# Estimating impact in empirical microeconomics: Two applications for the case of Tajikistan and a simulation study

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# Introduction

The estimation of impact, i.e. causally attributing outcomes to some influence, is a central problem in development economics. The question of measuring how effective (for example) a project intervention was is of paramount interest for researchers, donors and policy makers alike. The results determine future program design, as well as further financial support. Gauging the true impact of an intervention is far from trivial, and might depend crucially on the method used. In general, a move from qualitative to quantitative evaluation techniques can be observed, meaning that is has become more or less standard to base the measurement of impact on extensive data, rather than peer group interviews and anecdotal evidence. With the increasing availability of tailor made, as well as multi-purpose survey data, the quantitative approach becomes more and more feasible. The choice of the appropriate method for analyzing the impact of treatment, however, remains crucial and is the subject of extensive debate and research.

The term "treatment" can be quite broadly defined here, meaning for example some project intervention, such as vaccination programs, building of new roads or providing access to clean water. In addition to that, treatment could also be a household choice, such as sending a labor migrant abroad, or, even more generally, some macroeconomic shock, for example a raise in tariffs, or the occurence of a financial crisis. In all of these cases, the econometric problem at the core is the same: Unless participation in the treatment, however defined, was truly random, comparison between the outcomes of the treated and non-treated most likely suffers from bias due to systematic differences between the two groups. The (impossible) solution to the problem would be to observe the treated at the same point in time, once with and once without having received treatment. Formally, the problem can be expressed like this, as the formula for the average treatment effect on the treated (ATT):

$$ATT = E[Y_1|T = 1] - E[Y_0|T = 1]$$

where $Y_1$ denotes the outcome with treatment, and $Y_0$ is the respective outcome without treatment. $T$ is a binary variable indicating the receipt of treatment. It becomes immediately clear that the second term, $E[Y_0|T = 1]$ is unobservable, since no outcomes without treatment for those actually treated can be obtained. This hypothetical scenario is called the counterfactual. Thus, the problem of impact estimation can be characterized as a missing data problem.

An ever-increasing analytical toolbox to tackle this problem is available. Generalizing, it can be said that one tries to proxy the counterfactual as best as possible by instead using $E[Y_0|T = 0]$, the outcome of non-participants (called control group). The difference between this proxy and the hypothetical, true counterfactual is referred to as (selection) bias:

$$Bias = E[Y_0|T = 1] - E[Y_0|T = 0]$$

Minimizing this bias is at the core of each impact evaluation method.

Two main groups of impact evaluation methods exists, full randomization, as well as quasi-experimental designs. If assignment to treatment can be said to have been truly random, the problem of bias as outlined above averages out, and a mere comparison of mean outcomes of treatment and control group gives the desired impact estimate. While this is arguably the most credible method to avoid bias, fully randomized set ups are not easy to come by, since more often than not possible future impact evaluations are not taken into account when planning a project intervention, meaning that the researcher has to make do with already existing, non-randomized data. There are also cases, where randomization of project participation is not feasible because of ethical concerns. How is one, for example, to motivate the random exclusion of children from a vaccination program (provided that sufficient funds exists to vaccinate the entire population in question)? Also, randomized participation might be impossible for technical reasons, as is the case with most infrastructure projects, such as building waterpipes or new roads. Finally, household choices, which are not part of an administered program, such as labor migration, obviously cannot be randomized. In situations like these, quasi-experimental methods are therefore the only way to try to estimate impact. Roughly, these methods can be classified according to four main groups, which are briefly outlined in the following section.

### 0.0.1 Different quasi-experimental methods

The first group tries to remedy bias by matching on observables. This means that the missing data problem is approached by constructing a control group which resembles the treated as closely as possible with regard to observable characteristics. Probably the most prominent example of this technique is propensity score matching, as introduced by Rosenbaum and Rubin, 1983. This approach has the great advantage of reducing the matching dimension to the so-called propensity score, an estimate of the probability to receive treatment on the basis of the chosen observable characteristics. An obvious drawback of matching on observables is the fact that the treatment decision might be influenced by hidden factors, or factors for which data could theoretically be collected, but so far do not exist.

