Social Network Analysis to Optimize Tax Enforcement Effort

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ABSTRACT

The tax gap is a phenomenon experienced by revenue collection agencies which describes the difference between the taxes due, as prescribed by legislation, and the actual taxes collected. The tax gap is mostly a result of taxpayer non-compliance, such as the failure to submit a tax return. Recent theories suggest that a taxpayer's social structure is a significant determinant of a taxpayer's attitude towards tax compliance. This study explores the proposal that social network analysis through decision support systems can facilitate the objective of revenue collection agencies to minimize the tax gap. The results suggest that an agency's limited enforcement capacity can achieve a greater impact on tax compliance by focusing on non-compliant social structures as opposed to single instances of non-compliance. The research fills a gap in literature by demonstrating IT's value proposition towards government financial services.

Keywords

Decision support systems, business intelligence, social network analysis, tax gap, tax compliance

INTRODUCTION

Revenue collection agencies world-wide have the responsibility of collecting taxes, duties and levies. The South African Revenue Service (SARS) performs this role in South Africa. Similar to other agencies, SARS experiences a phenomenon referred to as the tax gap which, in its simplest form, is described as the difference between the taxes due (as determined by legislation) and the actual taxes collected (OECD, 2008:10). The nature of the tax gap problem causes it to be a widespread and continuous challenge for revenue collection agencies (Slemrod, 2007:45).

Effective and efficient decision-making in revenue collection agencies is critical in addressing the tax gap. The limited resource capacity of revenue collection agencies emphasizes the critical role of decision-making to optimally support business operations. In the case of revenue collection agencies, one such example is the management of tax compliance and risk, which aims to minimize the tax gap (OECD, 2004:6). Amongst others, information systems and specifically decision support systems (DSS) facilitate organizational decision making by presenting decision makers with relevant information (Sun and Liu, 2001:247).

A DSS is a technological implementation that is used in conjunction with the cognitive actions of humans and is aimed at facilitating the decision-making process. A DSS utilizes data that is manipulated in a modeling layer and displayed as information through an interface (Shim, Warkentin, Courtney, Power, Sharda and Carlsson, 2002:111) for consumption by the decision-maker. One instance of DSS is that of Social Network Analysis (SNA). SNA visually displays a complex network of relationships between entities which might otherwise have been hidden in the data.

THEORETICAL BACKGROUND

Tax Gap

The tax gap within the United States (US) is estimated at a considerable gross value of 16.3%, totaling $40.7 billion for 2001 taxes, and has tripled in value based over the past two decades (Leviner, 2009:382). The estimated tax gap of other equivalent high-income countries ranges between 4% and 17% (Slemrod, 2007:33). South Africa's tax gap value for the same time period of 2001 is estimated at 13.9% approximately equating to R30 billion (Oberholzer and Stack, 2009:738). The management of tax compliance and risk uses different enforcement capabilities to address the tax gap of which tax audits

(OECD, 2008:16) and telephonic engagements with non-compliant taxpayers are most effective. However, in reality the enforcement capacity of revenue collection agencies is fractional in comparison with the potential number of non-compliant taxpayers. For example, the US Internal Revenue Service (IRS) audit capability annually covers a limited 1% to 2% of their tax register (Akinboade, Kinfack, Mokwena and Kumo, 2009:1129). This coverage percentage is believed to be consistent with other revenue collection agencies, including SARS. It is therefore critical for revenue collection agencies to optimally execute their enforcement capacity by using minimal resources to achieve a maximum audience.

Taxpayer Non-compliance

Past Perspectives

Taxpayer non-compliance has traditionally been approached from two perspectives. The first perspective was accepted by various academics in the past and more recently again supported by Alm, Martinez-Vazquez and Wallace (2004:120). The continuous monitoring of taxpayer compliance supported by rigorous enforcement is the only manner in which non-compliance can be minimized. It was therefore believed that an increased enforcement effort will ultimately lead to increased taxpayer compliance. The second perspective suggests that taxpayer non-compliance is mostly driven by a taxpayer's decision to maximize personal financial interest against the probability of being detected (Dell'Anno, 2009:995; Leviner, 2009:389). This perspective is often referred to as the deterrence model, which is based on the utility theory originally published by Allingham and Sandmo (1972).

