Queen Bees and Domestic Violence: Patrilocal Marriage in Tajikistan

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January 2016

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2016

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Acknowledgments

I would like to convey my gratitude to my advisor, Professor Charles M. Becker, for his guidance, enthusiasm and support at all stages of the research. I appreciated his insightful and thought-provoking comments, which helped sharpen my arguments and focus my ideas. I would like to also express my appreciation for Professor Federico Bugni for his insights on addressing the problem of missing data. I would like to mention Karen Li for assisting me in dealing with reverse geocoding and matching districts of Tajikistan with DHS clusters, and Jurgen Amann for his help in locating appropriate shape files and his efforts to fix the shape files provided by DHS. Their insight and contributions were crucial in the completion of this paper.

Abstract

According to the longstanding traditions, families in Tajikistan are preferably patrilocal, wherein newlywed couples move in with the husband's family. Such living arrangement may last for a period of time or for the rest of the life of the married couple. Strong anthropological evidence suggests that the husband's mother is endowed with ultimate power to control her daughter-in-law who is expected to be obedient. Based on Demographic and Health Survey data collected in Tajikistan in 2012 we conduct an empirical study aiming at finding statistical evidence of the correlation between higher level of domestic violence, measured along three dimensions - physical, severe physical and emotional – and the young married women's living arrangements. The observational study of the existence of the Queen Bee effect in patrilocal marriage establishes that there is a positive correlation between the incidences of domestic violence, particularly of emotional violence committed by the husband/partner given the presence of the Queen Bee. The result of the analysis indicates that women who live with the in-law family score 0.18 points higher on the incidents of emotional violence than the women who do not, which represents 11.4% of a standard deviation The study, however, does not find a similar correlation between physical violence, either severe or less severe, and a presence of the Queen Bee in the household.

JEL Classification: Z13; J12; J16

Keywords: Domestic Violence; Queen Bee; Social Norms; Tradition; Patrilocal Marriage; Tajikistan.

Introduction

When speaking of domestic violence, the image of an abusive male perpetrator and a battered female victim comes to mind. Such stereotype is usually unchallenged in popular consciousness as cases of male-on-female violence are the most frequent and most egregious, as man are on average physically more able to inflict harm on women than the other way around. Female-on-male violence, however, does occur more often than imagined. In fact, a study shows that 1 in 7 men in the U.S., compared to 1 in 4 women, have reported to experience physical abuse from the intimate partner in their lifetime.

Cases of female perpetrators of abuse do not attract much popular attention partly due to double standards in societies, which do not perceive female aggressors as capable of inflicting as much harm as their male counterparts. The cases of female-on-female violence is a still rarer subject of concern, while the cases are abundant. Oppression of women by women in the workplace, dubbed the Queen Bee syndrome by Stanes, Tavris & Jayaratne (1973), describes a paradoxical behavior of female executives, who, after having achieved higher ranks in the male-dominated workplace, are more likely to oppose the ascent of other women up the career ladder.

Queen Bee behavior is observed across patriarchal societies of the developing world as well. A vast body of literature documents oppressive cultural practices around the world where elder women often play a leading role perpetuating oppression against women. Some examples include: bridal kidnapping (Central Asia, Caucasus), "enslaving" of daughters-in-law (most of Central-Asia with varying severity across countries), genital mutilation (some counties in Africa and the Middle East), and Shim-pua marriages (China and Taiwan) – a traditional marriage, where the future bride is adopted from young age and raised by the in-law family alongside the future groom.

While cases of female-on-female violence are abundant, to our knowledge it is a still rare subject of study in the economics field. According to the Demographic and Health Survey conducted in Tajikistan in 2012, nearly 1 in 50 women surveyed reported having experienced physical abuse from their mothers-in-law. Since cases of female aggression against other females are not commonly recognized, let alone studied, we believe that the matter is much graver. Female perpetrators may often play an indirect role in oppressing other women, by actively maintaining cultural practices marginalizing younger women or being instigators of abuse against them. To our knowledge, no formal theoretical model exists to explain the paradoxical behavior of females in power: the exception is Turaeva (2015), who used Ramsey economic growth and overlapping generations models as a theoretical framework to explain Queen Bee behavior. The current study aims at filling the void left by the lack of research in the field and measuring the Queen Bee effect in the lives of young women living in patrilocal marriage in Tajikistan.

Section I includes a review of economic literature on domestic violence (DV). It is established that DV takes place in non-cooperative marriages, that is, a marriage in which spouses do not cooperate and a Nash equilibrium solution is achieved by maximizing individual utility of each spouse given the behavior and threat points of the other. Studies on DV find that woman's income (consumption) is positively correlated with the likelihood of leaving an abusive husband. A strong correlation between DV and socio-economic status of a woman is also supported by empirical evidence. Moreover, Rensetti (2009) finds a reciprocal economic stress – DV relationship: while economic stress contributes to the likelihood of DV, DV may result in economic hardships for the victims. Norms of male dominance are also alluded to when explaining the higher rates of domestic violence in more economically disadvantaged communities.

Section II contains a survey of anthropological literature documenting traditional relations between a Queen Bee, a mother-in-law, and her daughter-in-law in Central Asian communities, particularly Tajikistan. Families in Central Asia are generally patrilocal, as anthropological records indicate longstanding tradition of a *kelin* (literally, *newcomer*) moving in with the in-law family in communities across Central Asia. Evidence from Tajikistan and Uzbekistan highlight the centrality of the mother-in-law figure in the lives of young women, beginning from the bride selection process and continuing through the rest of the life of the daughter-in-law. Obedience to the mother-in-law is often cited as foremost valuable quality of the daughter-in-law, and the lack of obedience in general is quoted as a trigger for domestic abuse against women.

Section III reviews the data extracted from Demographic and Health Survey conducted in Tajikistan (TjDHS) in 2012 and lays out the methodology used conducting the study. The DHS sample includes data on 6,432 households with a total 38,805 observations, including 9,656 women aged 15-49, and is representative of all four provinces of Tajikistan – Sughd, Khatlon, Gorno-Badakhshan Autonomous Oblast (GBAO) and Districts of Republication Subordination (DRS) – and Dushanbe, the capital city. The survey questions were designed in a way of mitigating the problem of underreporting of domestic violence due to the sensitivity of the subject and cultural differences in understanding what violence constitutes. The study here is aimed at establishing a correlational relation between the presence of a Queen Bee in the household and incidents of domestic violence committed against women who indicate their relation to the head of the household as "daughter-in-law". Thus, a treatment group includes all married, Tajik women living with their in-law parents, and the control group includes all other categories of women in the sample, which include those women who identified themselves to be heads of household, wives of household heads, sisters, and granddaughters and any other category.

Section IV identifies problems with available data, such as survey nonresponse, and describes the way the missing data are dealt with. The patterns of *missingness* in data – such as *missing at random* (MAR), *missing completely at random* (MCAR), and *missing not at random* (MNAR) are identified as they relate to the data in question and several methods of dealing with missing data and associated pros and cons are discussed. Depending on the pattern of missingness in data several methods can be used: simple deletion, single and multiple imputation. To establish the pattern of missingness in the DHS data a test for randomness of the missing data are conducted by means of a logit regression. The test identified a MAR pattern, thus, the missing data were simply deleted from the sample.

In Section V we conduct a principal component analysis (PCA) in STATA to reduce the dimensionality of both the response and explanatory variables. Due to the nature of the survey questions, the incidents of domestic violence are reported across 13 survey questions that pose specific question of the type and frequency of the violence committed. After PCA the dimension of the response variable was reduced to three major components that are named as PHYS (for incidents of physical violence), SEV_PHYS (for incidents of severe physical violence); and EMOT (for emotional violence). PCA was also performed on explanatory variables and resulted in the reduction of the dimension of the variables from 26 variables to 8 major components, which include personal and financial characteristics of women in question, their family environment, socio-economic status, attitude to violence, and their husbands' characteristics.

Section VI presents the major results of the study achieved through propensity score matching (PSM). The motivation to use PSM is to balance characteristics in treatment and control groups in order to correctly estimate the effect of the treatment. We have good reason to believe that the prospects of living in the in-law family, possibly indefinitely, does enter into the selection process of the daughter-in-law, thus, creating selection bias. Girls who end up living in a traditional patrilocal families are the ones possessing certain characteristics: married at younger age, fewer years of schooling, and more likely to be financially dependent. The findings include identification of unmatched characteristics: balancing property was not satisfied along such characteristics as: FAM_SIZE (includes variables such as number of family members and women eligible for survey); PER_IND (characterizes women's independence to plan motherhood); FIN_IND (financial independence supported by land and real estate ownership); TENURE (stands for the length of marriage as characterized by the number and age of children and age of the head of household).

The balancing property was satisfied through reduction of the number of explanatory components to four. As a result the space of the explanatory variables was reduced to include: ACCEPT (denotes cultural acceptance of domestic violence; CONTROL (encompasses variables characterizing a husband as controlling); SEC (stands for socio-economic class, which includes such variables as education and wealth index); and SUBMIS (denotes lack of submissiveness on the part of the daughter-in-law as expressed in longer marriage to birth intervals and higher age at marriage).

By excluding variables that do not satisfy the balancing property, we reduce the dimension of explanatory variable to only those that are shared by women in both groups. The result of the analysis indicate that women who live with the in-law family score 0.18 points higher on EMOT - the principal component correlated with incidents of emotional violence - than the women who do not. 0.18 points represents 11.4% of a standard deviation.

Section VI is followed by concluding statements and motivation for future research that will involve conducting a spatial analysis of domestic violence to identify regional spillovers and their causes and, potentially the domestic violence hot-beds, for which much of the ground-work has already been done.

I: Prior Literature

The study of marriage entered the economics domain with Gary Becker's seminal work (1974). Becker's model along with proceeding studies focused on families whose members are cooperative and allocate goods to maximize the common utility function. The economic model of marriage later transformed from cooperative to bargaining models. McElroy & Horney (1981) and Manser & Brown (1980) view decision making of a married couple as an outcome of a two-person bargaining problem with a Nash solution. In such bargained utility model, although it is joint utility function that is maximized, the solution must provide each spouse equal or greater utility than that obtained from outside marriage options. This constraint constitutes the individual's threat point (Manser & Brown, 1980).

Although such cases are abundant, relatively little attention has been paid to families where couples do not cooperate. Household with accounts of domestic violence (DV) represent non-cooperative spouses. Farmer and Tiefenthaler (1997) propose a non-cooperative model of the family and analyze the equilibrium solution to a game in which each spouse with independent preferences and threat points maximizes his or her utility given the behavior and threat points of the other. The man maximizes his utility by choosing the level of transfer to and the level of violence he inflicts upon his wife; whereas the wife's threat point determines her utility from the transfer she receives from her husband along with the violence. Farmer and Tiefenthaler (1997) theorize that as the woman's income (consumption) increases, her marginal utility of additional unit of consumption decreases along with her tolerance of violence, thereby increasing her threat point. The inability to "buy" more violence on part of the husband leads to decrease of violence. The authors' conclusion seems intuitive: a woman's income is positively correlated with the likelihood of her leaving an abusive partner.

Empirical studies on domestic violence have found strong correlation between the risk of domestic violence and economic hardship. DV rates also have been found to vary by social class: studies are consistent in indicating the inverse relation between the financial status of the family and the likelihood of domestic violence (Lloyd, 1997; Benson, Fox, DeMaris & Van Wyk (2003); Benson and Fox (2004)). For example, Lloyd (1997) presents the results of a random household survey that examined the effects of domestic violence on the women's labor force participation: women who reported having experienced abuse (physical, emotional or sexual) were more likely to have experienced unemployment, and also had lower personal income. Benson and Fox (2004), also find confirmation to the inverse relation between income of the household and the likelihood of DV. Furthermore, Rensetti (2009) finds a reciprocal economic stress – DV relationship: while economic stress contributes to the likelihood of DV, DV may result in economic hardships for the victims of domestic violence through work absenteeism, lost opportunities and abusive partners deliberately sabotaging their spouse's employment.

Norms of male dominance are also alluded to when explaining the higher rates of domestic violence in more economically disadvantaged communities. It is found that when men fail in their traditional, breadwinner role they may search for other ways of asserting their dominance and it is often through violence. In the family domain this implies violence against the partner (Renzetti, 2009). Analyzing data from National Survey of Households and Families Benson and Fox (2004) found that families where husbands were consistently employed report a DV rate of 4.7%, which increases to 7.5% and 12.3%, respectively, in families where the male partner has experienced one or more periods of unemployment.

Although these studies concern primarily with male- on- female violence, there is a consensus that male partners may experience intimate partner abuse over their lifetime as well, though in relatively lower numbers. In fact, according to the report on intimate partner violence, 1 in 7 men (compared to 1 in 4 women) in the U.S. have experienced severe violence from their intimate partner in their lifetime (Breiding, Chen, & Black, 2014).

Female-on-female violence is a still rarer subject of study in social sciences. From one side, a perceived relatively lower incidence of female-on-female violence makes the phenomenon of a lesser concern to researchers and policy makers alike. Oppression of women by women in workplace, though, is a well-recognized phenomenon dubbed the Queen Bee syndrome. The Queen Bee syndrome denotes a paradoxical behavior of senior female executives toward junior female employees. It was first defined by Stanes, Tavris & Jayaratne (1973), who examined promotion rates across gender and explored the impact of women holding high position on the workplace. They found that women who achieved higher ranks in the male-dominated workplace were more likely to oppose the ascent of other women up the career ladder.

Queen Bee behavior is observed across patriarchal societies of the developing world as well. A vast body of literature documents oppressive cultural practices around the world where elder women often play a leading role perpetuating oppression against women. Some examples include: bride kidnapping (Central Asia, Caucasus), "enslaving" of daughters-in-law (most of Central-Asia with varying severity across countries), genital mutilation (some counties in Africa and the Middle East), and Shim-pua marriages (China and Taiwan), which is tradition of adopting and raising the future daughter-in-law from a young age.

Queen Bee behavior is defined as a syndrome, synonymous to a disorder or a sickness, as it is puzzling that women who are often victims of oppression can also be perpetrators of oppression against other women. To our knowledge, no formal economic model has been developed to explain the theoretical underpinnings of the paradoxical Queen Bee behavior. Turaeva (2015) uses Ramsey economic growth and overlapping generations models as a theoretical framework to explain the Queen Bee behavior. She argues that by the time a woman ascends to the status of the Queen Bee in a household – becomes a mother-in-law – she has accumulated large enough social capital and is well positioned to begin profiting from the system that endows her with authority over younger females in her household – the daughters-in-law. At such a stage the mother-in-law engages in a norm-enforcing behavior which, among many things, means exploiting her daughter-in-law's labor in fulfilling household chores.

Having established the theoretical underpinnings of the Queen Bee syndrome previously, in the current study we measure the effect of the presence of the Queen Bee on the incidence of domestic violence in patrilocal marriages in Tajikistan. According to the longstanding traditions; families in Tajikistan are preferably patrilocal, wherein newlywed couples move in with the husband's family, either in case of the youngest or the oldest son. Such living arrangement may last for a period of time, or for the rest of the life of the married couple. Strong anthropological evidence suggests that the husband's mother is endowed with ultimate power to control her daughter-in-law who is expected to be obedient. Based on Demographic and Health Survey data collected in Tajikistan in 2012 we conduct an empirical study aiming at finding statistical evidence of the correlation between higher level of domestic violence, measured along three dimensions - physical, severe physical and emotional – and the young married women's living arrangements.

II: Anthropological Evidence

Marriage customs in Central Asia are well documented by anthropologists and ethnographers and are common theme of films and media. In "A Quiet Bride" directed by Setdar Karadjaev and produced by Ashkhabad TV Studio of Turkmenistan S.S.R in 1967, a young Turkmen city girl comes to the village to get married to her fiancé. The young man offers his bride to go back to the city to avoid performing the wedding ceremony according to the strict Turkmen traditions but his fiancée is excited to stay and participate in traditional rituals. Besides, she wants her mother-in-law to-be to like her. The movie filled with light humor depicts the relations between the mother-in-law and the bride through droll situations making fun of the long-standing traditions in a gentle way. The young bride accepts and fulfills all the requirements of the mother-law such as being absolutely obedient to the mother-in-law, doing all chores around the house, attending to her husband, and following such traditions as speaking to the "grown-ups" only through her husband's younger sibling and covering her face when speaking to other males. The young woman follows all these requirements but cannot give up her profession and goes to work to the local hospital despite the mother's opposition. Her respectful persistence and good character soon melts the old woman's heart who finally accepts of her modern-minded daughter-in-law's ways.

This movie appealed to the audience in the rest of Central Asia, as people could draw many parallels between depicted traditions and relations between mothers- and daughters-in-law in their respective cultures. In real life, though, such situations rarely evoke warm feelings and even more rarely have a happy ending.

Families in Central Asia are generally patrilocal, and are slightly more so in historically sedentary populations of Central Asia (Tajikistan and part of Uzbekistan) than in predominantly nomadic populations (Kazakh, Kyrgyz and Turkmen populations). The anthropological records indicate the same tradition of a *kelin* (literally,*newcomer*) moving in with the in-law family in Uzbekistan (Akiner, 1997b, p. 276). Harris (2004, p. 108) highlights the crucial role of the future mother-in-law in selection of the bride and also identifies the mother-in-law as the person who will have most contact with the kelin, when the kelin lives with the family; and the harsh treatment of kelins. Researchers also point out the "nominal" power of the patriarch, the male head of the family (Louw, 2007, p. 76) and Harris (2004, p. 35), compared to the power that their spouses exert. Harris shares her observation of a Tajik family where male heads of family "have relatively few functions in relation to their families", while women are responsible for "the running of the home and social reproduction of its members". There are not many studies explicitly linking domestic abuse of kelins to the presence of the mother-in-law, as in many cases they are the instigators of the abuse, rather than direct perpetrators, but it could be inferred that the two events are correlated. Roy (2000, p. 183) mentions an occasion when Islam Karimov, the president of Uzbekistan, has "established a presidential contest for the best daughter–in–law, whose most valued quality is of course to obey her mother-in-law". Obedience, rather the lack of it, is often cited as one of the main reasons why Tajik women are battered, as "nobody beats a good, obedient wife" (Sharipova, 2008, p. 92).

Although we may establish a statistical evidence of the positive correlation between the incidents of domestic violence among women who live with their in-law families, we still cannot blame the mother-in-law directly, as there are other factors that we may not be able to account for in our analysis. For example, we do not include the fact of the presence of the father-in-law, who can be an equal accomplice in the mistreatment of the daughter-in-law. It is the ubiquitous anthropological evidence stating the centrality of the mother-in-law figure, not the father-in-law, in patrilocal families that leads us to believe that the Queen Bee syndrome takes place. Searching for a statistical evidence of the Queen Bee syndrome on the levels of domestic violence is the purpose of the current study.

III: Data and Methodology

The Demographic and Health Survey (TjDHS) was carried out for the first time in 2012 in Tajikistan. TjDHS 2012 was designed to be a representative sample of national data. The sample includes data on 6,432 households with a total 38,805 observations, including 9,656 women aged 15-49, and is representative of all four provinces of Tajikistan – Sughd, Khatlon, Gorno-Badakhshan Autonomous Oblast (GBAO), Districts of Republication Subordination (DRS) – and Dushanbe, the capital city. The sample households were selected in two stages: 1) 356 clusters were selected from a master sample designed from the 2010 Population Census; 2) participating households were listed in each cluster and were further systematically selected to participate in the Survey

The survey was conducted by the Statistical Agency and the Ministry of Health from July to September of 2012 with the support of the United States Agency for International Development (USAID) as part of the MEASURE DHS. Along with data on domestic violence against women, the purpose of the Survey was to collect data on maternity and child health, childhood mortality, and knowledge of and behavior towards tuberculosis, HIV, and other diseases.

The questionnaire used in TjDHS was based on model questionnaires developed by MEASURE DHS and were adapted to Tajikistan by experts from the Statistical Agency and the Ministry of Health. Fourteen teams each consisting of four female interviewers, a field editor, and a team supervisors were formed to conduct the Survey after having received three-week training in June of the same year.

TjHDS Key Findings on Domestic Violence (2012)

In Tajikistan 19 per cent of women experienced physical violence at least once since the age of 15 (Kyrgyzstan – 23%); 13 per cent experienced violence in the past 12 months. 27 percent of ever married women, who reported having ever experienced physical or sexual violence committed by their partner/spouse, endured physical injuries. Overall approximately one in five women experienced physical, emotional, or sexual violence from a husband. In 76.3 percent of cases respondents indicate their current husbands/partners as persons who committed violence; other categories included father/step-father (4.5%); mother/step-mother (9.7%); sister/brother (7.8%); **mother-in-law (1.6%)**

Problem of Underreporting

Domestic violence is usually a sensitive topic. In a shame-honor culture of Tajikistan in particular, collecting reliable data on violence is expected to be challenging. Due to a different understanding of what violence constitutes (which in popular understanding includes only physical demonstrations of abuse) as well as a stigma associated in identifying oneself to be a victim of domestic violence (Sharipova, 2008), it is expected that the incidences of violence are underreported.