The second group of impact evaluation methods can handle this problem when two basic conditions are fulfilled: Firstly, the researcher has to have data for the treated and the untreated both before and after the treatment was administered. Secondly, the bias-causing unobserved differences (or heterogeneity) between the two groups must be constant over time. In this case, treatment impact can be estimated by simply differencing before and after outcomes across both the treated and the untreated (also called double differencing, or DID for short).[1]

The third group of methods tries to make use of existing design features of project implementation. An example for this is the so-called regression discontinuity design approach (RDD). This is a valid tool if treatment depends on some arbitrary threshold, e.g. only farmers who own less than a certain amount of land are eligible for a micro credit. The idea behind RDD now is to compare outcomes between those individuals just above and just below this cut-off, assuming that they are essentially the same in terms of all other relevant characteristics, such as wealth,

[1] One prominent example is the study of Pitt and Khandker, 1998, using DID to estimate the effect of Grameen bank micro credits and gender on various indicators of living standards in Bangladesh.

socio-economic status etc.[2] While this approach is quite convincing, it can of course only be applied if such a threshold for treatment assignment exists, which might often not be the case.

The forth group of methods relies on some sort of exclusion restriction or instrument to estimate impact.[3] Here a selection equation determines the treatment participation, while a second estimates the outcome. Such models are either estimated using a two-step approach, or simultaneously via maximum likelihood. To obtain identification, the selection equation usually contains at least one variable which strongly influences treatment, but has no direct effect on outcome (and is therefore missing in the outcome equation). This variable(s) is called the exclusion restriction or instrument. Such methods have the advantage that they do not require the bias-causing heterogeneity to be constant over time, or to be captured solely by observable factors. However, they suffer from another, substantial weak point, namely the exogeneity assumption of the instrument. As already indicated above, in order to be valid an instrument needs to be both relevant (i.e. strongly determining the treatment decision), as well as exogenous, meaning that it must be uncorrelated with the error term of the outcome equation. While the first condition is easily verified, for example with the F-test of the first-stage regression, no true test exists for exogeneity. In some situations, one can indeed find plausible instruments. An example for this is the so-called "intention-to-treat" approach, where the possibility to receive treatment was randomized (e.g. by giving out vouchers), but the actual treatment decision was made by the respective individual. In most cases, however, exclusion restrictions are less convincing, and "proof" for their validity relies on the persuasive powers of the researcher. Needless to say, this is an unsatisfactory situation, especially when considering how widely used methods based on exclusion restrictions are in impact evaluation studies. A solution to this dilemma presents the so-called "identification by functional form"-assumption. As the name suggests, identification is obtained by relying on functional form, rather than by including an instrument in the first stage. The obvious drawback of this approach are possible model misspecifications, since the true functional form is

[2]See for example Angrist and Lavy, 1999, who use RDD to estimate the effect of class size on scholastic achievement in Israel.

[3]See Angrist and Krueger, 2009 for an overview of the history and applications of the IV technique.

generally unknown.

The following three chapters all deal with some aspect of the evaluation problem. The first chapter is an impact evaluation, methodologically speaking, however, not of an intervention or a program. Here, the impact of the household decision, namely sending a labor migrant abroad, is estimated using a standard IV approach. The second chapter is not an impact evaluation in the true sense of the word. It aims to quantify the effect of the recent financial crisis, i.e. a macroeconomic shock. This means that there is no control group, since the crisis hit worldwide. This problem is approached using a heterogeneous exposure variable.

The last chapter is more theoretical in nature. It tries to answer the question of whether to use an (uncertain) instrument, or rather rely on the functional form assumption when using a recursive bivariate probit model to estimate the impact of a binary treatment on a binary outcome. Model performance in the face of various misspecifications of the error term is simulated with and without a valid exclusion restriction, to derive a rule of thumb for the practitioner.

In the remainder of this introduction, the three chapters are briefly outlined.

