega} < J$. Finally, when $\tilde{\omega} = J$, I obtain,

$$\underset{\Pr(\tilde{\omega}=J)}{ME} = \frac{\partial \Pr(\tilde{\omega}=J|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*} = \sum_{j=(J/2)+1}^{J} \pi_{j,J} \frac{\partial \Pr(\tilde{y}=j|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*}, \tag{B.4}$$

where

$$\begin{aligned}\frac{\partial \Pr(\tilde{y}=J|\mathbf{z},\mathbf{x})}{\partial \mathbf{x}^*} &= \frac{\partial \Phi_2(\mathbf{x}'\beta, \mathbf{z}'\gamma - c_{J-1};\rho)}{\partial \mathbf{x}^*} \\ &= \phi(\mathbf{x}'\beta)\Phi\left(\frac{\mathbf{z}'\gamma - c_{J-1} - \rho\mathbf{x}'\beta}{\sqrt{1-\rho^2}}\right)\beta^* + \phi(\mathbf{z}'\gamma - c_{J-1})\Phi\left(\frac{\mathbf{x}'\beta - \rho(\mathbf{z}'\gamma - c_{J-1})}{\sqrt{1-\rho^2}}\right)\gamma^*.\end{aligned}$$

MEs for the BOPM are attained by setting $\rho = 0$ in the above expressions. Alternatively, by fixing $\pi_{jj} = 1$, one would obtain the MEs of the BOP as $\Pi_{(J/2)}$ in Eq. (6.10) would be an identity matrix and hence true and reported answers would coincide. Standard errors of the marginal effects are calculated by the Delta method.

Chapter 7
Overall conclusions

Social capital is an umbrella concept which embodies elements ranging from networks and trust to civism (van Oorschot et al. (2006)). The multifaceted character of social capital is what makes it an appealing notion, because it has a positive impact on key aspects of a society. Higher levels of social capital are normally associated with higher economic growth and an increasing human development. Social capital influences economic performance through trust as its pivotal element (Zak and Knack (2001), and Beugelsdijk et al. (2004)). Trust incentives markets to function efficiently by reducing inter-firm transaction costs, by increasing exchange of knowledge between firms and by enhancing the division of labour by lowering costs of coordination (Maskell (2000)). Trust, at the macro level, is also strongly associated with lower government corruption and higher bureaucratic quality and compliance with paying taxes (Halpern (2005)).

Moreover, there is a growing body of evidence on how social capital also plays an important role in shaping people's health via different channels (e.g., Poortinga (2006a), Sundquist and Yang (2007)). For example, at the individual level, social capital provides social and material support in adverse times (Ferlander (2007)) and, at the macro level, more trust in a society leads to a higher efficiency of health institutions (Szreter and Woolcock (2004), Helliwell (2006)). This dual impact of social capital on economic performance and well being, is the reason why I have relied on the multidimensional construct of social capital throughout my dissertation.

Education, the other key element of the thesis, is one of the most important determinants of social capital found in the literature (e.g., Helliwell and Putnam (2007), van Oorschot and Finsveen (2009)). Of the different levels of analysis of social capital, Halpern (2005) argues that education affects social capital primarily at the micro (individual) level. Regardless of their income level, more educated individuals are more likely to participate in social networks, be engaged in politics and volunteering activities, and have a higher trust in other people (Delhey and Newton (2003), Bekkers (2007)). The same evidence is contained in the meta analysis study of Huang et al. (2009) who assess the effect of schooling in a large number of evaluations and find that education is a strong and robust correlate of individual social capital.

Similarly to this strand of the literature, the thesis' chosen working hypothesis was with causality going from human to social capital. Nonetheless, because social capital can be both cause and effect and indicators of social capital are measured with error, I have accounted for the empirical problems such as simultaneity and misreporting.