To mitigate the effect of cultural differences on the understanding of what constitutes violence the questionnaire was prepared with specific questions on the incidences of violent acts, such as:

"Did your (last) (husband/partner) ever:

- Push you, shake you, or throw something at you?
- Slap you?
- Twist your arm or pull your hair?
- Punch you with fist or something that could hurt you"

The examples of questions testing on the subject of emotional or sexual abuse included:

- Physically force you to have sexual intercourse with him when you did not want to?
- Say or do something to humiliate you in front of others?
- Insult you or make you feel bad about yourself?

For the purpose of this exercise we will include on the responses to the acts of physical and emotional abuse, excluding the responses on the sexual abuse. While the design of the survey has generally mitigated the effect of the differing cultural understanding of what violence is, we do not believe that the problem of underreporting was resolved. In fact, we believe that the highly descriptive nature of the questions may have deterred women from giving truthful answers, or might have led them to downplay the severity of the incidences. Women might be inclined to check the option "Slap you", instead of "Punch you with fist or something that could hurt you".

Design of the study

In our study of domestic violence in patrilocal families we can only establish a correlational relation between the presence of the mother-in-law and the level of the domestic violence experienced by younger married women. Verifying causal relationship would necessitate designing an experiment by assigning young married women to living with their in-laws – which is an infeasible and outright unethical endeavor. Of 9,656 women interviewed only 4,048 were randomly chosen to participate in the domestic violence module.

For the purposes of this study we further filter out all unmarried women and women whose native language is Russian. The reason for filtering out unmarried women for the purpose of the study is obvious, while including only women whose native language is not Russian is necessitated by cultural differences between Russian and non-Russian ethnicities in Tajikistan, which also include Kazakh, Uzbek and Kyrgyz ethnicities. This particular relationship dynamics between the mothers-in-law and their daughters-in-law is observed among Central Asian ethnicities, while Russian culture does not generally endow mothers-in-law with as much power over the daughters-in-law.

After trimming the data we have 3,956 observations remaining that we assign into two groups: the treated group is that where women live with the in-law family, i.e. their relationship to the head of the household is indicated as "daughter-in-law", and the control group includes all other women. Stratification of the sample into these two groups is a straightforward procedure as the data include women's response in terms of their relations to the head of household. This variable is designated qbee*:*

Table 1

***Qbee* Distribution**			
Relationship to household head	Frequency	Percent	Cumulative
Head	191	4.83	4.83
Wife	2,124	53.69	58.52
Daughter	93	2.35	60.87
Daughter-in-law	1,455	36.78	97.65
Granddaughter	2	0.05	97.70
Mother	8	0.20	97.90
Sister	7	0.18	98.08
Other Relative	71	1.79	99.87
Adopted/Foster Child	3	0.08	99.95
Not Related	2	0.05	100.00
Total	**3,956**	**100.00**	

We further create a dummy variable $TREAT$ which determines whether the observation is in the treatment or control group. Then, $TREAT = 1$ will indicate the treatment group and $TREAT = 0$ will indicate the control group.

IV: Data Cleaning

In order to proceed with the analysis we must first ensure the data are complete. The overview of the data (Appendix: Table 1) shows that a number of observations in both explanatory and response variables are missing.

Implications of Missing Data

In order to treat the missing data properly, it is important to establish the *mechanism of missingness*. If we can infer that the data are missing at random (MAR), or completely at random (MCAR), as opposed to missing not at random (MNAR), then the nonresponse can be ignored. Simply eliminated randomly missing data can be problematic from the power perspective, as the sample size for the analysis is reduced, but simply deleting randomly missing data will not bias the results (Osborne, 2013).

Let θ be a true parameter of population and let $\hat{\theta}$ be the estimator of the parameter based on the sample data. Ideally, we want $Bias_{\theta} = E_{\theta}(\hat{\theta}) - \theta = 0$.

$$\min MSE_{\theta}(\hat{\theta}) = V_{\theta}(\hat{\theta}) + \left(Bias_{\theta}(\hat{\theta})\right)^2 \tag{1}$$

where MSE is the mean squared error, a measure of the distance between the estimator and the parameter, which we want to minimize. The minimum MSE conveys the efficiency of the estimator of the parameter of the population.

Determining the unbiasedness and efficiency of the estimate poses new challenges if there are missing data. Traditionally, the types of non-response in surveys are categorized as unit nonresponse and item nonresponse. The former occurs when the data collection fails due to logistical reason; e.g., the respondent was not home, while the latter occurs when the survey participant leaves some questions unanswered. Unit nonresponse has traditionally been treated by reweighting and the item nonresponse by single imputation (Schafer and Graham, 2002).

In the following we define an indicator variable M for missingness: $= 1$, when the data are present, and 0 otherwise. The distribution of such variable is often referred to as the missingness mechanism and we refer to the probability distribution of M as the distribution of missingness, or the probabilities of missingness.

Rubin (1976) first developed a classification of the distribution of M according to the nature of the relationship of missingness to the data. Following Schafer and Graham (2002) we express such relationship as $Y_{com} = (Y_{obs}, Y_{mis})$, where the complete set of data can be represented as the combined set of all observed and missing data. Missing data are MAR if $(M|Y_{com}) = P(M|Y_{obs})$, i.e., the distribution of M does not depend on missing values, but on observed values. A special case of MAR is MCAR, missing completely at random, when the following holds: $P(M|Y_{com}) = P(M)$, which occurs when the distribution of M does not depend on observed data either. When MAR is violated, we have a case of MNAR, or missing not at random. MAR is called ignorable nonresponse and MNAR is called non-ignorable nonresponse.

Missing Data in the Sample

The largest number of missing data are observed among independent variables: *mar_to_birth* (8.28%) and *cur_age_child* (10.7%). Other covariates such as *employed, owns_house, owns_land, native_langauge beating_just (1 though 5), Contr_hus (1 – 5), hus_tot_school* have missing values under 1% of the total. Since simple case deletion of under 1% missing values will not affect the overall quality of the analysis, we simply delete observations with the missing values in these categories. After deleting the insignificant number of missing values in the aforementioned variables, only 8.27% and 10.67% of the values in *mar_to_birth* and *cur_age_child,* respectively, remain missing.

Having performed a test for randomness of missing values (see Appendix, pages 29-31), we establish that missing observations in both *mar_to_birth* and *cur_age_child* are missing at random (MAR). Thus, following the discussion on the methods of dealing with missing data (see Appendix, pages 27-28), we choose to simply delete incomplete observations.

V: Multidimensionality of Response and Explanatory Variables

The response variable is measured along 13 dimensions. In order to deal with the problem of multidimensionality of the data, we employ principal component analysis (PCA) in STATA to identify patterns in order to reduce the dimension of the data while keeping information intact. The objective is deriving a subspace of data with less than 13 dimensions that represent the data well. To do this, we need to compute eigenvectors (the components), which are associated with their eigenvalues, which represent the length and magnitude of the eigenvectors. The higher eigenvalues will contain more information about data distribution and those will be the candidates for forming the subspace.

The procedure for conducting PCA includes detecting highest correlation between the co-variables and then calculating eigenvalues based on the correlation matrix. For all steps of the analysis refer to the Appendix: STATA Output.

As we can see in Table 3 (Appendix, page 31) correlations among response variables range from as low as 0.1, for example, between *humiliated* and *knife* to as high as 0.9, for example, between *humiliated* and *emotional_vio.* While near perfect correlation in the latter example is trivial: the variable *emotional_vio* contains women's responses to the a question whether or not they have *ever* felt humiliated, insulted, or made feel bad in any other way. The differences between *humiliated – knife* (0.1), *humiliated-insulted* (0.5), and the *humiliated-pushed* (0.3) correlations are worth exploring further.

The underlying reason for the differing correlation is the nature of domestic abuse. Women who report feeling humiliated are most likely to have been insulted, or made feel bad in any other way; i.e. their partners have tendency to resort to the non-physical forms of abuse. Low correlation between the non-physical form of violence and more serious ones with potential serious bodily injuries, such as *knife*, or *strangled* is a somewhat surprising finding as it is reasonable to think the less harmful forms of abuse are a harbinger of the more serious ones. It may also be the case that those who suffer from "serious" abuse do not regard lesser abuse as worth reporting.

As we can see in Table 4 (Appendix, page 32), the first three components have eigenvalues higher than 1. The first component explain 38% variation in data, second – 12.6% percent variation. Cumulatively, the first three components explain 62.8% variation in the data. We choose to keep components with eigenvalues above 1 (Appendix: Figure 1).

To better interpret the principle components, we can use the VARIMAX command in STATA, which is one of the orthogonal rotation methods. VARIMAX enables minimization of the complexity of PCA interpretation by amplifying the larger components loadings and diminishing the smaller loadings. Component loadings represent the correlation between the components and the original variables. After rotating components and dropping the loading with absolute values less than 0.3, we can see which of the original variables load highly on the components:

Table 2

Rotated components
(blanks are abs (loading) < 0.3)

Variable	**Comp1**	**Comp2**	**Comp3**	**Unexplained**
humiliated			0.60	0.15
threatened			0.33	0.58
insulted			0.39	0.47
pushed		0.48		0.36
slapped		0.57		0.20
punched	0.32			0.50
kicked	0.50			0.28
strangled	0.40			0.58
knife				0.82
twisted				0.53
any_less_severe		0.59		0.10
emotional_vio			0.61	0.10
any_severe	0.54			0.17

We can see in Table 2 that component 1 represents the more severe forms of physical violence, which include the survey respondents reporting being kicked or dragged, strangled or burnt, or having ever experienced any severe form of violence. Remember that the response variable is a multinomial variable with the higher ordered responses being affirmative regarding the incidence of domestic violence. Therefore, component 1 can be an indicator of severe physical violence, and named as PHYS_SEV. Component 3 is an indicator of emotional violence, or EMOT, Component 2 is an indicator of less severe physical violence, PHYS.

Notice that variables *knife* (ever been threatened with knife/gun or any other weapon by partner/spouse) and *twisted* (ever had arms twisted or hair pulled by husband/partner) are not correlated significantly with any of the principal components; i.e., the variables are not correlated with any of the forms of the violence in question. One way to interpret such a result is taking into account the specific context of the domestic violence, which involves male husband/partner inflicting harm on the female spouse, and the connotation of the acts of violence such as *knife* and *twisted*. Using a weapon in a confrontation is a means of equalizing one's power with or surpassing the power of a counterpart in a confrontation. For example, a weaker husband may resort to weapons as an appropriate means to deal with a stronger wife. The act of twisting arms or pulling hair is often resorted to in a physical confrontation of individuals with comparable strength, with one attempting to subdue the other. For example, if an equally strong wife confronts the abusive husband by fighting back, the husband may have to subdue her by pulling her hair or twisting her arms. Since such a scenario can play out in a unique circumstances (the husband feeling the need to resort to weapons also interacts with their availability, as citizens are not allowed to own guns in Tajikistan; and/or a certain physical preparedness of the wife and her audacity to confront the husband, as women are traditionally raised to be submissive), it is reasonable that these two variables are not highly correlated with any of the principal components.

Next, we must justify the use of the principal component in lieu of the original variable. We can do that by using the Kaiser – Meyer – Olkin measure of sampling adequacy, which should be above 0.5. For full details of the principal component analysis of the response variable please refer to the Appendix: Table 5.

Principal Component Analysis of Explanatory Variables

For all the details of the analysis, please refer to the Appendix: STATA Output. The key findings of the PCA analysis are as follows:

Table 3

Rotated components
(blanks are abs (loading) < 0.3)

Variable	**Comp1**	**Comp2**	**Comp3**	**Comp4**	**Comp5**	**Comp6**	**Comp7**	**Comp8**
cur_age			0.55					
educ_years					0.58			
num_members				0.60				
num_chil_5			-0.43					
num_women				0.59				
age_hh				0.41				
wealth					0.46			
cur_age_chil			0.63					
mar_to_birth								0.60
term_preg							0.7	
age_at_mar								0.69
employed								
beating_just1		0.44						
beating_just2		0.47						
beating_just3		0.46						
beating_just4		0.42						
beating_just5		0.44						
owns_house						0.68		
owns_land						0.69		
contr_hus	0.34							
contr_hus2	0.44							
contr_hus3	0.46							
contr_hus4	0.49							
contr_hus5	0.48							
hus_tot_sch.					0.62			
total_abort							0.69	

In Table 3, component 1 encompasses variables indicating how controlling the husband is. The group of variables named *contr_hus* include women's responses to the question whether or not their spouses exhibit jealousy, suspect women of being unfaithful, or limit the time and frequency of women's visitants to their families and friends, where a higher order of responses is affirmative of the fact of being controlled by the husband. We thus name this component as CONTR.

Component number 2 includes variables on women's justification of the violence. For instance, the participants were asked whether or not they think that the beating is justified in cases of the wife's neglecting children, or burning meals. This variable represents the respondent's acceptance of the violence that is influenced by overall cultural acceptance of violence against women. Similar to the first component, higher order responses in this multinomial variable are affirmative, i.e., the respondents justify or do not condemn violence. We call this component ACCEPT. The third component includes such variables as *cur_age, cur_age_children, num_chil_5,* where the last stands for the number of children in the household under age of 5, which is also negatively correlated with the other two variables. Older women in the sample tend to have older children and a fewer number of children under 5 years old. Thus, we designate these components as TENURE to signify the length of the women's marriage. The fourth component includes variables assigned for the number of family members, the number of females in the household eligible for the survey (15-49 years old), and the age of the head of household. This component can be best characterized as family size, FAM_SIZE. Component 5 includes variables assigned for the total years of schooling of both the respondent and her spouse, as well the as the wealth index assigned to the household. These variables are positively correlated, leading to an intuitive interpretation: more affluent individuals tend to be more educated and choose a partner who is educated. Thus this component stands for socio-economic class, or SEC. Component 6 corresponds to financial independence of the women, FIN_IND. Component 7 can be summarized as personal independence, PER_IND; i.e., a woman's ability to make decisions regarding termination of pregnancy. Component 8 includes variables corresponding to the age at the time of marriage and how soon a married woman bears her first child. Newlywed women are commonly encouraged, or even put under pressure outright, to bear children soon after marriage. It is expected that women living with their in-laws would be more exposed to such pressure and often submit to the pressure. Positive correlation between the two variables mean that women who marry at older ages tend to take longer before having their first child. While the reason could be medical, i.e., older women have harder time getting pregnant, but given that women in Tajikistan get married at a young age on average, the reason for the delay of childbearing could also reflect some women's unwillingness to submit to the pressure. Thus, this component represents the lack of submissiveness, or SUBMIS.

It is interesting to note that variable *employed* does not substantially contribute to any of the components; i.e. there is no strong multicollinearity of the variable with other explanatory variables in the set. To interpret such a result one must remember that women's formal employment outside the realms of the household in Tajikistan remains a culturally sensitive issue. Thus, the factors that conventionally determine the employment status of an individual woman, such as education, social class, age, number of children and so forth, have less importance in the lives of daughters-in-law. It is often the case that women with university education become full-time homemakers after marriage. It is also often the case that regardless of low income in the household, women are not encouraged to seek employment; likewise, in the upper class families, daughters-in-law do not have any more autonomy in deciding whether or not to pursue a career. The factors contributing to the employment status are more relevant for the women who hold a different status in the families; i.e., they are not daughters- in-law.

VI: Queen Bee Effect: Effect of the Treatment

While every woman getting married faces the prospect of living with a Queen Bee at least for a period of time or indefinitely, we suspect there still exists a selection bias. Customarily, it is the first-born son who remains in the household with his spouse and children to take care of the aging parents and who also inherits the parent's assets. We have good reasons to believe that the birth order of the man does not enter the women's consideration of the marriage prospect. First, living with in-laws is a widely accepted tradition and respect for a mother-in-law figure (and father-in-law for that matter) is instilled in Tajik girls since young age. Second, it is not always the first-born son in the family who remains living with parents. The choice is often circumstantial. It is not unusual for the youngest son to carry the torch for the family.

However, we have good reasons to believe that the prospects of living in the in-law family, possibly indefinitely, does enter into the selection process of the daughter-in-law, where the mother of the prospective groom is the key player. The existence of brides of different culturally valued attributes and qualities, such as virginity, skills of housewifery, meek character, physical appearance, family background and so forth endows important roles and responsibilities on future mothers-in-law, as the selection process and final outcome are rife with uncertainties. The interaction of quality differences and uncertainty necessitates and explain the presence of a strong female figure on the marriage market, who serve as proxy for their sons, the prospective husbands.

In assessing the quality of the prospective daughter-in-law, a mother-in-law relies on some characteristics of a given prospective bride: age (most important), years spent in school; in case of advanced degree: years remaining to graduate, prospective profession; if graduated, whether or not in a workforce; family income and social status. The number of siblings is likely irrelevant, unless the number is large.

Although there are no used category in the brides market, the information asymmetry about the quality of the future daughter-in-law exists still exists. Parents know best if they have brought up an obedient daughter or not, or an overall adept girl willing to live in patrilocal family structure, something that the future mother-in-law and her son can never fully investigate via a background check.

Girls who will end up living in a traditional patrilocal families are the ones possessing certain characteristics. Such brides are more likely to have gotten married at younger age, are more likely to have fewer years of schooling and therefore are less likely to hold an advanced degree; are less likely to hold a formal job; are more likely to bear children in the first year after the marriage and have a close interval between subsequent births, especially if the children already born are female. Further, these women are less likely to own any property and more likely to be financially dependent.

Therefore, in order to correctly assess the Queen Bee effect we must employ a propensity matching technique to balance characteristics in treatment and control groups and estimate the effect of the treatment; i.e. the effect of being of living with a mother-in-law on the incidences of domestic violence. Let y_0 be a random variable that is the response variable in the absence of the treatment and $y_1$be the outcome when $TREAT = 1$; i.e when a woman indicated her relationship to the head of household as "daughter-in-law". The average treatment effect on the population is as follows (Greene, 2012, p. 934):

$$ATE = E[y_1 - y_0] \tag{2}$$

ATE denotes the effect of the treatment on the individual randomly selected from the entire population . A more desired estimate is $ATET -$ the average treatment effect on the treated – which is an estimation of the Queen Bee effect on in the lives of the daughters-in-law:

$$ATET = E[y_1 - y_0|TREAT = 1] \tag{3}$$

If the treatment is completely random then

$$E[y_j|TREAT = 1] = E[y_j|TREAT = 0] = E[y_j|TREAT = j]\,, where\ j = 0, 1 \tag{4}$$

$$ATE = E[y_1|TREAT = 1] - E[y_0|TREAT = 0] \tag{5}$$

The use of propensity matching technique to estimate the treatment effect is motivated by the expectation that the treatment assignment is not absolutely random.

Recall that after reducing the dimensionality of the response variables, three major components – PHYS_SEV, PHYS, EMOT – were identified. In the proceeding analysis we measure the Queen Bee effect in terms of each of the dimension of domestic violence. The goal is to estimate the average treatment effect of $TREAT$ on the treated and the average treatment effect in the population.

Propensity Score Matching

To establish a correlational relationship between the presences of the Queen Bee and the level of domestic violence we employ a propensity score matching technique. Matching involves selecting observations from the non-treated group to match to the ones in the control group, where the distribution of observed variables is as similar as possible to the distribution in the control group. Since assignment to the treatment group is not random, using propensity score matching (PSM) technique will allow to create a “quasi-randomized” experiment. PSM involves calculating the propensity score, which is the probability of being in the treatment group given the observation has same characteristics.

We match observations in the two groups by finding the propensity score using a parametric method, logit or probit technique, to estimate the probability of a person being in the treatment group while possessing certain characteristics. The probit/logit model uses $TREAT$ as dependent variable and all the characteristics of the observations as independent variables. Let $p(X)$ stand for propensity score, then:

$$p(X) = prob(TREAT = 1|X) = E(TREAT|x) \tag{6}$$

The propensity score is the conditional expectation of being in the treatment group given the characteristics X. PSM then assigns weights to the control group to make variables in the control group as similar as possible to the treatment group. After matching, the outcomes can be compared using weighted differences in mean outcomes between treatment and control group to find effect.

The estimation of the treatment effect through propensity score matching is conducted in STATA using $teffects\ psmatch$ command and $logit$ for the treatment model. The treatment effect was estimated for each of the components of the domestic violence – PHYS_SEV, PHYS, EMOT – and each individuals in each group were matched along eight explanatory variable – components – ACCEPT, CONTROL, FAM_SIZE, PER_IND, FIN_IND, SEC, TENURE, SUBMIS. The entire analysis can be found in the Appendix: STATA Output.