### 0.0.2 Evaluating the impact of labor migration on household expenditures using the IV approach

The first chapter uses a standard IV approach to gauge the impact of labor migration on household expenditures in Tajikistan. The effect of labor migration has been the topic of many research projects, and results are often conflicting. Similar to the evaluation of a micro credit program, when estimating the effect of migration one has to take into account the self-selection of individuals into treatment, which is the cause of bias in this case. Rather than being selected into treatment by a program planer, the family's decision to send a migrant abroad is determined by a number of individual characteristics, both observed and unobserved. The first chapter takes this into account by using an IV approach. Rather than relying on mere intuition, the first stage is based on a simple household-level model determining the migration decision, which is first theoretically derived and then empirically tested. The needed exclusion restriction is the percentage of migrant households in the cluster of the respective household, which is a standard instrument for estimating the impact of migration. The rationale behind it is straightforward and comes from the idea of migration networks (see, for example, Carrington and Vishwanath, 1996, Bauer et al., 2002, Woodruff and Zenteno, 2007, McKenzie and Rapoport, 2010): The more families in the vicinity have migrants, the easier it is to receive information and send a migrant yourself.

It is often assumed that international labor migration from Tajikistan, while having no noticeable effects on investment (usually defined as medium and long-term consumption, such as education, or investment into housing or business), on average leads to an increase in short-term consumption, mostly food. While only weak effects of migration measured by a simple dummy are visible, repeating the analysis instead using the length of the migration spell, as well as its squared term reveals that labor migration apparently takes a while to "kick in" and be profitable to those remaining at home. The observed long-term effects on household consumption patterns, albeit being rather small, actually speak in favour of investment of remittances, with the respective shares increasing over time, while the budget share spent on food slowly decreases.

### 0.0.3 Estimating the effect of a macroeconomic shock using a heterogeneous exposure approach

The second chapter, which is joint work with Antje Kroeger, deals with a somewhat different evaluation problem, namely the impact of the recent financial crisis on Tajik labor market dynamics. The challenge here is the obvious lack of control group data, since the crisis hit worldwide. Although this makes an impact evaluation in the true sense impossible, we try to assess the effect of the crisis by using a heterogeneous exposure approach. Here we argue that individuals working in the manufacturing sector are comparatively more afflicted by the crisis than those working in other areas, since this part of the economy suffered most. A multinomial probit regression is used to calculate transition probabilities and their determinants between employment categories between 2007 and 2009. A dummy indicating prior employment in the manufacturing sector is included in the model and interpreted as a proxy for exposure to crisis. Our results suggest a negative impact of the crisis on wage employment, which seems to be somewhat mitigated by labor migration in the rural areas. There, labor migration might indeed be a way of financing labor market exit, while for urban areas this cannot be observed. Also, there are no clear indications of the informal sector (measured as self-employment) to act as a shock absorber during the crisis.

### 0.0.4 A sensitivity analysis of the bivariate probit estimator in the presence of distributional misspecifications

The third chapter investigates the performance of the recursive bivariate probit estimator, with and without reliance on a valid exclusion restriction. The aim is to give some advice to the practitioner with regard to the use of instruments. How robust is the functional form assumption (meaning that models are estimated without an exclusion restriction) to misspecifications of the error distributions? Can possible bias due to non-normal errors be reduced by the inclusion of valid instruments, and, most importantly, could it be exacerbated by the use of faulty (i.e. endogenous) ones?

By simulating estimation entirely without an instrument (relying on functional form for identification), with a true instrument, as well as with a faulty (endogenous) one, some light is shed on this question. Results suggest that departures from normality lead to a noticeable increase in bias, especially if the error distribution is highly skewed. Furthermore, the response frequencies of the two binary outcome variables play an important role. Bias tends to increase for unbalanced distributions of the outcomes. With regard to the inclusion of doubtful instruments, rather than reliance on functional form, the results suggest that while valid instruments do little to improve estimation in the face of non-normal errors, endogenous instruments can noticeably worsen results if the true underlying error distribution is normal. A rough rule of thumb to be derived from this would therefore be to use the bivariate probit model only when errors can be assumed to be normal, and, in this case, rely on functional form rather than risking increased bias due to faulty instruments. While this advice sounds rather straightforward, the difficult decision as to when errors are normal remains to be made. While tests for this exist (see, for example, Murphy, 2007), their performance crucially depends on sample size, a feature that can also be observed for the simulations of chapter 3.