Recent Perspectives

Academics such as Kirchler (2007:107) have illustrated that an intensified enforcement capacity can also have undesired effects and even contrasting consequences. For example, the introduction of excessive penalties is likely to result in compliance resistance by taxpayers, and perhaps even promote bribery and corruption. This will consequently result in lower taxes collected and ultimately lead to the distrust of the revenue collection agency.

Recent opinions have evolved to a multi-level perspective in which taxpayers are considered to be part of a greater 'whole' (Torgler, 2007:5). From this perspective, the influences and consequences of tax non-compliance have a much larger impact than previously considered. Braithwaite (2003:49) describes 'the whole' to consist of multiple levels ranging from an individual level (focusing on the taxpayer), a group level (certain segments such as turnover, geography and tax type, to name but a few) and society (the collective to which the tax system applies). However, one must acknowledge taxpayer non-compliance to have a 'social multiplier effect' when considering that a taxpayer forms part of the greater whole (Fortin, Lacroix and Villeval, 2007:2090). This implies that the successful non-compliance of one taxpayer is likely to also prompt non-compliance of another taxpayer.

Decision Support Systems (DSS)

DSS is the specific instance of information systems that focus on the enablement of managerial decision-making (Arnott and Pervan, 2005:67). DSS historically mainly supported personal decision-making, but recent DSS developments have made significant contributions in the field of group decision-making. DSS evolved substantially in the fields of data warehouses, business intelligence and data mining whilst also embracing web technologies (Shim et al. 2002:112). Power (2002:13-16) takes a more functional perspective when categorizing DSS as being either data-driven, model-driven or knowledge-driven. Data-driven DSS store large volumes of data and provide an interface for the data to be accessed. Such examples are data warehouses and business intelligence reporting. Model-driven DSS are parameter-driven statistical and analytical tools allowing users to analyze a particular situation, such as those used in SNA. Knowledge driven DSS simulates, in a limited manner, certain human intellectual capabilities and consequently recommend specific actions to users based on certain criteria in the data.

SNA is a specific instance of model-driven DSS that visually represents the relationships amongst entities in a specific social structure. SNA is used to identify key entities in a particular network, illuminate hidden relationships between loosely connected entities and to visually explore the manner in which entities are grouped (Carley, Diesner, Reminga and Tsvetovat, 2007:1325). Jyun-Cheng and Chui-Chen (2008:1670) explain SNA relationships to be in the form of either groups or networks. Entities in group relationships have specific interactions in dense proximity, whereas network relationships have a variety of interactions in wide proximity – at times also consisting of many group relationships. Examples of SNA are illustrated in Figure 1. In its simplest form, a group or network consists of two entities linked through a relationship. The addition of entities to a group will result in an increase of relationships and ultimately convert a group structure to a network structure.
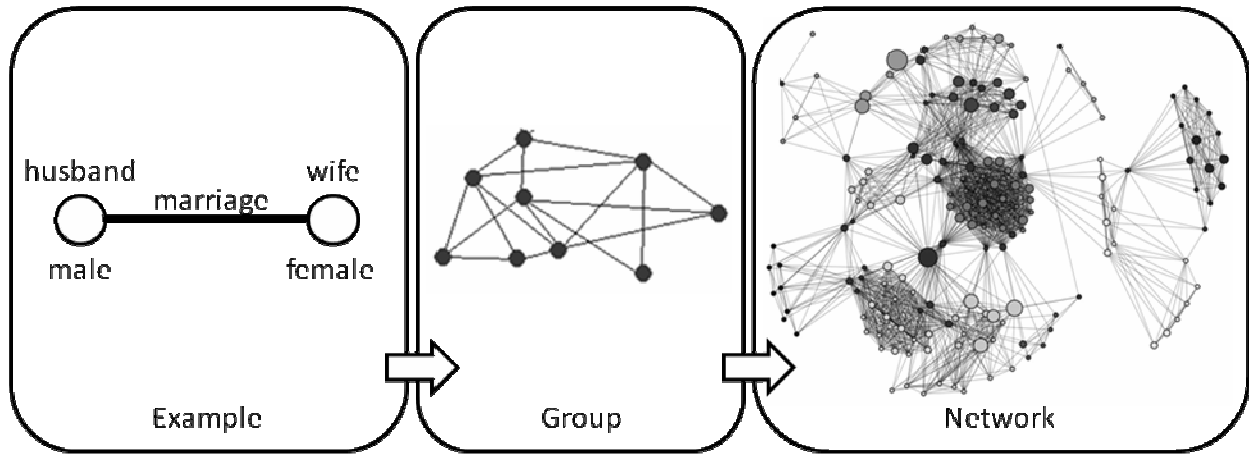
Figure 1. Social Network Analysis