At the macro-level, however, social capital is directly affected by history and culture, social structures, labour-market trends and the size and nature of the welfare state. For example, a more extended welfare state supposes to create a national norm of social solidarity and fellow feeling which is conducive to higher trust levels amongst individuals (van Oorschot and Finsveen (2010)). Besides schooling, religion is often cited as another important determinant at the micro-level. Some studies find that a country with a dominant protestant culture tends to show a higher level of trustworthiness (Delhey and Newton (2005), van Oorschot et al. (2006)). Trust is often considered endogenous to certain elements of the social structure (Torsvik (2004)). In fact, some countries are immersed in social traps due to an overall institutional environment problem (Rothstein (2005)). Because political institutions' efficiency, religious composition and welfare policies differ across countries, then, the contextual factors of the two countries would likely influence relationships within the human to social capital framework. In this dissertation I have investigated this relationship for two different countries, as causality from education to measures of social capital might be local to social structures and, in consequence, it would be rather erroneous to make generalisations exclusively based upon one country.

Specifically, in this dissertation I have examined, for both Italy and the UK, the impact of education on a range of civic outcomes that embody some of the main dimensions of social capital. The dissertation's main interest was to attain a "credible" relationship between education and civic outcomes. Unobserved factors driving education choices (endogeneity) and the tendency of individuals to under-report socially undesirable behaviours (misclassification) are both elements which contribute to obscuring the true relationship between education and civic outcomes. Controlling for measurement error in the two components of this association is vital. One could not argue of the benefits of education in terms of economic growth and health via its impact on key facets of social capital, if the observed relationship is plagued with inaccuracies. Therefore, I methodologically accounted for these empirical concerns and also investigated whether they varied by countries' contextual factors. Finally, I proposed an extension to discrete choice models to deal with highly skewed responses of a misclassified outcome.

The dissertation's main empirical contribution was given by using an array of civic outcomes and, crucially, because I accounted for misclassification. Previous research in the economic literature studying the causal link of education and civic outcomes (e.g., Dee (2004)) does not explicitly control for misclassification and focuses on only one aspect of social capital, civic engagement. Including civic behaviours into the analysis allowed me to provide evidence on how, after accounting for misreporting, education is related to indicators of social trust. Moreover, because of the two countries' analysis, I was able to investigate issues such as the extent to which educational effects on social capital differ under varying social structures.

I concentrated on these two countries as a way of finding out whether the extent of the problem of endogeneity and misreporting in the human to social capital framework is country specific. On the one hand, the interest in Italy was twofold. Firstly, the economic literature on civic returns tends to be centered in works for the US and UK (e.g., Milligan et al. (2004)). Secondly, it contains unique features, particulary compelling regional differences in social capital which lead some authors (e.g., Fukuyama (1995)) to classify it as a low trust society, and southern Italian regions cited as examples of situations of social trap. Indeed, the Italian case has been very popular within the social capital literature since publication of the seminal study by Putnam et al. (1993). On the other hand, the UK was included in the thesis as a way to validate the results for Italy, but also so as to inspect the extent in which simultaneity and misreporting are in fact influenced by macro characteristics. Note that Italy and the UK are distinct as far as religious composition and welfare policies are concerned. Knowing whether unobservables behind education choices and social desirability (SD) are local to social structures, is vital, particularly since there is mixed evidence on how social capital is distributed across Europe (e.g., Delhey and Newton (2005), van Oorschot et al. (2006), van Oorschot and Finsveen (2010)).

Figure 7.1 illustrates the dissertation's main results in a diagram, showing key differences of the two countries.[1] The figure and its notation follow the one presented in the introductory Chapter 1 which contained the thesis' outline, that is, Figure 1.1. To begin with, I reintroduce the notation. Let x be the observed value of the education covariate and x^* its true value which accounts for endogeneity, obtained by the IV approach. This is the first empirical issue in the causality of education with civic outcomes. The observed dependent variable y represents the array of civic outcomes, which are composed of y_1 (civic opinions) and y_2 (civic behaviours). Due to SD, civic outcomes y are likely to be misreported since, typically, individuals would tend to underreport socially undesirable behaviours and over-report socially desirable ones. Hence, the true dependent variables of civic opinions and civic behaviours are instead given, respectively, by ω_1 and ω_2, with estimated misclassification matrices that link

[1]More detailed results and conclusions were already included at the end of Chapters 4, 5, and 6.