# Chapter 1

# Low-skilled labor migration in Tajikistan: Determinants and effects on expenditure patterns

## 1.1 Introduction

The impact of remittances from labor migration in developing countries has been the topic of extensive research. The question of how they influence overall poverty outcomes (see, for example, Adams and Page, 2005, Gupta et al., 2009), as well as the income distribution of the recipient country has been of central interest (e.g. Adams, 1989, Barham and Boucher, 1998, Acosta et al., 2008, Shen et al., 2010). However, some studies also take a more micro-oriented approach and investigate the effects on well-being of the households remaining at home. Results of these studies are mixed, some concluding that remittances are mostly used to cover day-to-day needs, rather than being invested productively (see, for example Lipton, 1980, Orozco et al., 2005, Cohen, 2005, Matthieu, 2011), while others find significant increases in household investments (e.g. Adams, 1989, Adams and Page, 2005, Acosta et al., 2007, Woodruff and Zenteno, 2007). A closely related question in this context are the determinants of labor migration. Since leaving one's home country is usually quite costly both financially and emotionally, the driving factors have to be substantial to justify such a big step. It is straightforward to assume that unemployment faced at home plays a role, or, if that is not the case, that earning prospects abroad are significantly better. Also, the decision to migrate most likely is not an individual one, but one made at the household level (see, for example Stark, 1984, Taylor, 1987, Kainaiaupuni, 2000). If a household member is to go abroad, the necessary financial means for the journey etc. have to be available, also there might be a need to reshift responsibilities and the work burden within the household, especially if the family member leaving was previously unemployed and doing chores at home. This might lead to a reduction in labor supply offered domestically, for which the literature finds some evidence. (see Justino and Shemyakina, 2010 for Tajikistan, as well as Amuedo-Dorantes and Pozo, 2006 and Funkhouser, 1992 for the Latin American context). Finally, the existence of migrant networks seems to play an important role, facilitating orientation in the foreign job market (Carrington and Vishwanath, 1996, Bauer et al., 2002, Woodruff and Zenteno, 2007, McKenzie and Rapoport, 2010).

Somewhat less attention has been given to the question whether there exists a difference between short and long-term effects of remittances from labor migration. Most of the existing work (see, for example, Taylor, 1992) base the (assumed positive) long-term effects mainly on productive asset accumulation. In this paper, an alternative hypothesis is introduced. It is assumed that the early effects of labor migration might be almost non-existent or in some cases even negative, since the initial costs of migration, which especially for Tajikistan seem substantial, first have to be redeemed by inflowing remittances. This process is slowed down due to the fact that new migrants need some time to establish themselves in the new working environment and find profitable jobs. It is further delayed by a possible reduction in domestic work income due to reduced labor supply of the remaining family members, who have to fill the gap the migrant left behind. The contribution of this paper is therefore three-fold: First, the determinants of low-skilled[1] labor

[1] Since the majority of labor migrants takes on low-skilled jobs, such as construction work, abroad (even if the amount of people with secondary education is quite high among migrants), the analysis is limited to the effects of such types of employment. It needs to be noted, however, that the inclusion of high-skilled labor migrants does not really change the results obtained, since the number of observations is very low here.

migration in the Tajik context are theoretically modelled and empirically tested. Using the results to control for the selectivity of migration, the impact of migration on household expenditure shares is then estimated. Finally, this analysis is extended to include the length of the migration spell, rather than a simple dummy or the amount currently remitted, to gauge possible long-term effects. Additionally, effects of migration on labor supply are also (albeit tentatively) investigated. To the author's best knowledge, this is the first time this is attempted for the case of Tajikistan. However, since the data used are cross-sectional, naturally the analysis of long-term effects is somewhat limited. Further research on this topic is needed, making use of panel data sets with detailed migration information.[2]