The major findings are the following:

- Unmatched Characteristics

For each of the component of domestic violence, the balancing property was not satisfied along such characteristics as FAM_SIZE, PER_IND, FIN_IND, TENURE. It is trivial that the two groups would not match on the FAM_SIZE and TENURE characteristics, since larger family sizes tend to include two to three generations of the family members and older women tend not to have their in-law parents living. It is quite tragic that the two groups would not match along the PER_IND and FIN_IND characteristics. Women in the control group – the daughters-in-law - lack personal and financial independence, where the latter is defined by the fact of holding property, compared to their peers who do not live with their in-law family. By implication, we are unable to reject the possibility that differences in wealth or socio-economic status drive the results reputed below.

- Re-specification of the Propensity Score

To satisfy the balancing property the number of explanatory components was reduced to four through the process of step-by-step elimination. As the result the space of the explanatory variables was reduced to include: ACCEPT, CONTROL, SEC, SUBMIS. By excluding variables that do not satisfy balancing property, we reduce the dimension of explanatory variable to only those that are shared by women in both groups. The resulting collection of matching characteristic is telling on its own and intuitive: the tradition of living with the mother-in-law is pervasive. It transcends socio-economic barriers, irrespective of the individual's level of autonomy or cultural attitude towards domestic violence, or the man's culturally informed way of demonstrating masculinity.

- Treatment Effects

After satisfying the balancing property the following results were found in terms of each of the dimensions of domestic violence:

PHYS_SEV – ATE and ATET are not statistically significantly different from zero (Appendix: STATA Output)

PHYS_SEV - ATE and ATET are not statistically significantly different from zero (Appendix: STATA Output)

EMOT – ATE and ATET are statistically significant (Table 4)

Table 4

Treatment-effects estimation

Estimator:	propensity-score matching
Outcome model:	matching
Treatment model:	logit
Number of obs =	3,534
Matches: requested =	1
Min =	1
Max =	1

EMOT	Coef.	AI Robust Std. Err.	z	P > |z|	[95% Conf. Interval]	
ATET						
TREAT (1 vs 0)	0.18127	0.0709586	2.55	0.011	0.0421905	0.320343
ATE						
TREAT (1 vs 0)	0.18492	0.0686544	2.69	0.007	0.0503599	0.3194801

First of all, recall that variable EMOT is a principal component (PC) that is highly correlated with the variables dealing with the non-physical form of violence, such as *humiliated, insulted, threatened* and *emotional_vio*. PC EMOT has mean 0 (precisely: 4.47e-10), standard deviation of 1.58, minimum score of -1.27 and maximum score of 11.22. EMOT increases as the survey responses go from 0, indicating response "never" [never experienced any form of emotional abuse], to higher order responses: "often" (1), sometimes (2), yes but not in the past 12 months (3). The result of the analysis indicate that women who live with the in-law family score 0.18 points higher on EMOT than the women who do not, which represents 11.4% of a standard deviation.

Conclusion

According to the results in Table 4, the observational study of the existence of the Queen Bee effect in a patrilocal marriage established that there is a positive correlation between the incidences of domestic violence, particularly, of the emotional violence committed by husband/partner and the presence of the Queen Bee. Women's principal component score reflecting emotional violence is 0.18 points higher when they live with the in-law family, which represents 11.4% of one standard deviation. The study, however, did not find such correlation between physical violence, either severe or less severe, and the presence of the Queen Bee in the household, which is not a surprising result. Regardless of the inferior position of the daughter-in-law, conspicuous abuse of the daughter-in-law as expressed in the physical manifestation of the violence is still frowned upon especially by the older generation, although a small number of women, 1.6% of the entire sample, did indicate that their mothers-in-law had ever laid her hands on them. Emotional abuse, on the other hand, does not generate a physical evidence and in many cultures, including Tajikistan, is not generally regarded as abuse; thus the presence of in-law parents does not prevent the intimate partner from committing it. In fact, the result of the study shows that that the presence of the in-laws contributes to the incidents the domestic violence.

Future Research: Spatial Analysis of Domestic Violence

The DHS Survey identifies regional variations the level of domestic violence. For example, in terms of physical violence, 13% of women living in the Districts of the Republican Subordination (DRS) – the central province of Tajikistan - who were selected for domestic violence module indicated that they experienced physical violence in their life since the age 15. This comes in marked contrast with 22.2% of women living in Sughd region, who indicated that they experienced physical violence in their lives since the age of 15 (2012, p. 196). Sughd, the northern region of Tajikistan, is a more developed, industrialized region of Tajikistan where women historically have been more educated and employed in both private and public sectors. Thus, women in the northern region tend to be more outspoken and transgress culturally appropriate norms of behavior. Alternatively, they also simply may be keener on reporting the violence. DRS, on the contrary, is rural, less developed, and more conservative, where women tend to be less educated and married at younger age, are more obedient and docile, thus experience less abuse since, as mentioned earlier "nobody beats a good, obedient wife" (Sharipova, 2008, p. 92); alternatively, they simply may not report abuse for all the reasons mentioned above. Going forward it will be a compelling study to conduct a spatial analysis of domestic violence to identify regional spillovers and their causes and, potentially the domestic violence hot-beds.

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Appendix

***Table 1*: Overview of Data**

Total number of observations – 3,396

Explanatory Variables

Variable name	Description	Response range/category	Data type	Missing values (%)
cur_age	Current age	17 – 49	Numerical, discrete	0
educ_years	Total number of years of schooling	0-21	Numerical, discrete	0
num_members	Number of household members	1-24	Numerical, discrete	0
num_women	Number of women in the household, ages 15-49	1-8	Numerical, discrete	0
qbee	Relationship to household head	Head; wife; daughter; daughter-in-law; granddaughter; mother; sister; etc…	Categorical, multinomial	0
mar_to_birth	Marriage to first birth interval, in months	0-221, incl. negative interval	Numerical, discrete	8.28
term_preg	Ever terminated pregnancy	Yes/no	Categorical, binary	
mar_status	Marital status	Married only	Categorical, nominal	0
age_at_mar	Age at first cohabitation	10-47	Numerical, discrete	0
employed	Currently working	Yes/no	Categorical, binary	0.17
owns_house	Respondent owns a house	Does not own; owns alone; owns jointly; both alone and jointly	Categorical, multinomial	0.30
owns_land	Respondent owns land	Does not own;	Categorical,	0.54

		owns alone; owns jointly; both alone and jointly	multinomial	
native_langauge	Native language of the respondent	Tajik; Uzbek; Kyrgyz; other	Categorical, multinomial	0.07
Cur_age_child	Current age of child	0 – 27	Numeric, discrete	10.7
beating_just (1 though 5)	Beating is justified if wife (1-goes out without telling husband; 2 – neglects children; 3 – argues with husband; 4 – refuses to have sex ; 5 – burns the food)	No; yes; don't know	Categorical, multinomial	0.10 - 0.15
Contr_hus (1 – 5)	Controlling husband (1 – husband is jealous; 2 – accuses wife of unfaithfulness; 3 – does not allow wife to meet with family/friends; 4 - limits wife's contact with family; 5 – whants to know where wife is all the time)	No; yes; don't know	Categorical, multinomial	0.37 - 0.44
hus_tot_school	Husband's total years of schooling	0 - 22	Numeric, discrete	0.12
Region	Place of the respondent's residence	Dushanbe; Sughd; Khatlon; DRS; GBAO	Numeric, discrete	0
Rur_urb	Type of place of residence	Rural; urban	Categorical, binary	0
Num_chil_5	Number of children of age 5 and under	0 -9	Numeric, discrete	0
age_hh	Age of the head of the household	17-95	Numeric, discrete	0
Wealth	Wealth index	Poorest; poorer; middle ; richer; richest	Categorical, multinomial	0

Response Variables

Variable name	Description	Response range/category	Data type	Missing values (%)
humiliated	Ever been humiliated by husband/partner	Never; often; sometimes; yes, but not in the past 12 month	Categorical, ordinal	0.35%
threatened	Ever been threatened with harm by husband/partner	Never; often; sometimes; yes, but not in the past 12 month	Categorical, ordinal	0.37
insulted	Ever been insulted or made feel bad by husband/partner	Never; often; sometimes; yes, but not in the past 12 month; yes, but frequency in the past 12 months mi	Categorical, ordinal	0.37
Emotional_vio	Experienced any emotional violence	Yes/no	Categorical, binary	0.35
pushed	Ever been pushed, shook or had something thrown by husband/partner	Never; often; sometimes; yes, but not in the past 12 month; yes, but frequency in the past 12 months mi	Categorical, ordinal	0.37
slapped	Ever been slapped by husband/partner	Never; often; sometimes; yes, but not in the past 12 month; yes, but frequency in the past 12 months mi	Categorical, ordinal	0.37
punched	Ever been punched with fist or hit by something harmful by husband/partner	Never; often; sometimes; yes, but not in the past 12 month; yes, but frequency in the past 12 months mi	Categorical, ordinal	0.40
kicked	Ever been kicked or dragged by husband/partner	never, often, sometimes, yes, but not in the past 12 month, yes, but frequency in the past 12 months mi	Categorical, ordinal	0.37
Strangled	Ever been strangled or burnt by husband/partner	Never; often; sometimes; yes, but not in the past 12 month	Categorical, ordinal	0.42

knife	Ever been threatened with knife/gun or other weapon by husband/partner	never, often, sometimes, yes, but not in the past 12 month	Categorical, ordinal	0.40
Twisted	Ever had arm twisted or hair pulled by husband/partner	Never; often; sometimes; yes, but not in the past 12 month; yes, but frequency in the past 12 months mi	Categorical, ordinal	0.37
any_severe	Experienced any severe violence by husband/partner	Yes/no	Categorical, binary	0.40
any_less_severe	Experienced any severe violence by husband/partner	Yes/no	Categorical, binary	0.37

Methods of dealing with missing data

Case deletion

Simple deletion of the missing data may be problematic if a large portion of the observations is missing. There are two types of deletion method: list-wise deletion (LD) and pairwise deletion (PD), or available case analysis – these are the traditional methods of dealing with missing data. Under MCAR, the remaining observations give unbiased estimates, but under MAR and MNAR the resulting estimates are usually erroneous (Osborne, 2013, p. 117). Under either case, deletion of the missing data leads to reduction of the power of the analysis, which potentially deteriorates the quality of the results. Power is the probability of rejecting the null hypothesis when the alternative hypothesis is false, thus committing Type II error. Software is available for computing power, or G*Power. Osborne (2013) estimates a sample of size 20 gives a power of 0.5, which means that with such a sample size there is 50% chance of committing Type II errors. Thus, the simple deletion method is reasonable when only a small portion of the data are missing and the missing data are MAR (Osborne, 2013, p. 118).

Single Imputation

- Mean substitution

Imputing unconditional means, or mean substitution – replacing each missing value with the sample mean, resolves the power issue, may give an accurate prediction of the missing values but distorts the sample's correlations and variances. In a large sample with 95% confidence interval for the population mean is $\bar{y} \pm 1.96\frac{S}{\sqrt{N}}$, where $\bar{y}$ is the sample mean, $S$is the sample standard error and N is the sample size. Mean substitution biases the sample variance downwards ($S^2 < \sigma^2$); i.e., the sample variance becomes lower than the true population variance; and overestimates the sample size. The confidence interval is a range of values around the sample mean that is likely to contain the true population mean. Thus, the coverage probability is:

$$P\left(\bar{y} - 1.96\frac{S}{\sqrt{N}} \leq \mu \leq \bar{y} + 1.96\frac{S}{\sqrt{N}}\right) = 0.95 \qquad (1)$$

Under MCAR the coverage probability after mean substitution, when the response rate, $r = \frac{S}{\sqrt{N}} = 0.75$ with 25% missing values, the coverage probability is reduced to $P(1.96r \leq Z \leq 1.96r)$, where $Z = \sqrt{N}\frac{\bar{y}-\mu}{\sigma}$ $and\ Z \sim N(0,1)$. Therefore $P(Z \leq 1.96 * 0.75) + P(Z \leq 1.96 * 0.75) = 0.4292 * 2 = 85.8\%$

Thus, the error rate is nearly three times as high as in the complete data case. In addition to reducing variances, mean substitution also reduces the covariance and inter-correlation between variables. Thus, in case of MCAR mean substitution is a less preferable method than simple deletion (given reasonably small portion of missing values).

- Imputing from an unconditional distribution

To offset the drawbacks of the mean substitution, other single imputation methodologies have been used that preserve the shape of the distribution. One procedure is known as *hot deck imputation*, which is the process of filling the missing data with the actual data drawn from the observed values randomly. Although this method does not distort the variance it still distorts the correlations (Schafer & Graham, 2002).

- Imputing conditional means

Conditional mean substitution, also known as a *cold deck* imputation is performed by running a regression model for predicting Y from a set of independent variables. The regression is first run on the set of the observed values of Y, then using the covariate values for the missing observations, one obtains the predicted values $\hat{Y}$ for the missing values of Y, and this way $\hat{Y}$ estimates the conditional mean of Y given independent variables. Such a method produces more accurate predictions but distorts the covariances and correlations as it overestimates the strength of relationship between Y and X.

Multiple imputation method

The multiple imputation (MI) method (Rubin, 1987) addresses the problems posed by the conditional mean imputation. With multiple imputation, Y_{mis} is replaced with a number of random draws from the predictive distribution (Schafer & Schenker, 1997). MI is a Monte Carlo technique, where each missing values is replaced by the jth element of a list of $m > 1$ simulated values, where $j = 1, \dots \dots m$. Such procedure produces m data sets, each of which is analyzed by the same complete-data method. (Schafer & Graham, 2002). A crucial feature of MI is that the missing values for each participant are predicted from his or her own observed characteristics.

Test for Randomness of Missing Values

To perform a test for randomness of missing values, we create a dummy variable $r.$ Let $r = 1$, be the incidents of missing values in *mar_to_birth* variable, and $r = 0$, when the data are observed. We use the logistic regression to predict the randomness of missingness based on the variables *age_at_mar* and *cur_age* as a set of independent variable. The dependent variables is a dichotomous variable:

$$r_i = \begin{cases} 1 \; if \; ith \; person \;\; missed \; the \; question \\ 0 \;\; otherwise \end{cases} \tag{2}$$

Since the dependent variable is a dichotomous dummy variable, we cannot use a regular linear model for testing the randomness of missing values and instead employ a logit model.

We view r_i as realizations of random variable R_i that takes the values between 1 and 0 with probabilities p_i and 1- p_i, respectively. Thus $Y_i \sim Bernouli\ (p_i)$, which can be written in compact form as:

$$P(R_i = r_i) = \; p_i{}^{r_1}(1 - p_i)^{1 - r_1}, \tag{3}$$

For $R_i = 0{,}1.$

$$P(R_i = r_i) = \begin{cases} 1 - p_i \; when \; r_i = 0 \\ p_i \; when \; r_i = 1 \end{cases} \tag{4}$$

Let p_1 and p_2 be the probabilities of missing and not missing the survey question:

$$p_1 = Prob(R = 1|\boldsymbol{X}) = F(\boldsymbol{X}, \boldsymbol{\beta}) \tag{5}$$

$$p_2 = Prob(R = 0|\boldsymbol{X}) = 1 - F(\boldsymbol{X}, \boldsymbol{\beta}) \tag{6}$$

Then,

$$E[p|\boldsymbol{X}] = 0[1 - F(\boldsymbol{X}, \boldsymbol{\beta})] + 1[F(\boldsymbol{X}, \boldsymbol{\beta})] = \; F(\boldsymbol{X}, \boldsymbol{\beta}) \tag{7}$$

Here, $F(\cdot)$ is the cdf of the random variable. The vector of parameters $\boldsymbol{\beta}$ shows the effect of changes in $\boldsymbol{X}$ on probability. We are interested in finding the marginal effects at the means (MEMS) of the different categories of women with regard to their relationship to the head of household on the probability of leaving the survey question blank.

Ideally, we would like the probabilities of leaving the question blank to be a linear function of the covariate X_i, i.e., $F(\boldsymbol{X}, \boldsymbol{\beta}) = x_i'\beta$. But since $0 < p_i < 1$, while the linear predictor can take any real value, the predicted value may not be in the plausible range. To fix this problem we need to transform to data and we can do it in two steps:

1) We find the odds of missing the survey question:

$$Odds_i = \frac{p_i}{1 - p_i} \tag{8}$$

The odds can take any positive value, thus have no upper bound restrictions.

2) We then take the log of odds ratio to remove the lower bound restriction, this will give the $logit\ (p_i)$

$$x_i'\beta = logit\ (p_i) = \log(\frac{p_i}{1 - p_i}) \tag{9}$$

Solving for p_i will give us:

$$p_i = logit^{-1}(x_i'\beta) = \frac{\exp(x_i'\beta)}{1 + (x_i'\beta)} = \Lambda(x_i'\beta) \tag{10}$$

Finally, in order to estimate the marginal effects of being in a different category of relationship to the head of household on the probability of nonresponse to the survey question on domestic violence, the marginal effect in the logit model can be calculated by differentiating with respect to the covariates:

$$\frac{\partial E[p|\boldsymbol{X}]}{\partial \boldsymbol{X}} = \Lambda(x_i'\beta)[1 - \Lambda(x_i'\beta)]\beta \tag{11}$$

Since in our model $qbee$ is a multinomial categorical variable while derivatives are taken with respect to small changes it is not appropriate to employ the above equation in finding the marginal effect. The appropriate marginal effect for a binary independent variable would be (Greene, 2012, p. 730) : $Marginal\ Effect\ = Prob(R = 1|\bar{\boldsymbol{x}},\ \boldsymbol{X} = 1) - Prob(R = 1|\bar{\boldsymbol{x}}, \boldsymbol{X} = 0)$, there $\bar{x}$ is the means of other covariates included.

The marginal effects at means for *qbee* variable (Table 2) show the predicted probabilities of leaving the survey question without response for two hypothetical, average individuals with average an age of 32 years, married at age 20, living in a family with 6.5 members and so on, compared to the reference category. In this case the reference category are the respondents who indicated themselves to be head of household. The marginal effect calculation did not show any statistically significant results (p-value greater than 5%). Therefore, we can conclude we are not dealing with the case of MNAR. In this case, the missing data are ignorable. The logit regression and marginal effects estimation on variable *cur_age_child* showed similar results (Appendix: STATA output). Since the number of the missing values is reasonably small, we may simply delete the missing values.