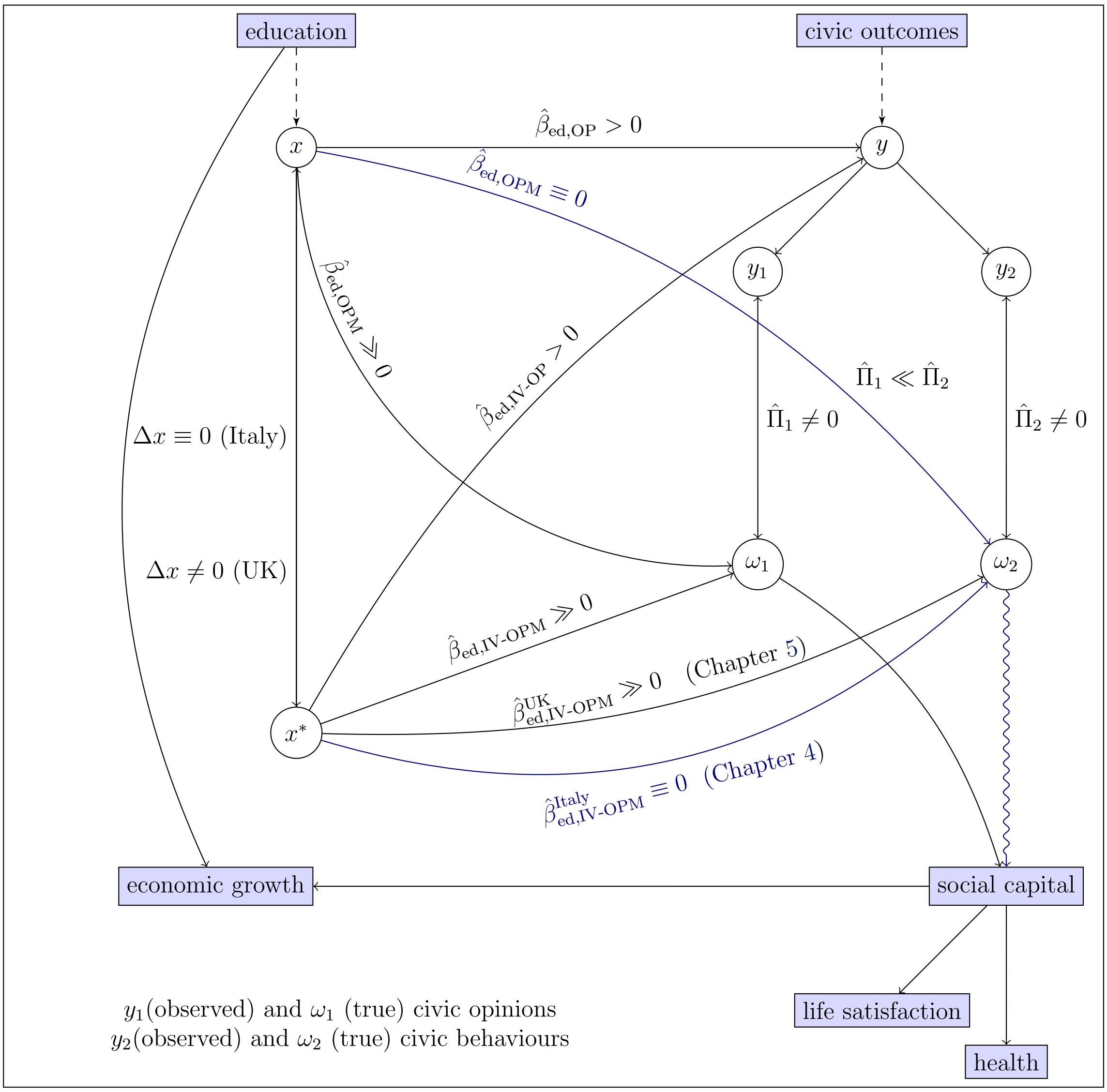

FIGURE 7.1.— Dissertation's main results.

them with the observed answers $\hat{\Pi}_1$ and $\hat{\Pi}_2$. This is the second empirical issue in the causality of education with civic outcomes. These two (true) civic outcomes embody the main dimension of social capital which, in turn, has an effect on health, life satisfaction and economic growth.