## 1.2 The case of Tajikistan

The Republic of Tajikistan is a small, landlocked country in Central Asia, the poorest among the states of the former Soviet Union.[3] A number of factors make the economic development of Tajikistan problematic. First of all, over 90% of its territory is mountainous, with about 50% as high as (or higher than) 3000 meters above sea level, and only approximately 7% of it suitable for farming. Natural resources are limited. Both agriculture and industry are almost exclusively centered on cotton production and aluminum,[4] a remainder from central planning under the Soviets, leaving the economy very vulnerable to fluctuations in demand for these commodities. To add to this, the country suffered a devastating civil war (1992-1997), following the break-up of the Soviet Union, which also strongly impeded Tajikistan's economic development. In such a setting, labor migration seems like a natural mitigation strategy, and indeed, Tajikistan has one of the highest (if not the highest) percentage of remittances to GDP.[5] The most popular country of destination is Russia, since many Tajiks still have at least a working

[2]Although the TLSS 2007 used here can be used as a panel with the TLSS 2009, results might be distorted due to the external shock caused by the financial crisis during that period.

[3]In 2010 it had a HDI of 0.58 and therefore ranked 112th among 169 countries (see UNDP, 2010a).

[4]Another branch of industry now gaining in importance, but still comparatively small is electricity generation through hydropower.

[5]Some estimates yield figures as high as 45% in 2008 (see Ratha et al., 2008. A more recent figure is 35%, Yang, 2011).

knowledge of Russian, and are allowed to enter the country without visa.[6]

### 1.2.1 Tajik labor migration

While the effect of labor migration on the households at home has been the topic of various research, the case of Tajikistan, which is one (if not the) leading country in terms of labor migration, so far has been somewhat neglected. The (to the author's knowledge) only paper attempting a methodologically rigorous impact evaluation of labor migration on consumption and investment patterns in Tajikistan is the work by Matthieu, 2011. Using propensity score matching on the 2003 Tajikistan Living Standard Survey (TLSS) he finds a positive significant effect of external remittances on per capita food consumption, while "investment" expenditures (in his definition those include expenditures on health, education, agriculture, rent, utilities, as well as transfers to others) are negatively affected. Olimova and Olimov, 2007 reach the same conclusion doing a descriptive analysis of migrant families, with focus on the high-altitude regions of Tajikistan. They assume that remittances from labor migrants are mostly used to cover day-to-day needs, and do not lead to significant capital accumulation or investment. A number of other articles (e.g Mughal, 2007, Olimova and Bosc, 2003) support this theory, albeit without empirically testing it.

## 1.3 Data

The data source used is the 2007 Tajikistan Living Standard Survey (TLSS 2007), prepared by the World Bank in collaboration with UNICEF and carried out by the National Committee for Statistics (former Goskomstat, now Tajstat). The survey is representative on the national, rural/urban, as well as the district (oblast[7]) level, with the sampling frame based on the 2000 Census of Tajikistan.

[6]While entering Russia is easy for Tajik citizens, obtaining legal residence and work permits is often significantly more difficult, giving rise to large amounts of illegal workers and the associated problems. Especially following the recent financial crisis, Russian immigration laws have tightened, making legal labor migration harder for Tajiks.

[7]Tajikistan is divided into 5 administrative regions or oblasts: Dushanbe, RRS, Soghd, Khatlon, and GBAO.

The survey has a complex survey design, with a total of 270 clusters, where each cluster is either fully urban or fully rural and contains 18 households. The total number of households is 4860. Due to missings in some needed variables, the final estimation sample comprises of 4715 households. The survey includes data on the socio-demographic composition of the household, labor market activities, the health and education of individuals, transfers to the household from various sources and a very detailed module on migration.

## 1.4 Modeling determinants of labor migration

Since labor migration is a highly selective process, further analysis of its impacts needs to be preceded by a solid investigation of its determinants. In the following, a simple, one-period income optimization model on the household level[8] is derived, similar to the one used by McKenzie and Rapoport, 2007.