Managing Tax Compliance through Decision Support Systems

Much like any other organization, tax compliance can be managed at a strategic, operational and tactical level, as presented in Figure 2 (OECD, 2008:10). Strategic compliance management considers the tax system in its entirety whereas operational compliance management focuses on whole taxpayer segments. Tactical compliance management considers targeted individuals, or groups of which social structures such as marriage, employee and employer relationships and tax consultant and taxpayer relationships are but a few examples. The different DSS defined by Power (2002:13-16) can be associated with the types of compliance-management levels. Knowledge driven DSS are associated with strategic management, data driven DSS with operational management, and model driven DSS with tactical management. Model driven DSS is often used to conduct SNA, and DSS tools such as Analyst Notebook and SAS are widely recognized as industry leaders in this domain.

Figure 2. Compliance Management and Decision Support Systems (Derived from OECD, 2008:10; Power, 2002:13-16)

RESEARCH OBJECTIVE

Despite the significance of the tax gap phenomenon, very little academic literature addresses IT's value proposition to minimize taxpayer non-compliance. In particular, hardly any literature exists which explores how DSS can facilitate the management of tax compliance and risk through SNA. Some publications do exist which propose DSS frameworks for the private sector. However, the distinct nature of the public sector and especially revenue collection agencies allows for limited value to be derived from these publications – at most through theory abstraction and generalization. After all, more than two decades ago Henderson and Schilling (1985:157) referred to IT and specifically DSS when they stated "[d]esigning a[n IT] solution to a public sector problem is largely an art".

Given the limited enforcement capacity of revenue collection agencies together with the proposition that a taxpayer is influenced by his/her social structure, an opportunity exists for SNA to enhance the manner in which revenue collection agencies enforce tax compliance. If a taxpayer's compliance is indeed influenced by social structure, then the inverse might also prove true, namely that a taxpayer's non-compliance can be indirectly influenced by social structure when a revenue collection agency's enforcement effort impacts the social structure.

WORKING THEORIES

Kinship is the most basic instance of social structure of which descent and marriage are prime examples. Findler and Dhulipalla (1999:168) argue that the human relationship of marriage continues to be the most influential determinant of human behavior. Kinship in the form of marriage was referenced in this case study to determine whether a taxpayer's non-compliance is influenced by his/her social structure. Based on the limited social structures explored, the theories tested in this case study are working theories to be refined by future research. The study tested the following working theories:

- **Working theory 1 (WT1):** A non-compliant taxpayer becomes compliant when a revenue collection agency requests the taxpayer to do so. WT1 was tested by means of a call center agent telephonically engaging with a married female taxpayer requesting the taxpayer to become compliant. The theory was considered true when a statistically significant amount of taxpayers became compliant, but false if taxpayers remained non-compliant.
- **Working theory 2 (WT2):** Revenue collection agencies can obtain automatic taxpayer compliance by influencing the social structure in which the taxpayer operates. WT2 was tested against the social structure of marriage in which both the husband and wife are non-compliant and WT1 proved true. Thus, WT2 is only considered for the male/husband cases where the female/wife taxpayers became compliant after engaging with a call center agent. WT2 was proven true when both husband and wife became compliant after the engagement. WT2 was proven false when a husband failed to become compliant despite his wife becoming compliant after interaction with a call center agent.