The parametric models defined by the different variables of Figure 7.1 are as follows. The first model is the OP, which does not account for either endogeneity or misclassification, consisting of the linkage of the observed version of the independent (x) and dependent variables (y); its schooling's coefficient is denoted as $\beta_{\text{ed,OP}}$. Because unobservables have an effect on schooling decisions, they are depicted by a variation in the observed valued of schooling (Δx). Thus, the true value of education, which is obtained by the fitted value IV approach, is defined as $x^* = x + \Delta x$. The second parametric model accounting for endogeneity is the IV-OP, linking the true value of education (x^*) and the observed value of civic outcomes (y). The schooling's coefficient is $\beta_{\text{ed,IV-OP}}$. Controlling only for misreporting defines the third model, the OPM, which links the observed value of education (x) with the true values of civic opinions (ω_1) and civic behaviours (ω_2), and its coefficient for education is denoted by $\beta_{\text{ed,OPM}}$. Finally, the full model, which accounts for both empirical concerns in the human to social capital framework is the IV-OPM, where the true value of education x^* is linked to true values of civic outcomes (ω) by the coefficient $\beta_{\text{ed,IV-OPM}}$.

As displayed in Figure 7.1, education, for both Italy and the UK, is statistically significant for most civic outcomes' specifications within the OP; that is, $\hat{\beta}_{\text{ed,OP}} > 0$. Thus, I am able to reproduce the result found in most empirical studies that schooling is one of the strongest determinants of social capital in different countries (e.g., Delhey and Newton (2003), Li et al. (2005), Helliwell and Putnam (2007)). I found an equivalent result when controlling for unobservables: $\hat{\beta}_{\text{ed,IV-OP}} > 0$, with the common upward bias in the coefficient due to endogeneity. Yet the effect of unobservables diverges for the two countries. Whereas education is exogenous in the civic outcomes' specifications for Italy ($\Delta x \equiv 0$), it is endogenous for the UK ($\Delta x \neq 0$). This means that the hypothesis of the civic voluntarism model (Verba et al. (1995)) holds in the UK: unobserved factors which lead individuals to develop a taste for education, are likely to be positively correlated with civic outcomes. In other words, the transmission of interest in issues of the political sphere and attitudinal behaviours occur in the UK, as suggested by the civic voluntarism model, at the family level, due to resources and psychological factors, but not however, in Italy. For example, privileged families are more likely to boast a politically rich home environment dominated by frequent political discussions, with politically active parents acting as role models (Verba et al. (2005)). In fact, this result is very important for how causality varies for the two countries.

As far as misreporting is concerned, I found that, as hypothesised, it is a crucial empirical issue ($\hat{\Pi}$) throughout the thesis, since indicators are self-reported and also recover sensitive information. Indeed, most civic outcomes are misclassified for both countries, and misreporting is more severe for civic behaviours due to a larger influence of SD ($\hat{\Pi}_1 \ll \hat{\Pi}_2$), leading to substantial changes in the estimated effects. Civic opinions, which essentially are measures of political engagement, tend to be over-reported. Specifically, individuals who apparently show the highest political engagement are more likely to misreport due to factors such as stigma and feelings of guilt, or because they are more concerned with their class interests (e.g., Bernstein et al. (2001)). Because civic behaviours measure sensitive topics and people's morality, the misclassification problem is more severe. Certainly, estimations by educational levels show a significant misreporting of civic behaviours regardless of the schooling level considered, but, for civic opinions, misreporting only holds for the group of more educated individuals. The higher misreporting for the former indicators might be explained by empirical research in social psychology which normally finds a stronger effect of descriptive social norms (see, e.g., Cialdini et al. (2006)).