Table 2

Logit Regression Results

Number of Observations = 3,934

	dy/dx	Delta-method Std. Err.	z	P > |z|	[95% Conf. Interval]	
qbee						
Wife	-0.0062	0.0070	-0.89	0.374	-0.01997	0.00751
Daughter	-0.0129	0.0071	-1.81	0.070	-0.02690	0.00104
Daughter-in-law	-0.0011	0.0076	-0.15	0.884	-0.01598	0.01377
Granddaughter	.	(not estimable)				
Mother	.	(not estimable)				
Sister	.	(not estimable)				
Other Relative	-0.0036	0.0094		0.703	-0.02209	0.01489
Adopted/Foster Child	.	(not estimable)				
Not Related	.	(not estimable)				

Table 3

Correlations of response variables

Number of observations = 3,956

	humil.	*threat.*	*insul.*	*push.*	*slap.*	*punch.*	*kick.*	*strang.*	*knife*	*twisted*	*any_less*	*emot.*	*any_sev*
humil.	1.000												
threat.	0.3816	1.000											
insul.	0.4514	0.3969	1.000										

push.	0.2780	0.2532	0.2332	1.000									
slap.	0.2799	0.2091	0.1856	0.5354	1.000								
punch.	0.24799	0.2953	0.2998	0.3408	0.3459	1.000							
kick.	0.2576	0.2790	0.3583	0.2858	0.2744	0.4616	1.000						
strang.	0.1699	0.2953	0.2673	0.1652	0.1411	0.2971	0.3051	1.000					
knife	0.0977	0.1221	0.0866	0.0974	0.0743	0.1651	0.1658	0.2778	1.000				
twisted	0.2543	0.2763	0.2725	0.4093	0.3381	0.5095	0.4108	0.2755	0.1639	1.000			
any_less	0.3255	0.2414	0.2418	0.6829	0.8749	0.4222	0.3105	0.1759	0.0920	0.4021	1.000		
emot.	0.9170	0.4460	0.5250	0.2890	0.2819	0.2693	0.2822	0.2035	0.1288	0.2648	0.3543	1.000	
any_sev	0.2806	0.3187	0.3679	0.2919	0.2676	0.4723	0.9252	0.4731	0.2360	0.4447	0.3341	0.3264	1.000

Table 4

Principal components/correlation
Number of obs = 3,956
Number of comp. = 13
Trace = 13
Rho = 1.0000

Rotation: (unrotated = principal)

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	4.94	3.31	0.38	0.38
Comp2	1.64	0.07	0.13	0.51
Comp3	1.57	0.60	0.12	0.63
Comp4	0.97	0.20	0.08	0.70
Comp5	0.78	0.06	0.06	0.76
Comp6	0.72	0.11	0.06	0.82
Comp7	0.61	0.04	0.05	0.86
Comp8	0.57	0.04	0.04	0.95
Comp9	0.53	0.09	0.04	0.95
Comp10	0.44	0.33	0.04	0.98
Comp11	0.11	0.04	0.01	0.99
Comp12	0.07	0.21	0.00	0.99
Comp13	0.05	.	0.00	1.00

Figure 1

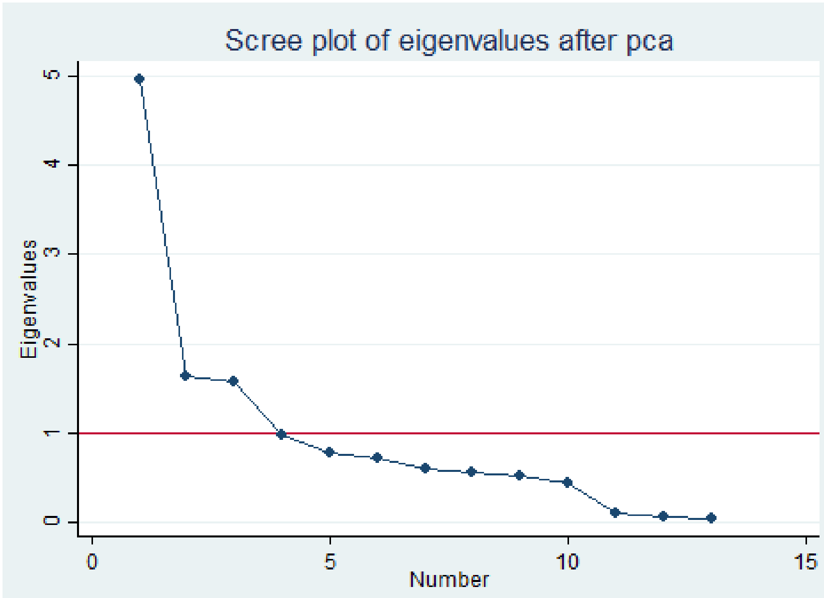

Table 5

Kaiser – Meyer – Olkin measure of sampling adequacy

Variable	kmo
humiliated	0.68
threatened	0.92
insulted	0.91
pushed	0.82
slapped	0.68
punched	0.91
kicked	0.64
strangled	0.65
knife	0.86
twisted	0.92
any_less_severe	0.68
emotional_vio	0.67
any_severe	0.66

STATA Output

Principal Component Analysis: Response Variable

Statistics/Data Analysis

```
1 . global xlist humiliated threatened insulted pushed slapped punched kicked strangled knife twisted

3 .
4 . global ncomp 3

5 . describe $xlist
```

variable name	storage type	display format	value label	variable label
humiliated	byte	%8.0g	D103A	**ever been humiliated by husband/partner**
threatened	byte	%8.0g	D103B	**ever been threatened with harm by husband/partner**
insulted	byte	%8.0g	D103C	**ever been insulted or made to feel bad by husband..**
pushed	byte	%8.0g	D105A	**ever been pushed, shook or had something thrown by**
slapped	byte	%8.0g	D105B	**ever been slapped by husband/partner**
punched	byte	%8.0g	D105C	**ever been punched with fist or hit by something…**
kicked	byte	%8.0g	D105D	**ever been kicked or dragged by husband/partner**
strangled	byte	%8.0g	D105E	**ever been strangled or burnt by husband/partner**
knife	byte	%8.0g	D105F	**ever been threatened with knife/gun or other weapon..**
twisted	byte	%8.0g	D105J	**ever had arm twisted or hair pulled by husband…**
any_less_severe	byte	%8.0g	D106	**experienced any less severe violence (d105a-c,j) by**
emotional_vio	byte	%8.0g	D104	**experienced any emotional violence (d103x series)*****
any_severe	byte	%8.0g	D107	**experienced any severe violence (d105d-f) by husband..**

```
6 . summarize $xlist
```

Variable	Obs	Mean	Std. Dev.	Min	Max
humiliated	**3,956**	**.1620324**	**.5501723**	**0**	**3**
threatened	**3,956**	**.0427199**	**.2982377**	**0**	**3**
insulted	**3,956**	**.0573812**	**.3402886**	**0**	**4**
pushed	**3,956**	**.1953994**	**.6360347**	**0**	**4**
slapped	**3,956**	**.317998**	**.8079814**	**0**	**4**
punched	**3,956**	**.0803842**	**.4232311**	**0**	**4**
kicked	**3,956**	**.0568756**	**.3506191**	**0**	**4**
strangled	**3,956**	**.0131446**	**.1584665**	**0**	**3**
knife	**3,956**	**.0032861**	**.0794375**	**0**	**3**
twisted	**3,956**	**.0705258**	**.3899247**	**0**	**4**
any_less_s~e	**3,956**	**.1683519**	**.3742258**	**0**	**1**
emotional_~o	**3,956**	**.0935288**	**.2912089**	**0**	**1**
any_severe	**3,956**	**.0298281**	**.1701344**	**0**	**1**

```
7 . corr $xlist
(obs=3,956)
```

	humili~d	threat~d	insulted	pushed	slapped	punched	kicked	strang~d	knife	twi
humiliated	**1.0000**									
threatened	**0.3816**	**1.0000**								
insulted	**0.4514**	**0.3969**	**1.0000**							
pushed	**0.2780**	**0.2532**	**0.2332**	**1.0000**						
slapped	**0.2799**	**0.2091**	**0.1856**	**0.5354**	**1.0000**					
punched	**0.2470**	**0.2953**	**0.2998**	**0.3408**	**0.3459**	**1.0000**				
kicked	**0.2576**	**0.2790**	**0.3583**	**0.2858**	**0.2744**	**0.4616**	**1.0000**			
strangled	**0.1699**	**0.2931**	**0.2673**	**0.1652**	**0.1411**	**0.2971**	**0.3051**	**1.0000**		
knife	**0.0977**	**0.1221**	**0.0866**	**0.0974**	**0.0743**	**0.1651**	**0.1658**	**0.2778**	**1.0000**	
twisted	**0.2543**	**0.2763**	**0.2725**	**0.4093**	**0.3381**	**0.5095**	**0.4108**	**0.2755**	**0.1639**	**1.**
any_less_s~e	**0.3255**	**0.2414**	**0.2418**	**0.6829**	**0.8749**	**0.4222**	**0.3105**	**0.1759**	**0.0920**	**0.**
emotional_~o	**0.9170**	**0.4460**	**0.5250**	**0.2890**	**0.2819**	**0.2693**	**0.2822**	**0.2035**	**0.1288**	**0.**
any_severe	**0.2806**	**0.3187**	**0.3679**	**0.2919**	**0.2676**	**0.4723**	**0.9252**	**0.4731**	**0.2360**	**0.**

```
8 . pca $xlist
```

Principal components/correlation

Number of obs	=	3,956
Number of comp.	=	13
Trace	=	13
Rho	=	1.0000

Rotation: (unrotated = principal)

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	4.9486	3.31085	0.3807	0.3807
Comp2	1.63775	.0658115	0.1260	0.5066
Comp3	1.57194	.596966	0.1209	0.6276
Comp4	.974977	.198119	0.0750	0.7026
Comp5	.776857	.0600592	0.0598	0.7623
Comp6	.716798	.109502	0.0551	0.8175
Comp7	.607296	.0404019	0.0467	0.8642
Comp8	.566894	.0367777	0.0436	0.9078
Comp9	.530116	.093304	0.0408	0.9486
Comp10	.436812	.326073	0.0336	0.9822
Comp11	.110739	.0394346	0.0085	0.9907
Comp12	.0713047	.0213966	0.0055	0.9962
Comp13	.0499081	.	0.0038	1.0000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8
humiliated	0.2837	0.1842	-0.4996	0.0131	-0.2464	0.1376	-0.1995	-0.2353
threatened	0.2510	0.2004	-0.1631	0.0781	0.5547	-0.1990	0.6355	-0.3209
insulted	0.2655	0.2602	-0.2041	-0.1326	0.1631	-0.0983	0.0177	0.8628
pushed	0.2810	-0.3888	-0.0282	0.0676	0.0630	-0.0476	0.1106	0.1327
slapped	0.2804	-0.4982	-0.0524	0.0680	-0.1093	-0.2297	-0.0056	-0.0209
punched	0.2943	-0.0355	0.2139	-0.0814	0.2527	0.4523	-0.1184	-0.0210
kicked	0.3102	0.1810	0.3474	-0.3673	-0.3428	-0.0984	0.1968	-0.0539
strangled	0.2147	0.2445	0.2499	0.3454	0.3043	-0.4686	-0.6010	-0.1129
knife	0.1222	0.1634	0.2067	0.8023	-0.3367	0.2141	0.2890	0.1602
twisted	0.2875	-0.0739	0.1893	-0.0365	0.2861	0.5778	-0.1573	-0.0462
any less s~e	0.3184	-0.4900	-0.0535	0.0635	-0.0749	-0.1649	-0.0149	0.0273
emotional ~o	0.3025	0.2093	-0.4867	0.0270	-0.1981	0.0922	-0.1324	-0.1543
any_severe	0.3302	0.2213	0.3626	-0.2373	-0.2738	-0.1661	0.0617	-0.1040

Variable	Unexplained
humiliated	0
threatened	0
insulted	0
pushed	0
slapped	0
punched	0
kicked	0
strangled	0
knife	0
twisted	0
any less s~e	0
emotional ~o	0
any_severe	0

```
9 . pca $xlist, comp($ncomp) blanks(.3)
```

Principal components/correlation

Number of obs	=	3,956
Number of comp.	=	3
Trace	=	13
Rho	=	0.6276

Rotation: (unrotated = principal)

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	4.9486	3.31085	0.3807	0.3807
Comp2	1.63775	.0658115	0.1260	0.5066
Comp3	1.57194	.596966	0.1209	0.6276
Comp4	.974977	.198119	0.0750	0.7026
Comp5	.776857	.0600592	0.0598	0.7623
Comp6	.716798	.109502	0.0551	0.8175
Comp7	.607296	.0404019	0.0467	0.8642
Comp8	.566894	.0367777	0.0436	0.9078
Comp9	.530116	.093304	0.0408	0.9486
Comp10	.436812	.326073	0.0336	0.9822
Comp11	.110739	.0394346	0.0085	0.9907
Comp12	.0713047	.0213966	0.0055	0.9962
Comp13	.0499081	.	0.0038	1.0000

Principal components (eigenvectors) (blanks are abs(loading)<.3)

Variable	Comp1	Comp2	Comp3	Unexplained
humiliated			-0.4996	.1539
threatened				.5806
insulted				.4748
pushed		-0.3888		.3604
slapped		-0.4982		.2
punched				.4974
kicked	0.3102		0.3474	.2804
strangled				.5759
knife				.8152
twisted				.5257
any less s~e	0.3184	-0.4900		.1008
emotional ~o	0.3025		-0.4867	.103
any_severe	0.3302		0.3626	.1736

```
10. rotate, varimax blanks(.3)
```

Principal components/correlation

Number of obs	=	3,956
Number of comp.	=	3
Trace	=	13
Rho	=	0.6276

Rotation: orthogonal varimax (Kaiser off)

Component	Variance	Difference	Proportion	Cumulative
Comp1	3.07221	.476024	0.2363	0.2363
Comp2	2.59618	.106271	0.1997	0.4360
Comp3	2.48991	.	0.1915	0.6276

Rotated components (blanks are abs(loading)<.3)

Variable	Comp1	Comp2	Comp3	Unexplained
humiliated			0.5995	.1539
threatened			0.3317	.5806
insulted			0.3935	.4748
pushed		0.4798		.3604
slapped		0.5729		.2
punched	0.3194			.4974
kicked	0.4984			.2804
strangled	0.3965			.5759
knife				.8152
twisted				.5257
any less s~e		0.5864		.1008
emotional ~o			0.6091	.103
any_severe	0.5368			.1736

Component rotation matrix

	Comp1	Comp2	Comp3
Comp1	0.6644	0.5381	0.5186
Comp2	0.3816	-0.8410	0.3837
Comp3	0.6426	-0.0570	-0.7641

11. estat loadings

Principal component loadings
component normalization: sum of squares(column) = 1

	Comp1	Comp2	Comp3
humiliated	.2837	.1842	-.4996
threatened	.251	.2004	-.1631
insulted	.2655	.2602	-.2041
pushed	.281	-.3888	-.02823
slapped	.2804	-.4982	-.05243
punched	.2943	-.03547	.2139
kicked	.3102	.181	.3474
strangled	.2147	.2445	.2499
knife	.1222	.1634	.2067
twisted	.2875	-.07395	.1893
any less s~e	.3184	-.49	-.05348
emotional ~o	.3025	.2093	-.4867
any_severe	.3302	.2213	.3626

12. predict PHYS_SEV PHYS EMOT, score

Scoring coefficients for orthogonal varimax rotation
sum of squares(column-loading) = 1

Variable	Comp1	Comp2	Comp3
humiliated	-0.0623	0.0262	0.5995
threatened	0.1384	-0.0241	0.3317
insulted	0.1445	-0.0644	0.3935
pushed	0.0203	0.4798	0.0182
slapped	-0.0375	0.5729	-0.0057
punched	0.3194	0.1760	-0.0244
kicked	0.4984	-0.0051	-0.0351
strangled	0.3965	-0.1043	0.0142
knife	0.2764	-0.0834	-0.0319
twisted	0.2845	0.2061	-0.0239
any less s~e	-0.0098	0.5864	0.0180
emotional ~o	-0.0318	0.0145	0.6091
any_severe	0.5368	-0.0291	-0.0209

13. estat kmo

Kaiser-Meyer-Olkin measure of sampling adequacy

Variable	kmo
humiliated	**0.6757**
threatened	**0.9203**
insulted	**0.9053**
pushed	**0.8200**
slapped	**0.6807**
punched	**0.9102**
kicked	**0.6372**
strangled	**0.6474**
knife	**0.8563**
twisted	**0.9153**
any less s~e	**0.6779**
emotional ~o	**0.6743**
any_severe	**0.6555**
Overall	**0.7315**

Principal Component Analysis: Explanatory Variable

Statistics/Data Analysis

```
1 . log using "C:\Users\mt216\Desktop\Nov28\Untitled13.smcl"

      name:  <unnamed>
       log:  C:\Users\mt216\Desktop\Nov28\Untitled13.smcl
  log type:  smcl
 opened on:  29 Nov 2015, 17:31:14

2 . do "C:\Users\mt216\AppData\Local\Temp\STD00000000.tmp"

3 . global xlist cur_age educ_years num_members num_chil_5 num_women age_hh wealth cur_age_child_imp
  >  beating_just2 beating_just3 beat_just4 beat_just5 owns_house owns_land contr_hus contr_hus2 contr

4 .
5 . global ncomp 8

6 . summarize $xlist
```

Variable	Obs	Mean	Std. Dev.	Min	Max
cur_age	3,956	32.8458	8.186016	17	49
educ years	3,956	10.21764	2.906969	0	21
num members	3,956	6.522245	2.802791	1	24
num chil 5	3,956	1.155713	1.175399	0	9
num_women	3,956	1.548028	.8428887	1	6
age_hh	3,956	49.12285	13.88375	17	95
wealth	3,956	3.332154	1.464243	1	5
cur age ch~p	3,956	4.857829	5.076154	-3.810233	27
mar to bir~p	3,956	33.35286	114.7033	-2.636776	996
term_preg	3,956	.2712336	.4446526	0	1
age_at_mar	3,956	20.12563	3.294809	10	47
employed	3,956	.2550556	.4359476	0	1
beating ju~1	3,956	.8447927	1.473122	0	8
beating ju~2	3,956	.8187563	1.576298	0	8
beating_ju~3	3,956	.8988878	1.841202	0	8
beat_just4	3,956	.9974722	2.201136	0	8
beat just5	3,956	.7836198	1.907519	0	8
owns house	3,956	1.534378	1.131586	0	3
owns land	3,956	.8940849	1.190419	0	3
contr_hus	3,956	.8356926	1.035306	0	8
contr_hus2	3,956	.281092	1.149223	0	8
contr hus3	3,956	.3319009	1.187931	0	8
contr hus4	3,956	.2229525	1.092134	0	8
contr hus5	3,956	.5533367	1.137983	0	8
hus_tot_sc~l	3,956	11.84808	2.839388	0	22
total abort	3,956	.2257331	.6582013	0	10

```
7 . corr $xlist
  (obs=3,956)
```

	cur_age	educ_y~s	num_me~s	num_ch~5	num_wo~n	age_hh	wealth	cur_ag~p	mar_to~p	term
cur_age	1.0000									
educ years	0.1311	1.0000								
num members	-0.1946	-0.1531	1.0000							
num chil 5	-0.4087	-0.1410	0.6057	1.0000						
num women	-0.0502	-0.0752	0.6380	0.2597	1.0000					
age hh	-0.0508	-0.0289	0.3821	0.1179	0.2456	1.0000				
wealth	-0.0131	0.2650	-0.1985	-0.0925	-0.1033	-0.1302	1.0000			
cur_age_ch~p	0.7365	0.1189	-0.2734	-0.5287	0.0440	-0.0138	0.1033	1.0000		
mar_to_bir~p	0.0793	-0.0040	-0.0086	-0.0032	0.0218	0.0243	-0.0328	0.0419	1.0000	
term_preg	0.1948	0.0390	-0.0293	-0.0794	-0.0074	-0.0379	0.0426	0.1451	0.0200	1.
age_at_mar	0.1597	0.2297	-0.1036	-0.0253	-0.0503	0.0720	0.0152	-0.0199	0.1879	-0.
employed	0.2016	0.2094	-0.0492	-0.0973	0.0055	-0.0132	-0.0187	0.1613	0.0106	0.
beating ju~1	-0.0626	-0.1246	0.0299	0.0617	0.0040	0.0272	-0.0878	-0.0661	0.0278	-0.
beating ju~2	-0.0641	-0.1204	0.0197	0.0215	0.0165	0.0243	-0.0830	-0.0612	0.0070	-0.
beating_ju~3	-0.0648	-0.1380	0.0199	0.0332	0.0147	0.0091	-0.0620	-0.0632	0.0019	-0.

beat_just4	-0.0510	-0.1317	0.0269	0.0343	0.0172	0.0038	-0.0554	-0.0453	0.0050	0.
beat just5	-0.0532	-0.1139	0.0128	0.0059	0.0065	0.0154	-0.0484	-0.0563	0.0018	-0.
owns house	0.1976	-0.0035	-0.0761	-0.1046	-0.0656	-0.0554	-0.0920	0.1218	0.0041	0.
owns land	0.1336	-0.0630	0.0311	-0.0399	0.0090	0.0051	-0.3039	0.0451	0.0113	0.
contr hus	-0.0872	-0.0292	0.0159	0.0320	-0.0078	0.0025	0.0275	-0.0722	0.0208	-0.
contr hus2	-0.0221	-0.0381	0.0158	0.0060	-0.0056	0.0188	-0.0158	-0.0200	0.0119	-0.
contr hus3	-0.0599	-0.0320	-0.0137	-0.0033	-0.0158	-0.0020	0.0081	-0.0301	0.0217	-0.
contr hus4	-0.0434	-0.0354	0.0028	-0.0166	-0.0130	0.0109	0.0025	-0.0262	-0.0121	-0.
contr hus5	-0.0696	-0.0483	0.0030	0.0055	-0.0162	0.0078	-0.0073	-0.0546	-0.0112	-0.
hus tot sc~l	-0.0024	0.3583	-0.0848	-0.0187	-0.0710	-0.0974	0.3342	0.0095	-0.0240	0.
total_abort	0.1811	0.0614	-0.0140	-0.0915	0.0057	-0.0411	0.0759	0.1603	-0.0108	0.