EMPIRICAL RESULTS AND FINDINGS

The Case Study

A revenue collection agency forms an integral part of the economic services delivered by any government. The taxes collected enables government to facilitate economic growth and distribution, as well as to improve the social development of its citizens. SARS has been appointed as the agency responsible for the collection of revenue as well as the enforcement of tax regulation and compliance in South Africa. The revenue collected consists of taxes, duties and levies. The revenue collection targets defined for recent financial years, namely R598.7 billion (2010) and R647.2 billion (2011), have comfortably been achieved by SARS. As at the 2011 financial year end, the organization employed 14,967 staff. SARS's enforcement capacity conducted 79,631 audits with a success rate of 83% for investigative audits, resulting in a collection of R3.9 billion.

Another important enforcement capacity is the collection of outstanding tax returns. An outstanding tax return is best described as a period-based tax return for which the respective taxpayer has failed to submit the required tax return. This non-compliance is countered through the automatic allocation of administrative penalties to the taxpayer accounts. In addition to this, outstanding tax return cases are also telephonically pursued by the SARS outbound call center. The call-center agents typically act on an automatically generated list of non-compliant taxpayers by asking these taxpayers to submit the required outstanding tax returns within seven working days, or face legal action. Taxpayers with invalid contact details are escalated to a tracing department which uses external information to update the taxpayer's contact particulars before further engagement with the taxpayer.

Research Methodology and Variables

Case study research through the positivist research paradigm can provide detailed insights and social explanations. A case study research is described by Oates (2006:141) as a comprehensive and concentrated evaluation of a phenomenon in its natural presence, in an attempt to generate new knowledge on the subject. This case study's particulars are in accordance with Yin's (2009:47-53) prescription: the study focuses on a single case with SARS being the only unit of analysis. The research is considered a critical explanatory case because well formulated theories on tax non-compliance are evaluated against the mature knowledge domains of SNA and DSS. Although limited in nature, the study aims to generate theories representative of revenue collection agencies in general.

The data collection used in this study is by means of random statistical sampling. Using the terminology defined by Findler and Dhulipalla (1999:169), the social networks explored in this research are as follows:

- Each social structure was limited to two members, namely a male taxpayer and female taxpayer with both having at least one outstanding tax return;
- The primary relationship of the structure was that of kinship in the specific form of marriage; and
- The wife member was selected as the central member of this structure. This selection is based on the assumption that a wife is more likely to influence the structure through communication than the husband. The husband is therefore considered as the related member of the structure.

The case study's population consisted of 1,013 married couples which were randomly divided into an action group and control group sub-populations. The control group consisted of 535 couples (observations), whereas the action group consisted of 478 couples (observations). For the action group, the wife was telephonically contacted by a SARS call-center agent and requested to submit any of her outstanding tax returns. No contact was made with the control group, reflecting the "natural" taxpayer submission behavior materializing without any intervention by SARS. The presence of the call in the action group, and the absence thereof in the control group, allow for the call's impact on taxpayer compliance to be measured. The change in taxpayer compliance was analyzed three weeks after the conclusion of the SARS call center effort. The taxpayer was regarded as having become compliant if any, i.e. at least one, of the outstanding tax returns have been submitted during the three week duration.

The relationship between the call made to the wife, the submission behavior of the wife and the submission behavior of the husband was determined by a Logit model. A Logit model was selected since the modeling variables are binary resulting in ordinary least square assumptions to be violated. In binary regression models, the expected signs of the regression coefficients and their statistical significance are of greater importance than the goodness of fit. This is partly because of the limited variables used for the model as limited by the study's scope. Other variables, such as taxpayer's attributes could also be included for an increased goodness of fit. The cumulative logistic distribution function is represented by:

$$P_i = E(Y = 1 | X_i) = \frac{1}{1 + e^{-(\beta_0 + \beta_i X_i + \beta_j X_j)}}$$

$$Or \, P_i = \frac{1}{1 + e^{-Z_i}} = \frac{e^z}{1 + e^z}$$

Where $Z_i = \beta_0 + \beta_1 X_i + \beta_2 X_j$

Z_i ranges from $-\infty$ to $+\infty$.