Figure 7.1's fundamental difference originates from estimations on civic behaviours. Civic opinions' results, on the contrary, are the same for Italy and the UK, with the estimated schooling's coefficient being positive and statistically significant for the two countries. For Italy, the null of exogeneity of schooling is accepted and the correct model is the OPM, thus causality of education on civic opinions is depicted by the arrow going from x to ω_1 ($\hat{\beta}_{\text{ed,OPM}} \gg 0$). For the UK, unobservables drive education decisions so that the estimated coefficient is $\hat{\beta}_{\text{ed,IV-OPM}}$ ($\gg 0$), which estimates the relationship going from x^* to the civic opinion ω_1. When accounting for misclassification for civic behaviours in the OPM, however, the deeper influence of SD renders the link with education as statistically nonsignificant (for both countries), which is displayed in the Figure by $\hat{\beta}_{\text{ed,OPM}} \equiv 0$. In particular, this lack of causality for the Italian case (as the OPM is the chosen model) highlights the fact that, if one does not account for the tendency of individuals to provide socially desirable responses, this would lead to a spurious relationship between education and civic behaviours. For the UK, the chosen model is the IV-OPM ($\Delta x \neq 0$), and the upper bias introduced by endogeneity is such, that the impact of education on civic behaviours becomes statistically significant. This is the main difference with the Italian case: schooling has significant positive effects on all civic outcomes in the UK. In short, the fact that unobservables jointly affect education and civic outcomes seems to be local to social structures, whereas misreporting is not country specific and it is more related to the nature of the indicators measured. In the remainder of this section, each Chapter's results are discussed in more detail.

In Chapter 4, I investigated the Italian case. The range of civic measures used are: 'interest in politics', the 'problem of tax evasion', and the following behaviours: 'not paying for your ticket on public transport', 'keeping money obtained by accident when it could be returned' and 'not leaving your name for the owner of a car you accidentally scraped'. Given the distinct nature of these measures, I classified the first two as civic opinions and the last three as civic behaviours. This classification relies on the two main dimensions of social capital proposed by Uphoff (2000), that is, structural social capital (civic engagement) and cognitive social capital (social trust).

The former type is associated with various forms of social organisation while the latter indicates mental processes and resulting ideas, reinforced by culture and ideology, more specifically, by norms, values and beliefs. These two categories of social capital are interdependent (Woolcock and Narayan (2000), Sundquist and Yang (2007)).

I found that self-reported measures in Italy are prone to suffer from social desirability bias (SDB). Specifically, misreporting yielded a large bias in the impact of schooling but, also, and importantly, an overestimation of its precision. Crucially, even if there is a positive bias in the estimated coefficients, the increase of their standard error can obscure key empirical causality links. This is certainly the case of the association of education with civic behaviours, where qualitative overall conclusions were indeed affected by incorporating misclassification. That is, education has a positive and statistically significant effect on civic opinions but misreporting modified the relationship between schooling and civic behaviours, becoming statistically non-significant. This lack of causality suggests two possibilities. It may indicate that SDB operates differently within the two dimensions of social capital and it is a more important issue regarding measures of civic behaviours, than indicators on civic engagement. This agrees with studies showing that the facets of social capital tend to be positively correlated, but correlations are usually quite low (Rothstein (2001), Johnston and Percy-Smith (2003), van Oorschot et al. (2006)). Alternatively, it may reflect that the cultural component of social trust plays a deeper role than schooling. As argued before, lack of trust in Italy would lead to bad steady states and social traps, making misreporting perhaps more significant in this country. Furthermore, perhaps surprisingly, I accepted the hypothesis that education is exogenous in the IV-OPM models, rejecting the civic voluntarism's hypothesis of unobservables operating at the family level, being particularly cultivated at the beginning of the life-course.

More specifically, out of the five civic outcomes analysed in Chapter 4, I only found lack of evidence of misclassification for the civic opinion 'the problem of tax evasion'. Also, the misclassification problem is more severe for civic behaviours and empirically explained by the assumption of monotonicity of correct report, which justified my choice as regards to the classification of civic outcomes into two groups. Civic behaviours are misreported regardless of which education level I considered, that is, either the higher or lower educated group of individuals would tend to lie with regards to how they behave, as they are apparently reluctant to admit to an interviewer that they lack civic awareness, or have engaged in an illegal activity. The misclassification bias for civic behaviours obeys to an under-reporting of the lower civically behaved group whereas, for 'interest in politics', the group that apparently show a higher degree of political engagement are more prone to over-report it. These misreporting patterns obtained are in line with existing theories from political science and social psychology (e.g., Bernstein et al. (2001), Karp and Brockington (2005), Cialdini (2007)).