	beat_j~5	owns_h~e	owns_l~d	contr_~s	contr_~2	contr_~3	contr_~4	contr_~5	hus_to~l	tota
beat just5	1.0000									
owns house	0.0114	1.0000								
owns land	0.0496	0.5924	1.0000							
contr hus	0.0630	-0.0083	-0.0377	1.0000						
contr hus2	0.0672	-0.0072	-0.0429	0.4254	1.0000					
contr hus3	0.1068	0.0121	-0.0456	0.4105	0.5865	1.0000				
contr hus4	0.1305	0.0030	-0.0266	0.4220	0.6431	0.7172	1.0000			
contr hus5	0.1183	0.0315	-0.0263	0.4261	0.5948	0.6562	0.7928	1.0000		
hus_tot_sc~l	-0.0799	-0.0286	-0.0922	-0.0193	-0.0553	-0.0413	-0.0472	-0.0343	1.0000	
total_abort	-0.0348	0.0288	0.0170	-0.0354	-0.0221	-0.0312	-0.0292	-0.0213	0.0730	1.

```
8 . pca $xlist

Principal components/correlation                  Number of obs    =      3,956
                                                  Number of comp.  =         26
                                                  Trace            =         26
    Rotation: (unrotated = principal)             Rho              =     1.0000
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.84825	.917584	0.1480	0.1480
Comp2	2.93066	.233767	0.1127	0.2607
Comp3	2.6969	.738658	0.1037	0.3645
Comp4	1.95824	.29485	0.0753	0.4398
Comp5	1.66339	.204907	0.0640	0.5037
Comp6	1.45848	.15696	0.0561	0.5598
Comp7	1.30152	.156995	0.0501	0.6099
Comp8	1.14453	.164398	0.0440	0.6539
Comp9	.980128	.10903	0.0377	0.6916
Comp10	.871098	.12356	0.0335	0.7251
Comp11	.747538	.0566201	0.0288	0.7539
Comp12	.690918	.0257571	0.0266	0.7804
Comp13	.665161	.0579072	0.0256	0.8060
Comp14	.607253	.0305111	0.0234	0.8294
Comp15	.576742	.0730737	0.0222	0.8516
Comp16	.503669	.0499489	0.0194	0.8709
Comp17	.45372	.00729057	0.0175	0.8884
Comp18	.446429	.0267649	0.0172	0.9056
Comp19	.419664	.00216189	0.0161	0.9217
Comp20	.417502	.0615602	0.0161	0.9378
Comp21	.355942	.00558815	0.0137	0.9515
Comp22	.350354	.0324611	0.0135	0.9649
Comp23	.317893	.0795806	0.0122	0.9772
Comp24	.238312	.0473457	0.0092	0.9863
Comp25	.190967	.0262175	0.0073	0.9937
Comp26	.164749	.	0.0063	1.0000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8
cur_age	-0.1443	0.1969	0.3242	0.2781	0.1455	0.2096	-0.1140	-0.0770
educ years	-0.1414	0.1630	0.0602	-0.1981	0.1939	0.2221	0.4504	-0.1010
num members	0.0973	-0.2620	-0.3297	0.2631	0.3016	0.0650	0.0951	-0.1298
num chil 5	0.1095	-0.2604	-0.3526	0.0013	0.1003	-0.0730	0.2273	0.0987
num women	0.0463	-0.1730	-0.1979	0.2797	0.3603	0.1697	-0.0153	-0.2606
age hh	0.0474	-0.1190	-0.1427	0.2091	0.2139	0.2851	-0.0265	-0.0571
wealth	-0.0799	0.1489	0.0320	-0.3871	0.2099	-0.0532	0.1216	-0.2218
cur age ch~p	-0.1391	0.2171	0.3215	0.2185	0.1712	0.1844	-0.2526	-0.2677
mar to bir~p	-0.0000	0.0118	0.0326	0.0580	0.0407	0.2626	0.0556	0.5605
term preg	-0.0682	0.0781	0.1366	0.1430	0.4096	-0.4206	0.0323	0.3063
age at mar	-0.0436	0.0496	0.0474	-0.0576	0.0374	0.4505	0.2422	0.4700
employed	-0.0831	0.0679	0.0986	0.0666	0.1313	0.2626	0.1253	-0.0252
beating ju~1	0.2911	-0.1991	0.2551	-0.0687	0.0493	0.0391	0.0329	-0.0003
beating ju~2	0.3036	-0.1967	0.2739	-0.0764	0.0594	0.0405	0.0241	-0.0170
beating ju~3	0.2978	-0.1912	0.2691	-0.0815	0.0722	0.0020	0.0225	-0.0250
beat just4	0.2826	-0.1623	0.2497	-0.0521	0.0717	-0.0031	0.0410	-0.0213
beat just5	0.2947	-0.1690	0.2644	-0.0733	0.0481	0.0204	0.0431	-0.0433
owns house	-0.0174	0.0536	0.1558	0.3659	-0.2824	-0.1428	0.4366	-0.1244
owns land	0.0026	-0.0428	0.1281	0.4401	-0.2889	-0.1152	0.4102	-0.0341
contr hus	0.2358	0.2231	-0.1063	-0.0014	0.0112	-0.0142	0.0356	0.0118
contr hus2	0.2884	0.3109	-0.1134	0.0622	0.0273	0.0313	-0.0162	0.0151
contr hus3	0.3089	0.3245	-0.1056	0.0385	0.0145	0.0039	0.0088	0.0090
contr hus4	0.3296	0.3455	-0.1119	0.0546	0.0139	0.0103	0.0058	-0.0257
contr hus5	0.3205	0.3301	-0.1171	0.0545	0.0076	-0.0152	0.0320	-0.0069
hus tot sc~l	-0.1022	0.0986	0.0068	-0.2876	0.1975	-0.0624	0.4445	-0.2354
total_abort	-0.0752	0.0852	0.1246	0.1274	0.4255	-0.4356	0.0226	0.2436

Variable	Comp15	Comp16	Comp17	Comp18	Comp19	Comp20	Comp21	Comp22
cur_age	0.3400	0.3008	-0.0161	0.1285	0.0150	0.0318	0.0224	-0.0089
educ years	-0.5489	0.4694	-0.1201	-0.0405	0.0068	0.0183	-0.0144	-0.0390
num members	0.0720	0.1324	0.0202	0.0609	-0.0031	0.0029	0.0004	-0.0065
num chil 5	0.3568	0.4363	-0.0330	0.1233	0.0134	0.0687	0.0878	0.0347
num women	-0.3737	-0.4002	-0.0254	-0.1114	0.0139	-0.0413	-0.0834	-0.0152
age hh	0.1511	0.0117	-0.0097	-0.0038	-0.0123	0.0059	0.0104	0.0172
wealth	0.0409	-0.0647	0.0552	-0.0313	0.0978	-0.0096	0.2382	-0.0617
cur age ch~p	0.0767	0.0993	-0.0150	0.0076	0.0072	0.0638	0.0821	0.0109
mar to bir~p	-0.1018	0.0695	0.0219	0.0076	-0.0164	0.0040	-0.0038	-0.0254
term preg	0.0338	-0.0650	-0.4425	-0.0593	0.5047	-0.1532	-0.0608	-0.0664
age at mar	0.1283	-0.2945	0.0281	-0.0177	-0.0309	0.0056	-0.0128	0.0132
employed	0.1341	-0.1729	0.0763	0.0516	-0.0159	-0.0196	-0.0045	0.0175
beating ju~1	0.0554	-0.0271	0.1135	-0.1447	0.0955	0.2003	-0.0634	-0.2686
beating ju~2	-0.0531	-0.1238	0.0305	0.0092	0.1707	0.1498	-0.0568	0.4211
beating ju~3	0.0327	-0.0466	-0.5237	0.0927	-0.5651	-0.2364	0.1599	-0.2871
beat just4	0.0665	0.1987	0.0593	-0.5687	0.0358	0.2504	0.0080	0.1531
beat just5	-0.1155	0.0794	0.3417	0.5731	0.2580	-0.3679	-0.0809	-0.0183
owns house	0.0297	0.0098	-0.1060	0.0047	-0.1447	-0.0354	-0.5871	0.1282
owns land	-0.0701	-0.1144	0.1218	-0.0508	0.1420	0.0033	0.6605	-0.1267
contr hus	0.0143	0.0130	0.0226	0.0780	0.0113	0.0941	-0.0065	-0.0185
contr hus2	0.0880	0.1067	0.2299	-0.4427	-0.0345	-0.6896	-0.0213	0.0250
contr hus3	-0.0536	-0.0471	-0.2726	0.1954	-0.0900	0.0761	0.2345	0.6188
contr hus4	-0.0212	-0.0199	0.0150	0.0896	0.0386	0.1776	0.0352	-0.2113
contr hus5	0.0120	-0.0588	0.0171	0.0808	0.0737	0.3221	-0.1916	-0.4035
hus tot sc~l	0.4229	-0.2939	0.0543	0.0134	-0.0311	-0.0287	-0.0513	0.0487
total_abort	-0.1180	-0.0060	0.4598	0.0615	-0.4996	0.1413	0.0286	0.0729

```
9 . pca $xlist, comp($ncomp) blanks(.3)
```

Principal components/correlation

Number of obs	=	3,956
Number of comp.	=	8
Trace	=	26
Rho	=	0.6539

Rotation: (unrotated = principal)

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.84825	.917584	0.1480	0.1480
Comp2	2.93066	.233767	0.1127	0.2607
Comp3	2.6969	.738658	0.1037	0.3645
Comp4	1.95824	.29485	0.0753	0.4398
Comp5	1.66339	.204907	0.0640	0.5037
Comp6	1.45848	.15696	0.0561	0.5598
Comp7	1.30152	.156995	0.0501	0.6099
Comp8	1.14453	.164398	0.0440	0.6539
Comp9	.980128	.10903	0.0377	0.6916
Comp10	.871098	.12356	0.0335	0.7251
Comp11	.747538	.0566201	0.0288	0.7539
Comp12	.690918	.0257571	0.0266	0.7804
Comp13	.665161	.0579072	0.0256	0.8060
Comp14	.607253	.0305111	0.0234	0.8294
Comp15	.576742	.0730737	0.0222	0.8516
Comp16	.503669	.0499489	0.0194	0.8709
Comp17	.45372	.00729057	0.0175	0.8884
Comp18	.446429	.0267649	0.0172	0.9056
Comp19	.419664	.00216189	0.0161	0.9217
Comp20	.417502	.0615602	0.0161	0.9378
Comp21	.355942	.00558815	0.0137	0.9515
Comp22	.350354	.0324611	0.0135	0.9649
Comp23	.317893	.0795806	0.0122	0.9772
Comp24	.238312	.0473457	0.0092	0.9863
Comp25	.190967	.0262175	0.0073	0.9937
Comp26	.164749	.	0.0063	1.0000

Principal components (eigenvectors) (blanks are abs(loading)<.3)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8
cur age			0.3242					
educ years							0.4504	
num member			-0.3297		0.3016			
num chil 5			-0.3526					
num women					0.3603			
age hh								
wealth				-0.3871				
cur age ch			0.3215					
mar to bir								0.5605
term preg					0.4096	-0.4206		0.3063
age at mar						0.4505		0.4700
employed								
beating ju								
beating ju	0.3036							
beating ju								
beat just4								
beat just5								
owns house				0.3659			0.4366	
owns land				0.4401			0.4102	
contr hus								
contr hus2		0.3109						
contr hus3	0.3089	0.3245						
contr hus4	0.3296	0.3455						
contr hus5	0.3205	0.3301						
hus tot sc							0.4445	
total_abor					0.4255	-0.4356		

10. rotate, varimax blanks(.3)

Principal components/correlation

Rotation: orthogonal varimax (Kaiser off)

Number of obs	=	3,956
Number of comp.	=	8
Trace	=	26
Rho	=	0.6539

Component	Variance	Difference	Proportion	Cumulative
Comp1	3.3139	.131612	0.1275	0.1275
Comp2	3.18229	.963225	0.1224	0.2499
Comp3	2.21906	.137788	0.0853	0.3352
Comp4	2.08128	.409993	0.0800	0.4153
Comp5	1.67128	.00531228	0.0643	0.4795
Comp6	1.66597	.0875745	0.0641	0.5436
Comp7	1.5784	.288609	0.0607	0.6043
Comp8	1.28979	.	0.0496	0.6539

Rotated components (blanks are abs(loading)<.3)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8
cur_age			0.5521					
educ_years					0.5797			
num_members				0.5985				
num_chil_5			-0.4301					
num_women				0.5924				
age_hh				0.4148				
wealth					0.4619			
cur_age_ch~			0.6349					
mar_to_bir~								0.5966
term_preg							0.6987	
age_at_mar								0.6929
employed								
beating_ju~		0.4449						
beating_ju~		0.4660						
beating_ju~		0.4583						
beat_just4		0.4210						
beat_just5		0.4430						
owns_house						0.6760		
owns_land						0.6890		
contr_hus	0.3394							
contr_hus2	0.4431							
contr_hus3	0.4621							
contr_hus4	0.4937							
contr_hus5	0.4783							
hus_tot_sc~					0.6162			
total_abort							0.6883	

Component rotation matrix

	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8
Comp1	0.6672	0.6571	-0.2405	0.1212	-0.1972	-0.0091	-0.0975	-0.0451
Comp2	0.6960	-0.4113	0.3745	-0.3688	0.2355	-0.0036	0.1112	0.0478
Comp3	-0.2436	0.5878	0.5628	-0.4437	0.0609	0.2017	0.1810	0.0660
Comp4	0.0964	-0.1615	0.3436	0.4619	-0.4779	0.6060	0.1907	0.0356
Comp5	0.0329	0.1349	0.2113	0.5378	0.3447	-0.4172	0.5909	0.0703
Comp6	0.0079	0.0435	0.3572	0.2734	0.0850	-0.1711	-0.6291	0.6029
Comp7	0.0227	0.0695	-0.3250	0.0925	0.6537	0.6168	0.0373	0.2671
Comp8	-0.0049	-0.0513	-0.2987	-0.2580	-0.3467	-0.0909	0.4035	0.7418

11. estat loadings

Principal component loadings
component normalization: sum of squares(column) = 1

	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8
cur_age	-.1443	.1969	.3242	.2781	.1455	.2096	-.114	-.07702
educ years	-.1414	.163	.0602	-.1981	.1939	.2221	.4504	-.101
num members	.09734	-.262	-.3297	.2631	.3016	.06503	.0951	-.1298
num chil 5	.1095	-.2604	-.3526	.001349	.1003	-.07301	.2273	.09866
num women	.04631	-.173	-.1979	.2797	.3603	.1697	-.01529	-.2606
age hh	.04736	-.119	-.1427	.2091	.2139	.2851	-.02654	-.05712
wealth	-.07992	.1489	.03198	-.3871	.2099	-.05323	.1216	-.2218
cur age ch~p	-.1391	.2171	.3215	.2185	.1712	.1844	-.2526	-.2677
mar to bir~p	-.000031	.01179	.03261	.05804	.04071	.2626	.0556	.5605
term preg	-.06816	.07813	.1366	.143	.4096	-.4206	.03229	.3063
age at mar	-.04362	.04965	.0474	-.05764	.03743	.4505	.2422	.47
employed	-.08309	.06791	.09863	.06663	.1313	.2626	.1253	-.02517
beating ju~1	.2911	-.1991	.2551	-.06871	.04931	.03906	.0329	-.000256
beating ju~2	.3036	-.1967	.2739	-.0764	.05937	.04051	.02411	-.01704
beating ju~3	.2978	-.1912	.2691	-.08151	.07215	.002039	.0225	-.02502
beat just4	.2826	-.1623	.2497	-.05207	.07172	-.003148	.04101	-.02126
beat just5	.2947	-.169	.2644	-.07334	.04808	.02045	.04314	-.04333
owns house	-.01743	.05357	.1558	.3659	-.2824	-.1428	.4366	-.1244
owns land	.002588	-.04282	.1281	.4401	-.2889	-.1152	.4102	-.03413
contr hus	.2358	.2231	-.1063	-.00137	.01121	-.01419	.03558	.01178
contr hus2	.2884	.3109	-.1134	.06217	.02732	.03133	-.01622	.01513
contr hus3	.3089	.3245	-.1056	.03845	.01453	.003858	.00883	.008962
contr hus4	.3296	.3455	-.1119	.05458	.01391	.01029	.005845	-.02571
contr hus5	.3205	.3301	-.1171	.05452	.007626	-.01518	.03197	-.006871
hus tot sc~l	-.1022	.09862	.006838	-.2876	.1975	-.06241	.4445	-.2354
total_abort	-.07523	.08522	.1246	.1274	.4255	-.4356	.0226	.2436

12. predict ACCEPT CONTROL FAM_SIZE PER_IND FIN_IND SEC PLAN SUBMIS, score

Scoring coefficients for orthogonal varimax rotation
sum of squares(column-loading) = 1

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8
cur_age	-0.0071	-0.0054	0.5521	0.0394	-0.0182	0.0746	0.0665	0.0962
educ years	0.0042	-0.0203	0.0650	0.0372	0.5797	0.0609	-0.0441	0.2040
num members	0.0015	-0.0078	-0.1219	0.5985	-0.0100	0.0265	0.0403	-0.0398
num chil 5	-0.0147	-0.0073	-0.4301	0.2959	0.0377	0.0315	0.0502	0.0563
num women	-0.0002	0.0084	0.1283	0.5924	0.0234	-0.0353	-0.0058	-0.0833
age hh	0.0127	0.0047	0.1083	0.4148	-0.0456	-0.0513	-0.0808	0.1277
wealth	0.0156	0.0134	0.0121	-0.0908	0.4619	-0.2113	0.0289	-0.1504
cur age ch~p	0.0037	0.0003	0.6349	0.0496	-0.0039	-0.0368	0.0053	-0.0971
mar to bir~p	0.0078	-0.0030	-0.0403	-0.0378	-0.1446	-0.0368	0.1053	0.5966
term preg	-0.0012	0.0038	0.0059	-0.0025	-0.0078	0.0077	0.6987	0.0320
age at mar	-0.0037	0.0055	-0.0143	-0.0268	0.0973	-0.0112	-0.0553	0.6929
employed	-0.0164	0.0038	0.2122	0.1124	0.1648	0.0407	-0.0469	0.1982
beating ju~1	-0.0104	0.4449	-0.0109	0.0041	-0.0140	0.0009	-0.0118	0.0274
beating ju~2	-0.0056	0.4660	0.0055	0.0021	-0.0074	-0.0084	-0.0129	0.0147
beating ju~3	-0.0048	0.4583	-0.0036	-0.0026	0.0000	-0.0114	0.0150	-0.0140
beat just4	0.0131	0.4210	0.0009	0.0062	0.0048	0.0146	0.0270	-0.0075
beat just5	0.0105	0.4430	0.0058	-0.0066	0.0148	0.0138	-0.0140	-0.0114
owns house	0.0231	-0.0086	0.0223	-0.0404	0.0698	0.6760	-0.0053	-0.0549
owns land	-0.0178	0.0098	-0.0187	0.0224	-0.0424	0.6890	0.0054	0.0165
contr hus	0.3394	0.0037	-0.0513	-0.0048	0.0220	-0.0066	0.0039	0.0034
contr hus2	0.4431	-0.0119	0.0223	0.0172	-0.0240	-0.0171	-0.0003	0.0243
contr hus3	0.4621	0.0035	-0.0001	-0.0103	-0.0013	-0.0041	0.0043	0.0083
contr hus4	0.4937	0.0039	0.0183	0.0049	0.0019	0.0046	-0.0120	-0.0141
contr hus5	0.4783	0.0001	-0.0128	-0.0011	0.0060	0.0251	0.0071	-0.0097
hus tot sc~l	-0.0117	0.0097	-0.0882	0.0064	0.6162	0.0515	0.0449	-0.0801
total_abort	0.0009	-0.0043	0.0181	0.0119	0.0216	-0.0085	0.6883	-0.0257

13. estat kmo

Kaiser-Meyer-Olkin measure of sampling adequacy

Variable	kmo
cur_age	**0.5904**
educ years	**0.6971**
num members	**0.5620**
num chil 5	**0.7238**
num women	**0.5175**
age hh	**0.5552**
wealth	**0.6496**
cur age ch~p	**0.5766**
mar to bir~p	**0.5328**
term preg	**0.5638**
age at mar	**0.3492**
employed	**0.7316**
beating ju~1	**0.8291**
beating ju~2	**0.8282**
beating ju~3	**0.8690**
beat just4	**0.8733**
beat just5	**0.8712**
owns house	**0.5366**
owns land	**0.5337**
contr hus	**0.9244**
contr hus2	**0.9023**
contr hus3	**0.8795**
contr hus4	**0.7862**
contr hus5	**0.8212**
hus tot sc~l	**0.6700**
total_abort	**0.5749**
Overall	**0.7256**

Propensity Score Matching: Severe Physical Violence

Statistics/Data Analysis