P_i ranges between 0 and 1 and is non-linear related to Z_i.

$$1 - P_i = \frac{1}{1 + e^{Z_i}};$$

Therefore $\dfrac{P_i}{1 - P_i} = \dfrac{1 + e^{Z_i}}{1 + \frac{1}{e^{Z_i}}} = e^{Z_i}$

With $\dfrac{P_i}{1 - P_i}$ the odds ratio.

Taking the natural log:

$$L_i = In\left(\frac{P_i}{1 - P_i}\right) = Z_i = \beta_0 + \beta_1 X_i + \beta_2 X_j$$

Hence, L, the log of the odds ratio, is not only linear in X, but also linear in the parameters. L is referred to as the logit. The Logit model has the following features:

- As P goes from 0 to 1 (i.e. as Z varies from $-\infty$ to $+\infty$), the logit L goes from $-\infty$ to $+\infty$. In other words, although the probabilities lie between 0 and 1, the logits are not so bounded.

- Although L is linear in X, the probabilities themselves are not.

The logit becomes negative and increasingly large in magnitude as the odds ratio decreases from 1 to 0; and becomes increasingly large and positive as the odds ratio increases from 1 to infinity.

Models were estimated through Maximum Likelihood methods, using E-Views7. The following variables are specified in order to determine the relationship(s) between the call made to the wife, the tax return submission behavior of the wife, as well as the tax return submission behavior of the husband:

- Action_Group (Differentiating between the Control group and the Action group): The control group takes on a value of 0, and the action group a value of 1. This variable allows the impact of the call to be measured.

- Wife_Submit (Submission behavior of wives): Wives that submitted take on a value of 1; those that omitted to submit are represented by zeros. If at least one return has been submitted, the wife is regarded as having submitted.

- Husband_Submit (Submission behavior of husbands): Husbands that submitted take on a value of 1; those that omitted to submit are represented by zeros. If at least one return has been submitted, the husband is regarded as having submitted.

Population Statistics

Table 1 summarizes the submission statistics of the case study's control group and action group.

Control Group	535	Wife Submit	26	5%	Husband Submit	9	35%
					Husband Not Submit	17	65%
		Wife Not Submit	509	95%	Husband Submit	5	1%
					Husband Not Submit	504	99%
Action Group	478	Wife Submit	142	30%	Husband Submit	27	19%
					Husband Not Submit	115	81%
		Wife Not Submit	336	70%	Husband Submit	8	2%
					Husband Not Submit	328	98%
Total	1,013						

Table 1. Submission Behavior Summary

Overall Submission Behavior of Wife

5% of wives (26 observations) in the control group submitted outstanding tax returns, compared to 30% of wives (142 observations) in the action group, suggesting that the call center engagement with the wife has a significantly positive impact on her decision to become compliant.

Overall Submission Behavior of Husband, Regardless of Wife's Behavior

3% of husbands (14 observations) in the control group submitted outstanding tax returns; compared to 7% of husbands (35 observations) in the action group; suggesting that the call to the wife might impact positively on the husband's submission behavior, regardless of the wife's decision to submit or not.

Submission Behavior of Social Structure

2% of couples (9 observations) submitted at least one outstanding return (i.e. both husband and wife submitted) in the control group, compared to 6% (27 observations) in the action group, suggesting that the call to the wife is impacting positively on the couple's tax compliance behavior.

Submission behavior of husband, given submission behavior of wife

For the control group, the probability of a tax return submission by a husband, given that his wife has submitted, is 35% (9 observations from a population size of 26). A mere 1% of husbands in the control group submitted outstanding tax returns, when their wives did not. For the action group, the probability of a tax return submission by a husband, given that his wife has submitted, is 19% (27 observations from a population size of 142). Only 2% of husbands in the action group submitted outstanding tax returns, when their wives did not. It is concluded that husbands are more likely to submit tax returns if their wives have also submitted.

FINDINGS

Working Theory 1 (WT 1)

WT1 states that a non-compliant taxpayer will become compliant when a revenue collection agency requests the taxpayer to do so. In order to determine the impact of the call center engagements on the wife's compliance behavior, the Action_Group variable was modeled onto the Wife_Submit variable. The call to the wife had a significant positive impact on the wife's decision to submit. Wives that received calls were 8 times more likely to submit than those who did not. The overall accuracy of the estimated model can be assessed by the Expectation-Prediction table, which shows that the estimated model correctly predicts 75% of the observations. Both the H-L statistic and the Andrews statistics indicate that the data fits the model well.