The analysis for the UK was carried out in Chapter 5, for which I employed more indicators than Italy, yet the core group of civic outcomes are equivalent across the two countries. Civic opinions are: 'interest in politics', 'pay attention to politics', 'discuss politics' and being 'active in a voluntary organisation'. The three civic behaviours used are: 'failing to report accidental damage done to a parked vehicle', 'keeping money that you have found', and 'avoiding a fare on public transport'. I additionally included outcomes related to politics, voting and social trust. Namely, whether respondents believe that 'political activity takes too much time and effort', 'family and friends think that voting is a waste of time', 'feel very guilty if not vote', 'neglect my duty as a citizen if not vote', as well as outcomes concerning interpersonal trust and trust in institutions, that is, whether 'most people can be trusted' and whether they 'trust the local government'. This allowed me to add other dimensions of social capital (such as social participation and interpersonal trust) that are not captured by the previous indicators. These UK's indicators fit into the framework by van Oorschot et al. (2006), which contains three dimensions for social capital: i) networks, ii) trust, and iii) civism. Individuals' attitudinal and behavioural characteristics belong to the third dimension (civism), although I also included outcomes representing trust and network dimensions.

Chapter 5's estimations show that most civic outcomes are misclassified and, therefore, misclassification is an important empirical issue for the UK too. Most social capital indicators are self-reported and measure sensitive topics, so SD influences reported answers in spite of countries' macro characteristics as religion and welfare policies. SD operates regardless of the endogeneity of social structures, at least when one compares the social structures of European southern countries with Anglo-Saxon countries. On the one hand, the pattern of misreporting for civic opinions is also equivalent to the one in Italy. Specifically, individuals who apparently show the highest political engagement are more likely to over-report due to factors such as stigma and feelings of guilt. The fourth civic opinion, 'active in a voluntary organisation', is not misreported according to the misclassification test, because unlike measures of political engagement, the impact of SD is not as strong. The group of civic behaviours, on the other hand, suffer from misreporting to a larger degree (as in Italy) than indicators on civic engagement. The extent of misclassification is such that, for certain values, individuals are more likely to lie than to tell the truth. Also, the assumption of monotonicity of correct report holds, which means that the problem is decreasing, the more civically behaved individuals are, according to their reported answers.

With regards to the additional indicators, the negative link of schooling with the first two outcomes 'political activity takes too much time and effort' and 'voting is a waste of time', challenges the alternative mechanisms proposed by some studies in the economics field (e.g., Gibson (2001), Dee (2004)). That is, by raising the opportunity cost of an individual's time, increased schooling could reduce the amount of time and attention allocated to civic activities. On the contrary, when applied to political activities in the UK, the opportunity cost of time is lower for more educated individuals, who also do not consider the voting process futile. In fact, estimations suggest that the more educated an individual is, the less likely he would be to judge the time aspect of political activity as a reason for his lack of participation, and also the less likely he would be to consider voting a waste of time. The other indicators 'feel very guilty if not vote' and 'neglect my duty as a citizen if not vote' allowed me to investigate the extent to which, feelings of guilt and duty in the participation of the political process, vary by educational levels. Indeed, these feelings varied by schooling levels because, even after controlling for misclassification, the coefficient of education is statistically significant and positive for both outcomes. This offers extra support to the hypothesis of SD driving misclassification of civic outcomes. Moreover, self-reported data on generalised trust and trust in institutions are subject to SD and are misreported as well.

Contrary to the Italian case, endogeneity of education in the UK is accepted for most indicators. The direction of the bias introduced by endogeneity follows the same direction as the one introduced by endogeneity, with upward biases in both cases. Results appear to suggest that the extent of this correlation is such, that the impact of education on civic behaviours becomes statistically significant when accounting for endogeneity. This is the main difference with the Italian case: schooling has significant positive effects on all civic outcomes in the UK. Chapter 5's main finding is that educational achievement emerges as a strong predictor for the different dimensions of social capital. Estimations of education levels for the UK are in line with the the lower and higher educated sub-samples of individuals for the Italian case. For example, for civic opinions, misreporting only holds for the group of more educated individuals.