```
10.
11. global treatment TREAT

12. global ylist PHYS_SEV

13. global xlist ACCEPT CONTROL FAM_SIZE PER_IND FIN_IND SEC TENURE SUBMIS

14. global breps 5

15. describe $treatment $ylist $xlist

                 storage   display    value
variable name      type    format     label      variable label
--------------------------------------------------------------------------------
TREAT            byte      %9.0g                 RECODE of qbee (relationship to household head)
PHYS SEV         float     %9.0g                 Scores for component 1
ACCEPT           float     %9.0g                 Scores for component 2
CONTROL          float     %9.0g                 Scores for component 1
FAM SIZE         float     %9.0g                 Scores for component 4
PER IND          float     %9.0g                 Scores for component 7
FIN IND          float     %9.0g                 Scores for component 5
SEC              float     %9.0g                 Scores for component 6
PER IND          float     %9.0g                 Scores for component 7
SUBMIS           float     %9.0g                 Scores for component 8

16. summarize $treatment $ylist $xlist

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
       TREAT |      3,534    .3406904    .4740085          0          1
    PHYS SEV |      3,534   -4.57e-09    1.745534  -.9574195   20.77108
      ACCEPT |      3,534   -1.42e-09    1.773876  -1.260467   9.492954
     CONTROL |      3,534    2.73e-10    1.805192  -.9490442   15.89445
    FAM_SIZE |      3,534   -1.31e-10    1.443617  -2.313617   7.686239
-------------+---------------------------------------------------------
     PER_IND |      3,534   -7.75e-10     1.25713  -1.177323   11.08654
     FIN IND |      3,534    9.37e-12     1.29128  -2.349422   2.703691
         SEC |      3,534   -6.72e-10    1.286082  -5.165536   3.770026
     PER IND |      3,534   -7.75e-10     1.25713  -1.177323   11.08654
      SUBMIS |      3,534    1.57e-10    1.143865  -2.477531   10.42847
```

17. bysort $treatment: summarize $ylist $xlist

-> TREAT = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
PHYS_SEV	2,330	.0283401	1.839316	-.9574195	20.21262
ACCEPT	2,330	-.0341784	1.7137	-1.260467	9.444988
CONTROL	2,330	-.0374653	1.813146	-.9490442	15.87103
FAM SIZE	2,330	-.5606351	1.065653	-2.313617	7.686239
PER_IND	2,330	.1409324	1.339412	-1.093585	11.08654
FIN_IND	2,330	.1297371	1.239402	-2.074306	2.639933
SEC	2,330	.1115556	1.300357	-5.165536	3.770026
PER IND	2,330	.1409324	1.339412	-1.093585	11.08654
SUBMIS	2,330	-.013657	1.177426	-2.477531	10.42847

-> TREAT = 1

Variable	Obs	Mean	Std. Dev.	Min	Max
PHYS SEV	1,204	-.0548442	1.547252	-.8423139	20.77108
ACCEPT	1,204	.0661426	1.883856	-1.254708	9.492954
CONTROL	1,204	.0725034	1.788219	-.9321543	15.89445
FAM SIZE	1,204	1.08495	1.461172	-1.372819	7.677022
PER_IND	1,204	-.2727347	1.027207	-1.177323	6.940488
FIN IND	1,204	-.2510693	1.351766	-2.349422	2.703691
SEC	1,204	-.2158842	1.230103	-5.163577	3.507075
SUBMIS	1,204	.0264293	1.075931	-2.108523	7.697233

18. reg $ylist $treatment

Source	SS	df	MS		
				Number of obs =	3,534
				F(1, 3532) =	1.80
Model	5.49285005	1	5.49285005	Prob > F =	0.1794
Residual	10759.1657	3,532	3.04619642	R-squared =	0.0005
				Adj R-squared =	0.0002
Total	10764.6586	3,533	3.04688893	Root MSE =	1.7453

PHYS_SEV	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TREAT	-.0831842	.0619471	-1.34	0.179	-.2046399	.0382715
_cons	.0283401	.0361577	0.78	0.433	-.0425521	.0992322

19. reg $ylist $treatment $xlist
note: PER_IND omitted because of collinearity

Source	SS	df	MS		
				Number of obs =	3,534
				F(8, 3525) =	2.23
Model	54.191011	8	6.77387638	Prob > F =	0.0227
Residual	10710.4676	3,525	3.03843052	R-squared =	0.0050
				Adj R-squared =	0.0028
Total	10764.6586	3,533	3.04688893	Root MSE =	1.7431

PHYS_SEV	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TREAT	-.1352275	.0755694	-1.79	0.074	-.2833917	.0129368
ACCEPT	.0042992	.0168666	0.25	0.799	-.0287699	.0373684
CONTROL	.0330379	.0164156	2.01	0.044	.0008529	.065223
FAM SIZE	.0269257	.0244814	1.10	0.271	-.0210734	.0749248
PER IND	.0555718	.0237704	2.34	0.019	.0089666	.1021769
FIN IND	-.0438051	.0232896	-1.88	0.060	-.0894675	.0018573
SEC	-.0272966	.0238959	-1.14	0.253	-.0741479	.0195546
PER IND	0	(omitted)				
SUBMIS	.0259246	.0257488	1.01	0.314	-.0245595	.0764087

cons	**.0460707**	**.0390207**	**1.18**	**0.238**	**-.0304348**	**.1225762**

20. pscore $treatment $xlist, pscore(the_score) blockid(blocks) comsup

****
Algorithm to estimate the propensity score
****

The treatment is TREAT

RECODE of qbee (relationship to household head)	Freq.	Percent	Cum.
0	**2,330**	**65.93**	**65.93**
1	**1,204**	**34.07**	**100.00**
Total	**3,534**	**100.00**	

Estimation of the propensity score

note: PER_IND dropped because of collinearity
Iteration 0: log likelihood = **-2267.0341**
Iteration 1: log likelihood = **-1646.0038**
Iteration 2: log likelihood = **-1608.3571**
Iteration 3: log likelihood = **-1607.895**
Iteration 4: log likelihood = **-1607.8949**

Probit regression — Number of obs = **3534**; LR chi2(**7**) = **1318.28**; Prob > chi2 = **0.0000**; Pseudo R2 = **0.2907**

Log likelihood = **-1607.8949**

TREAT	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
ACCEPT	**.0065523**	**.0142451**	**0.46**	**0.646**	**-.0213675**	**.0344721**
CONTROL	**.0260453**	**.0135589**	**1.92**	**0.055**	**-.0005296**	**.0526202**
FAM SIZE	**.6065074**	**.0207545**	**29.22**	**0.000**	**.5658294**	**.6471854**
PER IND	**-.2092979**	**.0226538**	**-9.24**	**0.000**	**-.2536986**	**-.1648973**
FIN IND	**-.1712587**	**.0197802**	**-8.66**	**0.000**	**-.2100271**	**-.1324902**
SEC	**-.0396031**	**.0203821**	**-1.94**	**0.052**	**-.0795512**	**.000345**
SUBMIS	**.0412381**	**.0218046**	**1.89**	**0.059**	**-.0014981**	**.0839742**
_cons	**-.5117307**	**.0256165**	**-19.98**	**0.000**	**-.5619381**	**-.4615233**

Note: the common support option has been selected
The region of common support is [.05875213, .99999646]

Description of the estimated propensity score
in region of common support

Estimated propensity score

	Percentiles	Smallest		
1%	.0616481	.0587521		
5%	.0761342	.0589325		
10%	.0939188	.0591935	Obs	3,207
25%	.1478593	.0592022	Sum of Wgt.	3,207
50%	.2762242		Mean	.3611419
		Largest	Std. Dev.	.2638001
75%	.5114398	.9999602		
90%	.812487	.9999718	Variance	.0695905
95%	.9316362	.9999955	Skewness	.9388525
99%	.9961979	.9999965	Kurtosis	2.788074

****
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
****

The final number of blocks is 10

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks

****
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
****

Variable FAM_SIZE is not balanced in block 1

Variable PER_IND is not balanced in block 1

Variable PER_IND is not balanced in block 1

Variable FAM_SIZE is not balanced in block 2

Variable PER_IND is not balanced in block 2

Variable PER_IND is not balanced in block 2

Variable FAM_SIZE is not balanced in block 3

Variable FAM_SIZE is not balanced in block 4

Variable PER_IND is not balanced in block 4

Variable PER_IND is not balanced in block 4

Variable FAM_SIZE is not balanced in block 5

Variable PER_IND is not balanced in block 5

Variable FIN_IND is not balanced in block 5

Variable PER_IND is not balanced in block 5

Variable FAM_SIZE is not balanced in block 6

Variable PER_IND is not balanced in block 6

Variable FIN_IND is not balanced in block 6

Variable PER_IND is not balanced in block 6

Variable PER_IND is not balanced in block 8

Variable PER_IND is not balanced in block 8

Variable PER_IND is not balanced in block 9

Variable PER_IND is not balanced in block 9

Variable FIN_IND is not balanced in block 10

The balancing property is not satisfied

Try a different specification of the propensity score

Inferior of block of pscore	RECODE of qbee (relationship to household head) 0	1	Total
0	361	11	372
.1	208	7	215
.125	107	7	114
.1375	98	19	117
.15	352	37	389
.2	372	141	513
.3	200	174	374
.4	178	314	492
.6	67	218	285
.8	60	276	336
Total	2,003	1,204	3,207

Note: the common support option has been selected

```
*******************************************
End of the algorithm to estimate the pscore
*******************************************
```

21.
22. teffects psmatch ($ylist) (TREAT $xlist, logit), ate
note: PER_IND omitted because of collinearity

```
Treatment-effects estimation                   Number of obs      =      3,534
Estimator      : propensity-score matching     Matches: requested =          1
Outcome  model : matching                                     min =          1
Treatment model: logit                                        max =          1
```

PHYS_SEV	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE						
TREAT (1 vs 0)	-.2377605	.0861916	-2.76	0.006	-.4066929	-.0688281

23. teffects psmatch ($ylist) (TREAT $xlist, logit), atet
note: PER_IND omitted because of collinearity

```
Treatment-effects estimation                   Number of obs      =      3,534
Estimator      : propensity-score matching     Matches: requested =          1
Outcome  model : matching                                     min =          1
Treatment model: logit                                        max =          1
```

PHYS_SEV	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATET						
TREAT (1 vs 0)	-.1631876	.1428016	-1.14	0.253	-.4430736	.1166983

```
24.
25. drop the_score blocks

26.
27. //With smaller number of X valiable to satisfy the balancing property
28.
29.
30. global treatment TREAT

31. global ylist PHYS_SEV

32. global xlist ACCEPT CONTROL SEC SUBMIS

33. global breps 5

34. describe $treatment $ylist $xlist
```

variable name	storage type	display format	value label	variable label
TREAT	byte	%9.0g		**RECODE of qbee (relationship to household head)**
PHYS_SEV	float	%9.0g		**Scores for component 1**
ACCEPT	float	%9.0g		**Scores for component 2**
CONTROL	float	%9.0g		**Scores for component 1**
SEC	float	%9.0g		**Scores for component 6**
SUBMIS	float	%9.0g		**Scores for component 8**

```
35. summarize $treatment $ylist $xlist
```

Variable	Obs	Mean	Std. Dev.	Min	Max
TREAT	**3,534**	**.3406904**	**.4740085**	**0**	**1**
PHYS_SEV	**3,534**	**-4.57e-09**	**1.745534**	**-.9574195**	**20.77108**
ACCEPT	**3,534**	**-1.42e-09**	**1.773876**	**-1.260467**	**9.492954**
CONTROL	**3,534**	**2.73e-10**	**1.805192**	**-.9490442**	**15.89445**
SEC	**3,534**	**-6.72e-10**	**1.286082**	**-5.165536**	**3.770026**
SUBMIS	**3,534**	**1.57e-10**	**1.143865**	**-2.477531**	**10.42847**

```
36. bysort $treatment: summarize $ylist $xlist
```

-> TREAT = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
PHYS_SEV	**2,330**	**.0283401**	**1.839316**	**-.9574195**	**20.21262**
ACCEPT	**2,330**	**-.0341784**	**1.7137**	**-1.260467**	**9.444988**
CONTROL	**2,330**	**-.0374653**	**1.813146**	**-.9490442**	**15.87103**
SEC	**2,330**	**.1115556**	**1.300357**	**-5.165536**	**3.770026**
SUBMIS	**2,330**	**-.013657**	**1.177426**	**-2.477531**	**10.42847**

-> TREAT = 1

Variable	Obs	Mean	Std. Dev.	Min	Max
PHYS_SEV	**1,204**	**-.0548442**	**1.547252**	**-.8423139**	**20.77108**
ACCEPT	**1,204**	**.0661426**	**1.883856**	**-1.254708**	**9.492954**
CONTROL	**1,204**	**.0725034**	**1.788219**	**-.9321543**	**15.89445**
SEC	**1,204**	**-.2158842**	**1.230103**	**-5.163577**	**3.507075**
SUBMIS	**1,204**	**.0264293**	**1.075931**	**-2.108523**	**7.697233**

37. reg $ylist $treatment

Source	SS	df	MS
Model	5.49285005	1	5.49285005
Residual	10759.1657	3,532	3.04619642
Total	10764.6586	3,533	3.04688893

Number of obs	=	3,534
F(1, 3532)	=	1.80
Prob > F	=	0.1794
R-squared	=	0.0005
Adj R-squared	=	0.0002
Root MSE	=	1.7453

PHYS_SEV	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TREAT	-.0831842	.0619471	-1.34	0.179	-.2046399	.0382715
_cons	.0283401	.0361577	0.78	0.433	-.0425521	.0992322

38. reg $ylist $treatment $xlist

Source	SS	df	MS
Model	22.7932626	5	4.55865252
Residual	10741.8653	3,528	3.04474641
Total	10764.6586	3,533	3.04688893

Number of obs	=	3,534
F(5, 3528)	=	1.50
Prob > F	=	0.1872
R-squared	=	0.0021
Adj R-squared	=	0.0007
Root MSE	=	1.7449

PHYS_SEV	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TREAT	-.0944774	.0624261	-1.51	0.130	-.2168723	.0279176
ACCEPT	.0030848	.0168798	0.18	0.855	-.0300105	.03618
CONTROL	.032482	.0164124	1.98	0.048	.0003032	.0646608
SEC	-.019882	.02334	-0.85	0.394	-.0656433	.0258793
SUBMIS	.0224896	.025753	0.87	0.383	-.0280027	.0729819
_cons	.0321875	.0362476	0.89	0.375	-.0388808	.1032558

39. pscore $treatment $xlist, pscore(the_score) blockid(blocks) comsup

****
Algorithm to estimate the propensity score
****

The treatment is TREAT

RECODE of qbee (relationship to household head)	Freq.	Percent	Cum.
0	2,330	65.93	65.93
1	1,204	34.07	100.00
Total	3,534	100.00	

Estimation of the propensity score

```
Iteration 0:  log likelihood = -2267.0341
Iteration 1:  log likelihood = -2238.8453
Iteration 2:  log likelihood = -2238.831
```

Probit regression

Number of obs	=	3534
LR chi2(4)	=	56.41
Prob > chi2	=	0.0000
Pseudo R2	=	0.0124

Log likelihood = -2238.831

TREAT	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
ACCEPT	.0043967	.0124258	0.35	0.723	-.0199573	.0287507
CONTROL	.0151555	.0119735	1.27	0.206	-.0083121	.0386231
SEC	-.1234757	.0174822	-7.06	0.000	-.1577403	-.0892112
SUBMIS	.0290461	.0189768	1.53	0.126	-.0081477	.06624
_cons	-.4163445	.0218864	-19.02	0.000	-.459241	-.3734479

Note: the common support option has been selected
The region of common support is [.19617583, .59031676]

Description of the estimated propensity score
in region of common support

Estimated propensity score

	Percentiles	Smallest		
1%	.2227071	.1961758		
5%	.2415032	.2021643		
10%	.2619649	.2036559	Obs	3,530
25%	.2987655	.2059477	Sum of Wgt.	3,530
50%	.3414558		Mean	.3403867
		Largest	Std. Dev.	.0595543
75%	.378146	.5820683		
90%	.408803	.5889891	Variance	.0035467
95%	.4367075	.5902658	Skewness	.3688394
99%	.5078623	.5903168	Kurtosis	3.576885

****
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
****

The final number of blocks is 5

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks

****
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
****

The balancing property is satisfied

This table shows the inferior bound, the number of treated
and the number of controls for each block

Inferior of block of pscore	RECODE of qbee (relationship to household head) 0	1	Total
.1961758	**0**	**1**	**1**
.2	**196**	**41**	**237**
.25	**476**	**199**	**675**
.3	**1,390**	**760**	**2,150**
.4	**264**	**203**	**467**
Total	**2,326**	**1,204**	**3,530**

Note: the common support option has been selected

****
End of the algorithm to estimate the pscore
****

```
40.
41. teffects psmatch ($ylist) (TREAT $xlist, logit), ate
```

```
Treatment-effects estimation                   Number of obs      =      3,534
Estimator      : propensity-score matching     Matches: requested =          1
Outcome  model : matching                                     min =          1
Treatment model: logit                                        max =          1
```

PHYS_SEV	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE						
TREAT (1 vs 0)	**-.0601774**	**.071295**	**-0.84**	**0.399**	**-.1999131**	**.0795583**

```
42. teffects psmatch ($ylist) (TREAT $xlist, logit), atet
```

```
Treatment-effects estimation                   Number of obs      =      3,534
Estimator      : propensity-score matching     Matches: requested =          1
Outcome  model : matching                                     min =          1
Treatment model: logit                                        max =          1
```

PHYS_SEV	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATET						
TREAT (1 vs 0)	**-.0529275**	**.0776262**	**-0.68**	**0.495**	**-.205072**	**.0992171**

Propensity Score Matching: Physical Violence (PHYS)

```
50. global treatment TREAT
```

```
51. global ylist PHYS

52. global xlist ACCEPT CONTROL FAM_SIZE PER_IND FIN_IND SEC TENURE SUBMIS

53. global breps 5

54. describe $treatment $ylist $xlist

              storage   display    value
variable name   type    format     label      variable label
-------------------------------------------------------------------------------------------
TREAT           byte    %9.0g                 RECODE of qbee (relationship to household head)
PHYS            float   %9.0g                 Scores for component 2
ACCEPT          float   %9.0g                 Scores for component 2
CONTROL         float   %9.0g                 Scores for component 1
FAM SIZE        float   %9.0g                 Scores for component 4
PER IND         float   %9.0g                 Scores for component 7
FIN IND         float   %9.0g                 Scores for component 5
SEC             float   %9.0g                 Scores for component 6
PER IND         float   %9.0g                 Scores for component 7
SUBMIS          float   %9.0g                 Scores for component 8

55. summarize $treatment $ylist $xlist

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
       TREAT |      3,534    .3406904    .4740085          0          1
        PHYS |      3,534    2.08e-08    1.602532  -2.190639   10.15611
      ACCEPT |      3,534   -1.42e-09    1.773876  -1.260467   9.492954
     CONTROL |      3,534    2.73e-10    1.805192  -.9490442   15.89445
    FAM_SIZE |      3,534   -1.31e-10    1.443617  -2.313617   7.686239
-------------+---------------------------------------------------------
     PER IND |      3,534   -7.75e-10     1.25713  -1.177323   11.08654
     FIN IND |      3,534    9.37e-12     1.29128  -2.349422   2.703691
         SEC |      3,534   -6.72e-10    1.286082  -5.165536   3.770026
     PER IND |      3,534   -7.75e-10     1.25713  -1.177323   11.08654
      SUBMIS |      3.534    1.57e-10    1.143865  -2.477531   10.42847

56. bysort $treatment: summarize $ylist $xlist

-------------------------------------------------------------------------------------------
-> TREAT = 0

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
        PHYS |      2,330    -.003313    1.613751  -2.190639   10.15611
      ACCEPT |      2,330   -.0341784      1.7137  -1.260467   9.444988
     CONTROL |      2,330   -.0374653    1.813146  -.9490442   15.87103
    FAM SIZE |      2,330   -.5606351    1.065653  -2.313617   7.686239
     PER_IND |      2,330    .1409324    1.339412  -1.093585   11.08654
-------------+---------------------------------------------------------
     FIN_IND |      2,330    .1297371    1.239402  -2.074306   2.639933
         SEC |      2,330    .1115556    1.300357  -5.165536   3.770026
     PER IND |      2,330    .1409324    1.339412  -1.093585   11.08654
      SUBMIS |      2.330    -.013657    1.177426  -2.477531   10.42847

-------------------------------------------------------------------------------------------
-> TREAT = 1

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
        PHYS |      1,204    .0064114    1.581242  -1.479326   7.304356
      ACCEPT |      1,204    .0661426    1.883856  -1.254708   9.492954
     CONTROL |      1,204    .0725034    1.788219  -.9321543   15.89445
    FAM SIZE |      1,204     1.08495    1.461172  -1.372819   7.677022
     PER_IND |      1,204   -.2727347    1.027207  -1.177323   6.940488
-------------+---------------------------------------------------------
     FIN_IND |      1,204   -.2510693    1.351766  -2.349422   2.703691
         SEC |      1,204   -.2158842    1.230103  -5.163577   3.507075
      SUBMIS |      1.204    .0264293    1.075931  -2.108523   7.697233
```