Assume that the household's disposable income $\pi$ is given by

$$\pi = bL * log(F - K - m) - [(F - m)I - A] + m(w - c)$$

where

- $L$ = Farmable land available to HH
- $F$ = Number of HH members
- $K$ = Number of dependent HH members (either too young/old to work or disabled)
- $m$ = Number of migrants currently abroad
- $I$ = Subsistence cost per HH member
- $A$ = Amount of additional financial means (e.g. transfers from other family members, friends, etc.)

[8]Sending a migrant away is not only costly, but also has significant implications for family life, such as intra-household organization and sharing of work burden. Therefore it is argued that the decision to migrate is made on the household, rather than on the individual level.

- $w$ = Wage earned by migrant abroad
- $c$ = Cost of sending a migrant abroad
- $b$ = Some parameter $(0 < b > 1)$

Now maximize $\pi$ with respect to $m$, the number of migrants to be sent abroad, subject to the constraint that additional financial means $A$ must cover all migration costs $c$.[9]

$$\underset{m}{\text{Max}}\, \pi, s.t.\ A \geq mc$$

If the restriction is not binding (i.e. $\lambda = 0$):

$$m^* = \frac{-bL}{(I + w - c)} + (F - K)$$

The implications of this equation are straightforward and not surprising: A negative impact of farmable land on labor migration emerges, which makes sense in a predominantly rural country such as Tajikistan. If the household has enough land, more working age family members are needed to farm it. An increase in money needed to send a migrant away has the same effect. The decision to send a migrant is positively influenced by the amount of working age household members, the wage earned abroad, as well as the subsistence costs at home.
If, on the other hand, the restriction is binding, the above equation becomes

$$m^* = A/c$$

meaning that the amount of additional means needed to finance the departure of a migrant becomes the bottleneck and therefore the sole determinant of the decision to migrate. In the following, these theoretical results will be empirically

[9] It can be argued that this is somewhat artificial, since migration could also be financed using, for example, regular income. However, the implicit assumption made here is that migrant households are generally too poor to fully fund migration through income and therefore have to rely on external financing. If it were possible for them to cover the substantial sum needed to send a migrant fully with regular work income, migration most likely would not be economically necessary for the household.

tested, where the estimation serves as the first stage equation of the 2SLS approach to determine the impact of labor migration on expenditure patterns. The following section outlines the econometric strategy in more detail.

## 1.5 Econometric methodology

When analyzing the effects of labor migration on household-level expenditures, it has to be taken into account that there most likely also exists a reversed causality: Not only are expenditures influenced by migration, but they might also have an effect on the decision to migrate. A household has to have a certain amount of income in order to be able to afford sending a migrant. Also, if the income situation of the household is already satisfactory, migration might not be needed at all. To account for the endogeneity of labor migration, a 2SLS model is used. Following the related literature on network effects, the percentage of neighboring households with at least one migrant is used as an instrument in both cases.[10] As already mentioned in the introduction, the exogeneity of the instrument cannot be tested, and is motivated using the network hypothesis. And indeed it makes intuitive sense to argue that the density of migrants surrounding a household does have an effect on its income situation only through the enhanced chance of sending its own migrant abroad, making use of knowledge and contacts already established by others. The literature also finds evidence in favour of this (see, for example Carrington and Vishwanath, 1996, Bauer et al., 2002, Woodruff and Zenteno, 2007, McKenzie and Rapoport, 2010). Some critics of such cluster-percentage instruments however claim that these variables only reflect regional disparities. To check for this, the analysis was repeated including oblast dummies. Since they were never significant, one can conclude that systematic regional differences are not problematic here. The lack of significance is also the reason why they are omitted from the results shown in this paper.
To investigate the impact of the length of the migration spell, the 2SLS approach is slightly modified. It is assumed that the endogenous regressor (i.e. the length

[10] For each household, this value is calculated as the percentage of households with at least one migrant in the respective sampling cluster, excluding the household in question.

of the migration spell in months) enters the estimation equation once linearly, and once as its square, to capture possible reversing effects over time.[11]

## 1.6 Descriptives

Before the results of the analysis are presented, a short descriptive overview of the data is given. All figures are estimated proportions within the population. $N$ is the sample size in households or individuals, respectively.