The principal difference of Chapters 4 and 5 is how causality of schooling and civic behaviours varies in Italy and the UK. As far as civic opinions are concerned, the only difference between these two countries principally consists of the endogeneity of education. Causality of schooling for the different measures of political engagement in the UK are mostly driven by unobservables, but not for 'interest in politics' in Italy, where the null of exogeneity of education is accepted. The transmission of interest in issues of the political sphere occurs in the UK, as suggested by the civic voluntarism model, at the family level, but not in Italy. The dissertation's results agree with the mixed distribution of social capital within Europe.

In Chapter 6, motivated by civic behaviours' distributions, I proposed a theoretical extension to an ordered response model, a "hurdle ordered probit with misclassification" (HOPM). In the model, I addressed two problems regarding the distribution of a self-reported ordered outcome: its skewness and its misclassification. Because the dependent variable measures a sensitive topic (i.e., a civic behaviour), it is more probable to be misclassified. The argument is the same as in the previous Chapters: the bias (social desirability bias) occurs since respondents will tend to answer, though unconsciously, according to what is considered to be socially acceptable in order to gain approval of others, and will result in under-reporting undesirable behaviours and over-reporting desirable ones (Paulhus (1991), Tourangeau and Yan (2007)). I used an OPM to account for this. For the high degree of skewness (that is, the substantial proportion of values at one end of its distribution), I relied on a hurdle (or two-part) model. Combining a binary choice model and an OP model is a standard practice in the empirical literature. This modeling approach is well established within the field of health economics in the analysis of smoking, health expenditures, etc. (Jones (2000), Madden (2008), Kasteridis et al. (2010)). Hence, the proposed HOPM consists of two parts: (i) a split probit model which divides the distribution into two regimes by the median of the dependent variable, and (ii) an ordered probit with misclassification to deal with misreporting of observed answers in the top half of the scale. The model can be applied to questions on sensitive issues whose answers are given into an ordered 1 to J scale.

I carried out extensive simulations under different true models or data generation process (d.g.p.) to evaluate the models in terms of biases, precision of estimates, and marginal effects (MEs). Various tests and information criteria were also reported to compare the array of models' performance. The Monte Carlo simulations provided a good performance for the model, even when d.g.p. is given by the OP, the model still yielded accurate estimates and MEs. The $\bar{\chi}^2$ misclassification test always picks the correct model as well as the LR and Vuong tests. I then applied the model to a discrete civic behaviour (for Italy) measuring the willingness to leave the name when scraping a car ('not leaving name'), which is prone to suffer from SDB and consequently, is likely to be misreported. I found a significant amount of misclassification, being equally likely that individuals would either tell the truth or lie. In particular, if the splitting process and measurement error are ignored, inference would be erroneous. This is the first model which accounts for these two issues and potentially could be applied to self-reported data in other fields, such as happiness and job satisfaction outcomes.

I now mention some central issues which emerged from the thesis. To begin with, social capital is a valuable concept to study the mechanisms by which education affects civic outcomes. Its multidimensional character, including elements as diverse as civism, trust and networks, is what makes it an appealing concept for analysing causality of education on civic outcomes. I have relied on the social capital literature to classify civic outcomes, to put forward hypotheses regarding misreporting by groups of indicators, and to interpret the role of unobservables. Secondly, misreporting is a fundamental phenomenon within the human to social capital framework which should be controlled for. Civic outcomes are self-reported and measure sensitive topics, thus SD plays a major role in causality. Furthermore, if one does not account for misclassification, qualitative overall conclusions regarding the causality of education on civic outcomes could be affected, particularly for civic behaviours. Finally, because the two countries studied in the thesis do not differ substantially with regards to misreporting, this might indicate that SD influences measures of social capital beyond country effects or contextual factors (e.g., religion and welfare policies). This is in line with the similarity in the aggregate levels of social capital amongst European countries, found in the literature.

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