```
57. reg $ylist $treatment

      Source |       SS           df       MS      Number of obs   =     3,534
-------------+----------------------------------   F(1, 3532)      =      0.03
       Model |  .075064527         1  .075064527   Prob > F        =    0.8643
    Residual |   9073.0549     3,532  2.56881509   R-squared       =    0.0000
-------------+----------------------------------   Adj R-squared   =   -0.0003
       Total |  9073.12996     3,533  2.56810924   Root MSE        =    1.6028

------------------------------------------------------------------------------
        PHYS |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       TREAT |   .0097243   .0568864     0.17   0.864    -.1018092    .1212579
       _cons |   -.003313   .0332039    -0.10   0.921    -.0684136    .0617877
------------------------------------------------------------------------------

58. reg $ylist $treatment $xlist
  note: PER_IND omitted because of collinearity

      Source |       SS           df       MS      Number of obs   =     3,534
-------------+----------------------------------   F(8, 3525)      =      3.21
       Model |  65.5945039         8  8.19931298   Prob > F        =    0.0012
    Residual |  9007.53546     3,525  2.55532921   R-squared       =    0.0072
-------------+----------------------------------   Adj R-squared   =    0.0050
       Total |  9073.12996     3,533  2.56810924   Root MSE        =    1.5985

------------------------------------------------------------------------------
        PHYS |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       TREAT |   .0600789   .0693019     0.87   0.386    -.0757969    .1959547
      ACCEPT |  -.0197756   .0154677    -1.28   0.201    -.0501021    .0105509
     CONTROL |    .015299   .0150541     1.02   0.310    -.0142166    .0448147
    FAM_SIZE |  -.0138179   .0224509    -0.62   0.538    -.0578361    .0302003
     PER_IND |   .0988924    .021799     4.54   0.000     .0561526    .1416322
     FIN_IND |   .0014648    .021358     0.07   0.945    -.0404105    .0433401
         SEC |  -.0437148   .0219141    -1.99   0.046    -.0866803   -.0007493
     PER_IND |          0  (omitted)
      SUBMIS |  -.0040459   .0236133    -0.17   0.864    -.0503429    .0422512
       _cons |  -.0204683   .0357844    -0.57   0.567    -.0906286     .049692
------------------------------------------------------------------------------

59. pscore $treatment $xlist, pscore(the_score) blockid(blocks) comsup


  ****************************************************
  Algorithm to estimate the propensity score
  ****************************************************


  The treatment is TREAT

    RECODE of |
         qbee |
  (relationsh |
        ip to |
    household |
        head) |      Freq.     Percent        Cum.
  ------------+-----------------------------------
            0 |      2,330       65.93       65.93
            1 |      1,204       34.07      100.00
  ------------+-----------------------------------
        Total |      3,534      100.00


  Estimation of the propensity score
```

```
note: PER_IND dropped because of collinearity
Iteration  0:  log likelihood = -2267.0341
Iteration  1:  log likelihood = -1646.0038
Iteration  2:  log likelihood = -1608.3571
Iteration  3:  log likelihood =  -1607.895
Iteration  4:  log likelihood = -1607.8949

Probit regression                               Number of obs   =       3534
                                                LR chi2(7)      =    1318.28
                                                Prob > chi2     =     0.0000
Log likelihood = -1607.8949                     Pseudo R2       =     0.2907
```

TREAT	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ACCEPT	.0065523	.0142451	0.46	0.646	-.0213675	.0344721
CONTROL	.0260453	.0135589	1.92	0.055	-.0005296	.0526202
FAM_SIZE	.6065074	.0207545	29.22	0.000	.5658294	.6471854
PER_IND	-.2092979	.0226538	-9.24	0.000	-.2536986	-.1648973
FIN_IND	-.1712587	.0197802	-8.66	0.000	-.2100271	-.1324902
SEC	-.0396031	.0203821	-1.94	0.052	-.0795512	.000345
SUBMIS	.0412381	.0218046	1.89	0.059	-.0014981	.0839742
_cons	-.5117307	.0256165	-19.98	0.000	-.5619381	-.4615233

Note: the common support option has been selected
The region of common support is [.05875213, .99999646]

Description of the estimated propensity score
in region of common support

Estimated propensity score

	Percentiles	Smallest		
1%	.0616481	.0587521		
5%	.0761342	.0589325		
10%	.0939188	.0591935	Obs	3,207
25%	.1478593	.0592022	Sum of Wgt.	3,207
50%	.2762242		Mean	.3611419
		Largest	Std. Dev.	.2638001
75%	.5114398	.9999602		
90%	.812487	.9999718	Variance	.0695905
95%	.9316362	.9999955	Skewness	.9388525
99%	.9961979	.9999965	Kurtosis	2.788074

****
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
****

The final number of blocks is 10

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks

****
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
****

Variable FAM_SIZE is not balanced in block 1

Variable PER_IND is not balanced in block 1

Variable PER_IND is not balanced in block 1

Variable FAM_SIZE is not balanced in block 2

Variable PER_IND is not balanced in block 2

Variable PER_IND is not balanced in block 2

Variable FAM_SIZE is not balanced in block 3

Variable FAM_SIZE is not balanced in block 4

Variable PER_IND is not balanced in block 4

Variable PER_IND is not balanced in block 4

Variable FAM_SIZE is not balanced in block 5

Variable PER_IND is not balanced in block 5

Variable FIN_IND is not balanced in block 5

Variable PER_IND is not balanced in block 5

Variable FAM_SIZE is not balanced in block 6

Variable PER_IND is not balanced in block 6

Variable FIN_IND is not balanced in block 6

Variable PER_IND is not balanced in block 6

Variable PER_IND is not balanced in block 8

Variable PER_IND is not balanced in block 8

Variable PER_IND is not balanced in block 9

Variable PER_IND is not balanced in block 9

Variable FIN_IND is not balanced in block 10

The balancing property is not satisfied

Try a different specification of the propensity score

Inferior of block of pscore	RECODE of qbee (relationship to household head) 0	1	Total
0	**361**	**11**	**372**
.1	**208**	**7**	**215**
.125	**107**	**7**	**114**
.1375	**98**	**19**	**117**
.15	**352**	**37**	**389**
.2	**372**	**141**	**513**
.3	**200**	**174**	**374**
.4	**178**	**314**	**492**
.6	**67**	**218**	**285**
.8	**60**	**276**	**336**
Total	**2,003**	**1,204**	**3,207**

Note: the common support option has been selected

```
  *******************************************
  End of the algorithm to estimate the pscore
  *******************************************

60.
61. teffects psmatch ($ylist) (TREAT $xlist, logit), ate
  note: PER_IND omitted because of collinearity

  Treatment-effects estimation                   Number of obs      =      3,534
  Estimator      : propensity-score matching     Matches: requested =          1
  Outcome  model : matching                                     min =          1
  Treatment model: logit                                        max =          1
```

PHYS	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE						
TREAT (1 vs 0)	**.3616543**	**.2713052**	**1.33**	**0.183**	**-.1700942**	**.8934028**

```
62. teffects psmatch ($ylist) (TREAT $xlist, logit), atet
  note: PER_IND omitted because of collinearity

  Treatment-effects estimation                   Number of obs      =      3,534
  Estimator      : propensity-score matching     Matches: requested =          1
  Outcome  model : matching                                     min =          1
  Treatment model: logit                                        max =          1
```

PHYS	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATET						
TREAT (1 vs 0)	**.0258522**	**.110971**	**0.23**	**0.816**	**-.191647**	**.2433513**

```
63.
64. drop the_score blocks

65.
66. //With smaller number of X valiable to satisfy the balancing property
67.
68. global treatment TREAT

69. global ylist PHYS

70. global xlist ACCEPT CONTROL SEC SUBMIS

71. global breps 5

72. describe $treatment $ylist $xlist
```

variable name	storage type	display format	value label	variable label
TREAT	byte	%9.0g		**RECODE of qbee (relationship to household head)**
PHYS	float	%9.0g		**Scores for component 2**
ACCEPT	float	%9.0g		**Scores for component 2**
CONTROL	float	%9.0g		**Scores for component 1**
SEC	float	%9.0g		**Scores for component 6**
SUBMIS	float	%9.0g		**Scores for component 8**

73. summarize $treatment $ylist $xlist

Variable	Obs	Mean	Std. Dev.	Min	Max
TREAT	3,534	.3406904	.4740085	0	1
PHYS	3,534	2.08e-08	1.602532	-2.190639	10.15611
ACCEPT	3,534	-1.42e-09	1.773876	-1.260467	9.492954
CONTROL	3,534	2.73e-10	1.805192	-.9490442	15.89445
SEC	3,534	-6.72e-10	1.286082	-5.165536	3.770026
SUBMIS	3,534	1.57e-10	1.143865	-2.477531	10.42847

74. bysort $treatment: summarize $ylist $xlist

-> TREAT = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
PHYS	2,330	-.003313	1.613751	-2.190639	10.15611
ACCEPT	2,330	-.0341784	1.7137	-1.260467	9.444988
CONTROL	2,330	-.0374653	1.813146	-.9490442	15.87103
SEC	2,330	.1115556	1.300357	-5.165536	3.770026
SUBMIS	2,330	-.013657	1.177426	-2.477531	10.42847

-> TREAT = 1

Variable	Obs	Mean	Std. Dev.	Min	Max
PHYS	1,204	.0064114	1.581242	-1.479326	7.304356
ACCEPT	1,204	.0661426	1.883856	-1.254708	9.492954
CONTROL	1,204	.0725034	1.788219	-.9321543	15.89445
SEC	1,204	-.2158842	1.230103	-5.163577	3.507075
SUBMIS	1,204	.0264293	1.075931	-2.108523	7.697233

75. reg $ylist $treatment

Source	SS	df	MS			
				Number of obs	=	3,534
				F(1, 3532)	=	0.03
Model	.075064527	1	.075064527	Prob > F	=	0.8643
Residual	9073.0549	3,532	2.56881509	R-squared	=	0.0000
				Adj R-squared	=	-0.0003
Total	9073.12996	3,533	2.56810924	Root MSE	=	1.6028

PHYS	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TREAT	.0097243	.0568864	0.17	0.864	-.1018092	.1212579
_cons	-.003313	.0332039	-0.10	0.921	-.0684136	.0617877

76. reg $ylist $treatment $xlist

Source	SS	df	MS			
				Number of obs	=	3,534
				F(5, 3528)	=	1.00
Model	12.7882471	5	2.55764942	Prob > F	=	0.4185
Residual	9060.34171	3,528	2.56812407	R-squared	=	0.0014
				Adj R-squared	=	-0.0000
Total	9073.12996	3,533	2.56810924	Root MSE	=	1.6025

PHYS	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TREAT	-.0011321	.0573322	-0.02	0.984	-.1135398	.1112755
ACCEPT	-.0208968	.0155025	-1.35	0.178	-.0512914	.0094979
CONTROL	.0144217	.0150732	0.96	0.339	-.0151313	.0439748
SEC	-.0356169	.0214355	-1.66	0.097	-.0776442	.0064103
SUBMIS	-.0073713	.0236516	-0.31	0.755	-.0537435	.0390009
_cons	.0003857	.0332898	0.01	0.991	-.0648835	.0656549

```
77. pscore $treatment $xlist, pscore(the_score) blockid(blocks) comsup
```

****
Algorithm to estimate the propensity score
****

The treatment is TREAT

RECODE of qbee (relationship to household head)	Freq.	Percent	Cum.
0	2,330	65.93	65.93
1	1,204	34.07	100.00
Total	3,534	100.00	

Estimation of the propensity score

```
Iteration 0:  log likelihood = -2267.0341
Iteration 1:  log likelihood = -2238.8453
Iteration 2:  log likelihood = -2238.831
```

```
Probit regression                          Number of obs   =       3534
                                           LR chi2(4)      =      56.41
                                           Prob > chi2     =     0.0000
Log likelihood =  -2238.831                Pseudo R2       =     0.0124
```

TREAT	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ACCEPT	.0043967	.0124258	0.35	0.723	-.0199573	.0287507
CONTROL	.0151555	.0119735	1.27	0.206	-.0083121	.0386231
SEC	-.1234757	.0174822	-7.06	0.000	-.1577403	-.0892112
SUBMIS	.0290461	.0189768	1.53	0.126	-.0081477	.06624
_cons	-.4163445	.0218864	-19.02	0.000	-.459241	-.3734479

Note: the common support option has been selected
The region of common support is [.19617583, .59031676]

Description of the estimated propensity score
in region of common support

Estimated propensity score

	Percentiles	Smallest		
1%	.2227071	.1961758		
5%	.2415032	.2021643		
10%	.2619649	.2036559	Obs	3,530
25%	.2987655	.2059477	Sum of Wgt.	3,530
50%	.3414558		Mean	.3403867
		Largest	Std. Dev.	.0595543
75%	.378146	.5820683		
90%	.408803	.5889891	Variance	.0035467
95%	.4367075	.5902658	Skewness	.3688394
99%	.5078623	.5903168	Kurtosis	3.576885

****
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
****

The final number of blocks is 5

This number of blocks ensures that the mean propensity score is not different for treated and controls in each blocks

****
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
****

The balancing property is satisfied

This table shows the inferior bound, the number of treated and the number of controls for each block

Inferior of block of pscore	RECODE of qbee (relationship to household head) 0	1	Total
.1961758	0	1	1
.2	196	41	237
.25	476	199	675
.3	1,390	760	2,150
.4	264	203	467
Total	2,326	1,204	3,530

Note: the common support option has been selected

****
End of the algorithm to estimate the pscore
****

```
78.
79. teffects psmatch ($ylist) (TREAT $xlist, logit), atet
```

```
Treatment-effects estimation                   Number of obs      =      3,534
Estimator      : propensity-score matching     Matches: requested =          1
Outcome  model : matching                                     min =          1
Treatment model: logit                                        max =          1
```

PHYS	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATET						
TREAT (1 vs 0)	.0030286	.0784349	0.04	0.969	-.150701	.1567581

```
80. teffects psmatch ($ylist) (TREAT $xlist, logit), ate
```

```
Treatment-effects estimation                   Number of obs      =      3,534
Estimator      : propensity-score matching     Matches: requested =          1
Outcome  model : matching                                     min =          1
Treatment model: logit                                        max =          1
```

PHYS	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE						
TREAT (1 vs 0)	-.0058298	.066047	-0.09	0.930	-.1352794	.1236199

Propensity Score Matching: Emotional Violence (EMOT)

```
86. global treatment TREAT

87. global ylist EMOT

88. global xlist ACCEPT CONTROL FAM_SIZE PER_IND FIN_IND SEC TENURE SUBMIS

89. global breps 5

90. describe $treatment $ylist $xlist
```

variable name	storage type	display format	value label	variable label
TREAT	byte	%9.0g		**RECODE of qbee (relationship to household head)**
EMOT	float	%9.0g		**Scores for component 3**
ACCEPT	float	%9.0g		**Scores for component 2**
CONTROL	float	%9.0g		**Scores for component 1**
FAM SIZE	float	%9.0g		**Scores for component 4**
PER IND	float	%9.0g		**Scores for component 7**
FIN IND	float	%9.0g		**Scores for component 5**
SEC	float	%9.0g		**Scores for component 6**
PER IND	float	%9.0g		**Scores for component 7**
SUBMIS	float	%9.0g		**Scores for component 8**

```
91. summarize $treatment $ylist $xlist

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
       TREAT |      3,534    .3406904    .4740085          0          1
        EMOT |      3,534    4.47e-10    1.575313  -1.268915   11.21591
      ACCEPT |      3,534   -1.42e-09    1.773876  -1.260467   9.492954
     CONTROL |      3,534    2.73e-10    1.805192  -.9490442   15.89445
    FAM_SIZE |      3,534   -1.31e-10    1.443617  -2.313617   7.686239
-------------+---------------------------------------------------------
     PER_IND |      3,534   -7.75e-10     1.25713  -1.177323   11.08654
     FIN_IND |      3,534    9.37e-12     1.29128  -2.349422   2.703691
         SEC |      3,534   -6.72e-10    1.286082  -5.165536   3.770026
     PER_IND |      3,534   -7.75e-10     1.25713  -1.177323   11.08654
      SUBMIS |      3,534    1.57e-10    1.143865  -2.477531   10.42847

92. bysort $treatment: summarize $ylist $xlist

--------------------------------------------------------------------------------
-> TREAT = 0

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
        EMOT |      2,330   -.0438032    1.536443  -1.268915   11.21591
      ACCEPT |      2,330   -.0341784      1.7137  -1.260467   9.444988
     CONTROL |      2,330   -.0374653    1.813146  -.9490442   15.87103
    FAM_SIZE |      2,330   -.5606351    1.065653  -2.313617   7.686239
     PER_IND |      2,330    .1409324    1.339412  -1.093585   11.08654
-------------+---------------------------------------------------------
     FIN_IND |      2,330    .1297371    1.239402  -2.074306   2.639933
         SEC |      2,330    .1115556    1.300357  -5.165536   3.770026
     PER_IND |      2,330    .1409324    1.339412  -1.093585   11.08654
      SUBMIS |      2,330    -.013657    1.177426  -2.477531   10.42847

--------------------------------------------------------------------------------
-> TREAT = 1

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
        EMOT |      1,204    .0847687    1.645276  -1.113674   9.879296
      ACCEPT |      1,204    .0661426    1.883856  -1.254708   9.492954
     CONTROL |      1,204    .0725034    1.788219  -.9321543   15.89445
    FAM_SIZE |      1,204     1.08495    1.461172  -1.372819   7.677022
     PER_IND |      1,204   -.2727347    1.027207  -1.177323   6.940488
-------------+---------------------------------------------------------
     FIN_IND |      1,204   -.2510693    1.351766  -2.349422   2.703691
         SEC |      1,204   -.2158842    1.230103  -5.163577   3.507075
      SUBMIS |      1,204    .0264293    1.075931  -2.108523   7.697233

93. reg $ylist $treatment

      Source |       SS           df       MS      Number of obs   =     3,534
-------------+----------------------------------   F(1, 3532)      =      5.29
       Model |  13.1222577         1  13.1222577   Prob > F        =    0.0215
    Residual |  8754.40966     3,532  2.47859843   R-squared       =    0.0015
-------------+----------------------------------   Adj R-squared   =    0.0012
       Total |  8767.53192     3,533  2.48161107   Root MSE        =    1.5744

------------------------------------------------------------------------------
        EMOT |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       TREAT |    .128572   .0558786     2.30   0.021     .0190145    .2381295
       _cons |  -.0438032   .0326156    -1.34   0.179    -.1077505     .020144
------------------------------------------------------------------------------
```

94. reg $ylist $treatment $xlist

Source	SS	df	MS
Model	89.2412967	8	11.1551621
Residual	8678.29062	3,525	2.46192642
Total	8767.53192	3,533	2.48161107

Number of obs	=	3,534
F(8, 3525)	=	4.53
Prob > F	=	0.0000
R-squared	=	0.0102
Adj R-squared	=	0.0079
Root MSE	=	1.5691

EMOT	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TREAT	.1625976	.0680235	2.39	0.017	.0292282	.295967
ACCEPT	-.044879	.0151824	-2.96	0.003	-.0746461	-.0151119
CONTROL	.0457374	.0147764	3.10	0.002	.0167662	.0747086
FAM SIZE	-.0215896	.0220368	-0.98	0.327	-.0647958	.0216166
PER IND	.0459002	.0213968	2.15	0.032	.0039488	.0878517
FIN IND	-.0537404	.020964	-2.56	0.010	-.0948433	-.0126376
SEC	-.0013717	.0215098	-0.06	0.949	-.0435447	.0408013
PER IND	0	(omitted)				
SUBMIS	-.0237461	.0231777	-1.02	0.306	-.0691891	.021697
_cons	-.0553954	.0351243	-1.58	0.115	-.1242615	.0134706

95. pscore $treatment $xlist, pscore(the_score) blockid(blocks) comsup

****
Algorithm to estimate the propensity score
****

The treatment is TREAT

RECODE of qbee (relationship to household head)	Freq.	Percent	Cum.
0	2,330	65.93	65.93
1	1,204	34.07	100.00
Total	3,534	100.00	

Estimation of the propensity score