Regression Output
Dependent Variable: WIFE_SUBMIT
Method: ML - Binary Logit (Quadratic hill climbing)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ACTION_GROUP	2.113067	0.224599	9.408187	0.0000
C	-2.974352	0.201063	-14.79316	0.0000

McFadden R-squared	0.132487	Mean dependent var	0.165844
S.D. dependent var	0.372124	S.E. of regression	0.350995
Akaike info criterion	0.783383	Sum squared resid	124.5523
Schwarz criterion	0.793098	Log likelihood	-394.7833
Hannan-Quinn criter.	0.787073	Deviance	789.5666
Restr. deviance	910.1497	Restr. log likelihood	-455.0748
LR statistic	120.5831	Avg. log likelihood	-0.389717
Prob(LR statistic)	0.000000		

Obs with Dep=0	845	Total obs	1013
Obs with Dep=1	168		

Expectation-Prediction Evaluation for Binary Specification
Success cutoff: C = 0.5

	Estimated Equation		
	Dep=0	Dep=1	Total
E(# of Dep=0)	720.45	124.55	845.00
E(# of Dep=1)	124.55	43.45	168.00
Total	845.00	168.00	1013.00
Correct	720.45	43.45	763.90
% Correct	85.26	25.86	75.41
% Incorrect	14.74	74.14	24.59

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0486	0.0486	94	96.0916	7	4.90841	101	0.93680
2	0.0486	0.0486	96	96.0916	5	4.90841	101	0.00180
3	0.0486	0.0486	98	96.0916	3	4.90841	101	0.77990
4	0.0486	0.0486	97	97.0430	5	4.95701	102	0.00039
5	0.0486	0.0486	96	96.0916	5	4.90841	101	0.00180
6	0.0486	0.2971	82	78.2015	19	22.7985	101	0.81737
7	0.2971	0.2971	75	71.6987	27	30.3013	102	0.51167
8	0.2971	0.2971	75	70.9958	26	30.0042	101	0.76021
9	0.2971	0.2971	69	70.9958	32	30.0042	101	0.18886
10	0.2971	0.2971	63	71.6987	39	30.3013	102	3.55256
	Total		845	845.000	168	168.000	1013	7.55135

| H-L Statistic | 7.5514 | Prob. Chi-Sq(8) | 0.4785 |
| Andrews Statistic | 7.5193 | Prob. Chi-Sq(10) | 0.6757 |

Working Theory 2 (WT2)

WT2 states that revenue collection agencies can obtain automatic taxpayer compliance by influencing the social structure in which the taxpayer operates. In order to determine whether the call center engagement and the submission behavior of a male taxpayer's wife impacts on that of the husband, the Action_Group and Wife_Submit variables were modeled onto the Husband_Submit variable. Since the call to the male taxpayer's wife was found to be statistically insignificant, the model had to be refitted to exclude the Action_Group variable. The wife's submission behavior illustrated a positive significant impact on that of her husband. Husbands that have wives who submit are 17 times more likely to submit than those who did not. According to the Expectation-Prediction table, the model correctly predicted 92% of the observations. According to the H-L test statistic, the data fit the model well; this is however contradicted by the Andrew's statistic which is lower than the prescribed 0.05. The Andrew statistic can be improved by including more variables, as previously stated.