Table 1.1: Proportion of HHs with and without migrants

| | Proportion |
|---|---|
| No migrant | 0.886 |
| At least 1 migrant | 0.114 |
| $N$ | 4715 |

Table 1.1 shows the distribution of migration households. In Tajikistan, around 11% of households have at least one migrant. Note that for the purpose of this analysis, only migrants currently abroad, which remit in either cash and/or kind are counted.

Tables 1.2 -1.3 give some more information about personal characteristics of the migrant. As can be seen, most migrants are male (96%), have at least secondary education (84%) and are relatively young, with a mean age of 28.

Table 1.2: Gender distribution among migrants

| | Proportion |
|---|---|
| Female | 0.0421 |
| Male | 0.958 |
| $N$ | 734 |

[11]The first and second stage for this model are estimated manually, and are then bootstrapped with 200 repetitions to receive corrected standard errors.

Table 1.3: Proportion of secondary education or higher among migrants

| | Proportion |
|---|---|
| No sec. educ. | 0.157 |
| Sec. educ. or higher | 0.843 |
| *N* | 734 |

It is also interesting to see that a substantial part (around 65%) of those currently working abroad was unemployed prior to migration (table 1.4), which lends some evidence to the theory that labor migration might be a mitigation strategy for unemployment at home.

Table 1.4: Activity prior to migration

| | Proportion |
|---|---|
| Working | 0.286 |
| Unemployed | 0.646 |
| Studying or other | 0.0679 |
| *N* | 734 |

Also, about 80% of migrants come from rural areas, which is not surprising considering the fact that Tajikistan is a predominantly rural country, with only about 32% of the population being classified as urban. As already mentioned, the main country of destination is Russia (97%, see table 1.5):

Table 1.5: Country of destination

| | Proportion |
|---|---|
| Russia | 0.972 |
| Other CIS | 0.0108 |
| Rest of the world | 0.0167 |
| *N* | 734 |

## 1.7 Results

### 1.7.1 Testing the model

First, the validity of the migration model is tested, which will then serve as the first stage of the 2SLS impact regression. The outcome is a binary variable, which takes the value 1 if the household currently has at least one remitting migrant abroad, and zero otherwise.[12] A probit model with the following covariates is fitted:

- farmable land per capita
- the intra-household dependency ratio[13]
- a dummy indicating access to additional cash (e.g. possibility to borrow from friends/relatives, etc)
- the intra-cluster percentage of households with at least one migrant
- a dummy indicating whether the household head has secondary (or higher) education
- the age of the household head, as well as the age squared
- a dummy indicating whether the household head is currently unemployed
- a continuous variable measuring the altitude
- a dummy indicating whether the household is rural or urban

The first three covariates are directly derived from our model. The intra-cluster percentage of migrant-households is added as a proxy for migration networks. Since it will be used as an instrument in the following analysis, this regression can be seen as a relevance test. Finally, some additional household characteristics are added, in accordance to the related literature. Altitude is assumed to influence the migration decision, since job opportunities are hard to come by in the high-altitude

[12] In addition to this specification, the model was also tested using a categorical outcome (0, 1, 2 or more migrants). Results are very similar and are omitted here.

[13] Calculated as $\frac{\text{hh members younger than 14 or older than 65}}{\text{working age hh members}}$.

regions of the country, thus increasing the incentive to look for work elsewhere. In the Tajik context, the altitude variable can also be interpreted as an indicator for general infrastructure, such as transport, proximity to banks or post offices, which become scarce with increasing altitude. Also, a location dummy is included to indicate whether the household is rural or urban.