```
note: PER_IND dropped because of collinearity
Iteration 0:  log likelihood = -2267.0341
Iteration 1:  log likelihood = -1646.0038
Iteration 2:  log likelihood = -1608.3571
Iteration 3:  log likelihood = -1607.895
Iteration 4:  log likelihood = -1607.8949
```

Probit regression

Number of obs	=	3534
LR chi2(7)	=	1318.28
Prob > chi2	=	0.0000
Pseudo R2	=	0.2907

Log likelihood = **-1607.8949**

TREAT	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ACCEPT	.0065523	.0142451	0.46	0.646	-.0213675	.0344721
CONTROL	.0260453	.0135589	1.92	0.055	-.0005296	.0526202
FAM SIZE	.6065074	.0207545	29.22	0.000	.5658294	.6471854
PER IND	-.2092979	.0226538	-9.24	0.000	-.2536986	-.1648973
FIN IND	-.1712587	.0197802	-8.66	0.000	-.2100271	-.1324902
SEC	-.0396031	.0203821	-1.94	0.052	-.0795512	.000345
SUBMIS	.0412381	.0218046	1.89	0.059	-.0014981	.0839742
_cons	-.5117307	.0256165	-19.98	0.000	-.5619381	-.4615233

Note: the common support option has been selected
The region of common support is [.05875213, .99999646]

Description of the estimated propensity score
in region of common support

Estimated propensity score

	Percentiles	Smallest		
1%	.0616481	.0587521		
5%	.0761342	.0589325		
10%	.0939188	.0591935	Obs	3,207
25%	.1478593	.0592022	Sum of Wgt.	3,207
50%	.2762242		Mean	.3611419
		Largest	Std. Dev.	.2638001
75%	.5114398	.9999602		
90%	.812487	.9999718	Variance	.0695905
95%	.9316362	.9999955	Skewness	.9388525
99%	.9961979	.9999965	Kurtosis	2.788074

****
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
****

The final number of blocks is 10

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks

****
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
****

Variable FAM_SIZE is not balanced in block 1

Variable PER_IND is not balanced in block 1

Variable PER_IND is not balanced in block 1

Variable FAM_SIZE is not balanced in block 2

Variable PER_IND is not balanced in block 2

Variable PER_IND is not balanced in block 2

Variable FAM_SIZE is not balanced in block 3

Variable FAM_SIZE is not balanced in block 4

Variable PER_IND is not balanced in block 4

Variable PER_IND is not balanced in block 4

Variable FAM_SIZE is not balanced in block 5

Variable PER_IND is not balanced in block 5

Variable FIN_IND is not balanced in block 5

Variable PER_IND is not balanced in block 5

Variable FAM_SIZE is not balanced in block 6

Variable PER_IND is not balanced in block 6

Variable FIN_IND is not balanced in block 6

Variable PER_IND is not balanced in block 6

Variable PER_IND is not balanced in block 8

Variable PER_IND is not balanced in block 8

Variable PER_IND is not balanced in block 9

Variable PER_IND is not balanced in block 9

Variable FIN_IND is not balanced in block 10

The balancing property is not satisfied

Try a different specification of the propensity score

Inferior of block of pscore	RECODE of qbee (relationship to household head) 0	1	Total
0	**361**	**11**	**372**
.1	**208**	**7**	**215**
.125	**107**	**7**	**114**
.1375	**98**	**19**	**117**
.15	**352**	**37**	**389**
.2	**372**	**141**	**513**
.3	**200**	**174**	**374**
.4	**178**	**314**	**492**
.6	**67**	**218**	**285**
.8	**60**	**276**	**336**
Total	**2,003**	**1,204**	**3,207**

Note: the common support option has been selected

****
End of the algorithm to estimate the pscore
****

```
96.
97. teffects psmatch ($ylist) (TREAT $xlist, logit), atet
  note: PER_IND omitted because of collinearity

  Treatment-effects estimation                   Number of obs      =      3,534
  Estimator      : propensity-score matching     Matches: requested =          1
  Outcome  model : matching                                     min =          1
  Treatment model: logit                                        max =          1
```

EMOT	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATET						
TREAT (1 vs 0)	**.1198114**	**.1201817**	**1.00**	**0.319**	**-.1157404**	**.3553632**

```
98. teffects psmatch ($ylist) (TREAT $xlist, logit), ate
  note: PER_IND omitted because of collinearity

  Treatment-effects  estimation                  Number of obs      =      3,534
  Estimator      :  propensity-score  matching   Matches: requested =          1
  Outcome  model :  matching                                    min =          1
  Treatment  model:  logit                                      max =          1
```

EMOT	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE						
TREAT (1 vs 0)	**.576493**	**.3101388**	**1.86**	**0.063**	**-.0313678**	**1.184354**

```
99.
100 drop the_score blocks

101
102 //With smaller number of X valiable to satisfy the balancing property
103
104 global treatment TREAT

105 global ylist EMOT

106 global xlist ACCEPT CONTROL SEC SUBMIS

107 global breps 5

108 describe $treatment $ylist $xlist
```

variable name	storage type	display format	value label	variable label
TREAT	byte	%9.0g		**RECODE of qbee (relationship to household head)**
EMOT	float	%9.0g		**Scores for component 3**
ACCEPT	float	%9.0g		**Scores for component 2**
CONTROL	float	%9.0g		**Scores for component 1**
SEC	float	%9.0g		**Scores for component 6**
SUBMIS	float	%9.0g		**Scores for component 8**

```
109 summarize $treatment $ylist $xlist
```

Variable	Obs	Mean	Std. Dev.	Min	Max
TREAT	**3,534**	**.3406904**	**.4740085**	**0**	**1**
EMOT	**3,534**	**4.47e-10**	**1.575313**	**-1.268915**	**11.21591**
ACCEPT	**3,534**	**-1.42e-09**	**1.773876**	**-1.260467**	**9.492954**
CONTROL	**3,534**	**2.73e-10**	**1.805192**	**-.9490442**	**15.89445**
SEC	**3,534**	**-6.72e-10**	**1.286082**	**-5.165536**	**3.770026**
SUBMIS	**3,534**	**1.57e-10**	**1.143865**	**-2.477531**	**10.42847**

1

```
110 bysort $treatment: summarize $ylist $xlist

-> TREAT = 0

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
        EMOT |      2,330   -.0438032    1.536443  -1.268915   11.21591
      ACCEPT |      2,330   -.0341784      1.7137  -1.260467   9.444988
     CONTROL |      2,330   -.0374653    1.813146  -.9490442   15.87103
         SEC |      2,330    .1115556    1.300357  -5.165536   3.770026
      SUBMIS |      2,330    -.013657    1.177426  -2.477531   10.42847

-> TREAT = 1

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
        EMOT |      1,204    .0847687    1.645276  -1.113674   9.879296
      ACCEPT |      1,204    .0661426    1.883856  -1.254708   9.492954
     CONTROL |      1,204    .0725034    1.788219  -.9321543   15.89445
         SEC |      1,204   -.2158842    1.230103  -5.163577   3.507075
      SUBMIS |      1,204    .0264293    1.075931  -2.108523   7.697233

111 reg $ylist $treatment
      Source |       SS           df       MS
-------------+----------------------------------   Number of obs   =     3,534
       Model |  13.1222577         1  13.1222577   F(1, 3532)      =      5.29
    Residual |  8754.40966     3,532  2.47859843   Prob > F        =    0.0215
-------------+----------------------------------   R-squared       =    0.0015
       Total |  8767.53192     3,533  2.48161107   Adj R-squared   =    0.0012
                                                   Root MSE        =    1.5744

------------------------------------------------------------------------------
        EMOT |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       TREAT |    .128572   .0558786     2.30   0.021     .0190145    .2381295
       _cons |  -.0438032   .0326156    -1.34   0.179    -.1077505     .020144
------------------------------------------------------------------------------

112 reg $ylist $treatment $xlist
      Source |       SS           df       MS
-------------+----------------------------------   Number of obs   =     3,534
       Model |  60.0399315         5  12.0079863   F(5, 3528)      =      4.87
    Residual |  8707.49198     3,528  2.46810997   Prob > F        =    0.0002
-------------+----------------------------------   R-squared       =    0.0068
       Total |  8767.53192     3,533  2.48161107   Adj R-squared   =    0.0054
                                                   Root MSE        =     1.571

------------------------------------------------------------------------------
        EMOT |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       TREAT |   .1334588   .0562048     2.37   0.018     .0232617     .243656
      ACCEPT |  -.0458061   .0151976    -3.01   0.003    -.0756031   -.0160092
     CONTROL |   .0467939   .0147768     3.17   0.002      .017822    .0757658
         SEC |   .0133562    .021014     0.64   0.525    -.0278446    .0545569
      SUBMIS |  -.0265443   .0231865    -1.14   0.252    -.0720046    .0189159
       _cons |  -.0454682   .0326351    -1.39   0.164    -.1094538    .0185175
------------------------------------------------------------------------------
```

```
113 pscore $treatment $xlist, pscore(the_score) blockid(blocks) comsup
```

****
Algorithm to estimate the propensity score
****

The treatment is TREAT

RECODE of qbee (relationship to household head)	Freq.	Percent	Cum.
0	2,330	65.93	65.93
1	1,204	34.07	100.00
Total	3,534	100.00	

Estimation of the propensity score

```
Iteration 0:  log likelihood = -2267.0341
Iteration 1:  log likelihood = -2238.8453
Iteration 2:  log likelihood = -2238.831

Probit regression                               Number of obs   =       3534
                                                LR chi2(4)      =      56.41
                                                Prob > chi2     =     0.0000
Log likelihood =  -2238.831                     Pseudo R2       =     0.0124
```

TREAT	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ACCEPT	.0043967	.0124258	0.35	0.723	-.0199573	.0287507
CONTROL	.0151555	.0119735	1.27	0.206	-.0083121	.0386231
SEC	-.1234757	.0174822	-7.06	0.000	-.1577403	-.0892112
SUBMIS	.0290461	.0189768	1.53	0.126	-.0081477	.06624
_cons	-.4163445	.0218864	-19.02	0.000	-.459241	-.3734479

Note: the common support option has been selected
The region of common support is [.19617583, .59031676]

Description of the estimated propensity score
in region of common support

Estimated propensity score

	Percentiles	Smallest		
1%	.2227071	.1961758		
5%	.2415032	.2021643		
10%	.2619649	.2036559	Obs	3,530
25%	.2987655	.2059477	Sum of Wgt.	3,530
50%	.3414558		Mean	.3403867
		Largest	Std. Dev.	.0595543
75%	.378146	.5820683		
90%	.408803	.5889891	Variance	.0035467
95%	.4367075	.5902658	Skewness	.3688394
99%	.5078623	.5903168	Kurtosis	3.576885

****
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
****

The final number of blocks is 5

This number of blocks ensures that the mean propensity score is not different for treated and controls in each blocks

****
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
****

The balancing property is satisfied

This table shows the inferior bound, the number of treated and the number of controls for each block

Inferior of block of pscore	RECODE of qbee (relationship to household head) 0	1	Total
.1961758	**0**	**1**	**1**
.2	**196**	**41**	**237**
.25	**476**	**199**	**675**
.3	**1,390**	**760**	**2,150**
.4	**264**	**203**	**467**
Total	**2,326**	**1,204**	**3,530**

Note: the common support option has been selected

****
End of the algorithm to estimate the pscore
****

```
teffects psmatch ($ylist) (TREAT $xlist, logit), atet
```

Treatment-effects estimation — Number of obs = **3,534**
Estimator : **propensity-score matching** — Matches: requested = **1**
Outcome model : **matching** — min = **1**
Treatment model: **logit** — max = **1**

EMOT	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATET						
TREAT (1 vs 0)	**.1812667**	**.0709586**	**2.55**	**0.011**	**.0421905**	**.320343**

```
116 teffects psmatch ($ylist) (TREAT $xlist, logit), ate

Treatment-effects estimation                   Number of obs      =      3,534
Estimator      : propensity-score matching     Matches: requested =          1
Outcome  model : matching                                     min =          1
Treatment model: logit                                        max =          1
------------------------------------------------------------------------------
             |              AI Robust
        EMOT |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATE          |
       TREAT |
   (1 vs 0)  |     .18492   .0686544     2.69   0.007     .0503599    .3194801
------------------------------------------------------------------------------
```

Test of Randomness: Marriage-to-Birth (*mar_to_birth*)

```
 1 . log using "C:\Users\mt216\Desktop\nov15\9Untitled.smcl"

      name:  <unnamed>
       log:  C:\Users\mt216\Desktop\nov15\9Untitled.smcl
  log  type:  smcl
 opened  on:  15 Nov 2015, 17:41:57

 2 . do "C:\Users\mt216\AppData\Local\Temp\STD00000000.tmp"

 3 . logit R i.qbee age_at_mar cur_age educ_years num_members num_chil_5 num_women wealth

note: 5.qbee != 0 predicts failure perfectly
      5.qbee dropped and 2 obs not used

note: 6.qbee != 0 predicts failure perfectly
      6.qbee dropped and 8 obs not used

note: 8.qbee != 0 predicts failure perfectly
      8.qbee dropped and 7 obs not used

note: 11.qbee != 0 predicts failure perfectly
      11.qbee dropped and 3 obs not used

note: 12.qbee != 0 predicts failure perfectly
      12.qbee dropped and 2 obs not used

Iteration  0:  log likelihood = -1126.4134
Iteration  1:  log  likelihood  = -795.4541
Iteration  2:  log likelihood = -578.83151
Iteration  3:  log likelihood = -548.92984
Iteration  4:  log likelihood = -548.66052
Iteration  5:  log likelihood = -548.66024
Iteration  6:  log likelihood = -548.66024

Logistic regression                               Number of obs     =      3,934
                                                  LR chi2(11)       =    1155.51
                                                  Prob > chi2       =     0.0000
Log likelihood = -548.66024                       Pseudo R2         =     0.5129
```

R	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
qbee						
wife	-.5169806	.4715929	-1.10	0.273	-1.441286	.4073245
daughter	-1.788126	.6432371	-2.78	0.005	-3.048848	-.5274047
daughter-in-law	-.0747121	.5006516	-0.15	0.881	-1.055971	.9065469
granddaughter	0	(empty)				
mother	0	(empty)				
sister	0	(empty)				
other relative	-.2666115	.7029009	-0.38	0.704	-1.644272	1.111049
adopted/foster child	0	(empty)				
not related	0	(empty)				
age_at_mar	.2792448	.0253419	11.02	0.000	.2295756	.3289141
cur_age	-.2863729	.0181022	-15.82	0.000	-.3218525	-.2508932
educ_years	-.0708894	.0266333	-2.66	0.008	-.1230896	-.0186892
num_members	-.0972882	.0534065	-1.82	0.069	-.201963	.0073866
num_chil_5	-1.947292	.1368532	-14.23	0.000	-2.215519	-1.679065
num_women	.8235924	.1253228	6.57	0.000	.5779641	1.069221
wealth	.0173837	.0604424	0.29	0.774	-.1010812	.1358485
_cons	1.911624	.807274	2.37	0.018	.3293958	3.493852

Note: 1 failure and 0 successes completely determined.

```
4 . margins, dydx(qbee) atmeans

  Conditional marginal effects                     Number of obs    =      3,934
  Model VCE    : OIM

  Expression   : Pr(R), predict()
  dy/dx w.r.t. : 2.qbee 3.qbee 4.qbee 5.qbee 6.qbee 8.qbee 10.qbee 11.qbee 12.qbee
  at           :  1.qbee         =    .0485511 (mean)
                  2.qbee         =    .5399085 (mean)
                  3.qbee         =    .0236401 (mean)
                  4.qbee         =    .3698526 (mean)
                  10.qbee     =      .0180478   (mean)
                  age_at_mar    =     20.12405   (mean)
                  cur_age      =      32.82232   (mean)
                  educ_years    =    10.22166    (mean)
                  num_members    =    6.521098    (mean)
                  num_chil_5    =    1.155821    (mean)
                  num_women  =  1.546263 (mean) wealth
                  =     3.331723 (mean)
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
qbee						
wife	-.0062273	.0070108	-0.89	0.374	-.0199681	.0075136
daughter	-.0129327	.0071288	-1.81	0.070	-.0269049	.0010394
daughter-in-law	-.0011048	.0075896	-0.15	0.884	-.0159802	.0137706
granddaughter	.	(not estimable)				
mother	.	(not estimable)				
sister	.	(not estimable)				
other relative	-.0036006	.0094317	-0.38	0.703	-.0220864	.0148852
adopted/foster child	.	(not estimable)				
not related	.	(not estimable)				

Note: dy/dx for factor levels is the discrete change from the base level.

Test for Randomness: Current Age of Child (*cur_age_child*)

Statistics/Data Analysis

```
1 . log using "C:\Users\mt216\Desktop\nov15\10Untitled.smcl"
      name:  <unnamed>
       log:  C:\Users\mt216\Desktop\nov15\10Untitled.smcl
  log type:  smcl
 opened on:  15 Nov 2015, 17:53:22

2 . do "C:\Users\mt216\AppData\Local\Temp\STD00000000.tmp"

3 . logit Rm i.qbee age_at_mar cur_age educ_years num_members num_chil_5 num_women wealth

note: 5.qbee != 0 predicts failure perfectly
      5.qbee dropped and 2 obs not used

note: 8.qbee != 0 predicts failure perfectly
      8.qbee dropped and 7 obs not used

note: 11.qbee != 0 predicts failure perfectly
      11.qbee dropped and 3 obs not used

note: 12.qbee != 0 predicts failure perfectly
      12.qbee dropped and 2 obs not used

Iteration 0:  log likelihood = -1341.4927
Iteration 1:  log likelihood = -1007.2209
Iteration 2:  log likelihood = -888.48223
Iteration 3:  log likelihood = -881.19158
Iteration 4:  log likelihood = -881.15993
Iteration 5:  log likelihood = -881.15993

Logistic regression                             Number of obs     =      3,942
                                                LR chi2(12)       =     920.67
                                                Prob > chi2       =     0.0000
Log likelihood = -881.15993                     Pseudo R2         =     0.3431
```

Rm	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
qbee						
wife	-.2078897	.3272225	-0.64	0.525	-.849234	.4334546
daughter	-1.170087	.5126656	-2.28	0.022	-2.174894	-.1652812
daughter-in-law	.3143884	.3592273	0.88	0.381	-.3896841	1.018461
granddaughter	0	(empty)				
mother	2.824044	1.177108	2.40	0.016	.5169549	5.131133
sister	0	(empty)				
other relative	.6550299	.5437055	1.20	0.228	-.4106134	1.720673
adopted/foster child	0	(empty)				
not related	0	(empty)				
age_at_mar	.1636761	.0185683	8.81	0.000	.127283	.2000692
cur_age	-.1646192	.0110792	-14.86	0.000	-.186334	-.1429044
educ_years	-.0665643	.0220947	-3.01	0.003	-.1098691	-.0232596
num_members	-.141861	.0423584	-3.35	0.001	-.2248819	-.05884
num_chil_5	-1.613235	.1054119	-15.30	0.000	-1.819839	-1.406632
num_women	.830885	.0937213	8.87	0.000	.6471946	1.014575
wealth	-.1231122	.045921	-2.68	0.007	-.2131157	-.0331086
_cons	1.496812	.6141163	2.44	0.015	.2931659	2.700457

```
4 . margins, dydx(qbee) atmeans

  Conditional marginal effects                      Number of obs    =      3,942
  Model VCE    : OIM

  Expression   : Pr(Rm), predict()
  dy/dx w.r.t. : 2.qbee 3.qbee 4.qbee 5.qbee 6.qbee 8.qbee 10.qbee 11.qbee 12.qbee
  at           :  1.qbee         =    .0484526 (mean)
                 2.qbee          =    .5388128 (mean)
                 3.qbee          =    .0235921 (mean)
                 4.qbee          =     .369102 (mean)
                 6.qbee          =    .0020294 (mean)
                 10.qbee      =      .0180112   (mean)
                 age_at_mar     =     20.11948   (mean)
                 cur_age      =     32.84602   (mean)
                 educ_years    =    10.22146    (mean)
                 num_members    =    6.521816    (mean)
                 num_chil_5    =    1.155758    (mean)
                 num_women     =       1.54693 (mean)
                 wealth          =    3.331811 (mean)

  ------------------------------------------------------------------------------
                     |            Delta-method
                     |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
  -------------------+----------------------------------------------------------------
                qbee |
                wife |  -.0070361   .0120255    -0.59   0.558    -.0306055    .0165334
            daughter |   -.026368   .0130255    -2.02   0.043    -.0518975   -.0008385
     daughter-in-law |   .0135533   .0141769     0.96   0.339    -.0142329    .0413396
       granddaughter |          .  (not estimable)
              mother |    .365463   .2741848     1.33   0.183    -.1719293    .9028553
              sister |          .  (not estimable)
      other relative |   .0332387   .0313098     1.06   0.288    -.0281273    .0946047
adopted/foster child |          .  (not estimable)
         not related |          .  (not estimable)
  ------------------------------------------------------------------------------
  Note: dy/dx for factor levels is the discrete change from the base level.
```