Regression Output
Dependent Variable: HUSBAND_SUBMIT
Method: ML - Binary Logit (Quadratic hill climbing)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ACTION_GROUP	-0.087898	0.382530	-0.229782	0.8183
WIFE_SUBMIT	2.899547	0.380290	7.624572	0.0000
C	-4.124823	0.314594	-13.11156	0.0000

McFadden R-squared	0.212933	Mean dependent var	0.048371
S.D. dependent var	0.214655	S.E. of regression	0.201468
Akaike info criterion	0.310819	Sum squared resid	40.99529
Schwarz criterion	0.325391	Log likelihood	-154.4296
Hannan-Quinn criter.	0.316354	Deviance	308.8592
Restr. deviance	392.4181	Restr. log likelihood	-196.2090
LR statistic	83.55883	Avg. log likelihood	-0.152448
Prob(LR statistic)	0.000000		

Obs with Dep=0	964	Total obs	1013
Obs with Dep=1	49		

Regression Output
Dependent Variable: HUSBAND_SUBMIT
Method: ML - Binary Logit (Quadratic hill climbing)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
WIFE_SUBMIT	2.859600	0.336865	8.488856	0.0000
C	-4.158883	0.279508	-14.87931	0.0000

McFadden R-squared	0.212799	Mean dependent var	0.048371
S.D. dependent var	0.214655	S.E. of regression	0.201590
Akaike info criterion	0.308896	Sum squared resid	41.08571
Schwarz criterion	0.318611	Log likelihood	-154.4559
Hannan-Quinn criter.	0.312586	Deviance	308.9119
Restr. deviance	392.4181	Restr. log likelihood	-196.2090
LR statistic	83.50620	Avg. log likelihood	-0.152474
Prob(LR statistic)	0.000000		

Obs with Dep=0	964	Total obs	1013
Obs with Dep=1	49		

Expectation-Prediction Evaluation for Binary Specification
Success cutoff: C = 0.5

	Estimated Equation		
	Dep=0	Dep=1	Total
E(# of Dep=0)	922.91	41.09	964.00
E(# of Dep=1)	41.09	7.91	49.00
Total	964.00	49.00	1013.00
Correct	922.91	7.91	930.83
% Correct	95.74	16.15	91.89
% Incorrect	4.26	83.85	8.11

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0154	0.0154	100	99.4462	1	1.55385	101	0.20050
2	0.0154	0.0154	101	99.4462	0	1.55385	101	1.57813
3	0.0154	0.0154	98	99.4462	3	1.55385	101	1.36696
4	0.0154	0.0154	101	100.431	1	1.56923	102	0.20971
5	0.0154	0.0154	100	99.4462	1	1.55385	101	0.20050
6	0.0154	0.0154	99	99.4462	2	1.55385	101	0.13011
7	0.0154	0.0154	101	100.431	1	1.56923	102	0.20971
8	0.0154	0.0154	98	99.4462	3	1.55385	101	1.36696
9	0.0154	0.2143	87	86.3187	14	14.6813	101	0.03700
10	0.2143	0.2143	79	80.1429	23	21.8571	102	0.07605
		Total	964	964.000	49	49.0000	1013	5.37561

H-L Statistic	5.3756	Prob. Chi-Sq(8)	0.7168	
Andrews Statistic	104.2144	Prob. Chi-Sq(10)	0.0000	

CONCLUSION

The tax gap is likely to remain a significant challenge for revenue collection agencies. This study suggests that the limited enforcement capacity of revenue collection agencies can achieve significantly more by focusing on the social structure in which non-compliant taxpayers operate. These social structures include elementary kinship structures such as marriage and descent, but also more elaborate structures such as communities, institutions and even geographical clusters. Although limited in scope, this study empirically substantiates the proposal that taxpayer compliance is influenced by the social structures of the taxpayer. A single interaction with the social structure will have a cascading influence on the other social structure members. This is in contrast to the typical pursuit of single, unrelated instances of non-compliance which is characteristic to most revenue collection agencies. These social structures can be visualized, discovered and explored using SNA in conjunction with different DSS technologies, in particular data warehousing and business intelligence.

The paper, therefore, makes a contribution to Information Systems theory by illustrating how Social Network Analysis can be used to complement existing decisions support systems. It also demonstrates the value of quantitative case studies to amend theoretical knowledge. On a practical level, the study suggests an efficient way to maximize the impact of interventions to ensure tax compliance by using business intelligence gleaned from technical decision support systems. The research fills a gap in literature by demonstrating IT's value proposition towards government financial services. The study is limited to only

one form of social structure, and future research should try to verify the findings by applying the same principles to other social structures, as well as other business domains.

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