Looking at the results in table 2.9, we see a confirmation of our model: The lower the relative number of working age household members, the lower the probability to send a migrant abroad (which is strictly logical). Also, a significant positive impact on migration is observed for access to additional financing.[14] Farmable land per capita has the expected negative sign, however, the effect seems quite small and is just short of being significant on conventional levels. The network proxy has a strong, positive and significant effect on the probability to send a migrant abroad, and therefore meets the relevance criterion of a suitable instrument. If the household head has at least secondary education, the propensity to migrate is reduced, assuming that the family is relatively wealthy and might not need to send a member abroad to work and remit. The financial pressure of having an unemployed household head increases the chance of having a migrant, which is not surprising, while the age of the household head does not seem to influence migration.[15] As already expected, coming from urban areas reduces the probability of having a migrant.

### 1.7.2 Impact on expenditure shares

The descriptive comparison of mean expenditure shares in table 1.7 shows almost no difference between migrant and non-migrant households. However, the endogeneity of migration has not yet been controlled for.[16]

[14]Note that no endogeneity problem should arise with this variable, since additional financing is defined as coming from outside the household and should therefore not be influenced by the household's labor migrants.

[15]The model included also the squared age of the household head. However, since table 2.9 displays the marginal effects (at the mean of continuous variables), this is already accounted for.

[16] The displayed shares are exclusive categories and add up to 100%. Non-food expenditures comprise clothing, toiletries and other small items for daily use, while utilties are the costs for rent, heating, water and the like. It should be noted that this category does not contain the estimated rent of owned housing.

Table 1.6: Marginal effects of the probit model

| | (1) |
|---|---|
| land per capita | -0.00227 |
| | (-1.63) |
| tajik (d) | 0.00600 |
| | (0.53) |
| dep. ratio | -0.0390*** |
| | (-4.05) |
| access to cash (d) | 0.0849*** |
| | (4.55) |
| head sec. (d) | -0.0366*** |
| | (-3.02) |
| migrant hh cluster perc. | 0.426*** |
| | (16.25) |
| altitude | 0.00000830 |
| | (1.36) |
| head age | 0.000476 |
| | (0.97) |
| location (d) | -0.0375*** |
| | (-3.43) |
| head unemp (d) | 0.0449*** |
| | (3.20) |
| $N$ | 4715 |

$t$ statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7: Average expenditure shares for HHs with and without migrants

| | (1) Mean share for non-migrant hhs | (2) Mean share for migrant hhs | N |
|---|---|---|---|
| food | 0.691 | 0.697 | 4715 |
| non-food | 0.188 | 0.182 | 4715 |
| medical exp | 0.03 | 0.039 | 4715 |
| utilities | 0.051 | 0.051 | 4715 |
| education | 0.049 | 0.043 | 3589 |

As already outlined in the methodology section, this is done with a 2SLS approach, using the intra-cluster percentage of migrant households as instrument. The estimation equation is specified based on the approach used by Working, 1943 to estimate Engel curves. As in any Engel curve estimation, expenditure shares are linked to total expenditures. A myriad of suggested functional forms for this relationship exist in the literature (See, for example, Prais and Houthakker, 1971 for experiments with various forms). The specification postulated by Working assumes a linear relationship between expenditure shares and the log of total consumption. As is shown in Deaton and Muellbauer, 1980, such a relationship satisfies the requirements of a utility function. The estimation equation is further extended to accomodate possible economies of scale for different household sizes (see Deaton, 1997, p.231), and thus takes the form:

$$w_i = \alpha + \beta_1 log(x_i/n_i) + \beta_2 log(n_i) + \beta_3 m_i + \boldsymbol{\gamma}' \boldsymbol{z_i} + \epsilon$$

where $w_i$ is the respective expenditure share for household i, $x_i$ are total expenditures, $n_i$ is household size (excluding migrants currently absent), $m_i$ is a dummy variable to indicate whether the household has migrants, and $\boldsymbol{z_i}$ is a vector of additional covariates. Following Taylor and Mora, 2006, an alternative specification was also tested, which included an additional interaction term of the migration variable with the log of total expenditures, to allow for migration to also affect the influence of total expenditures on the shares. However, this interaction term

was never significant, which is why the above specification is used instead. This suggests that having a migrant in the household only influences expenditure directly, and that it does not affect the impact of overall income. This is a somewhat surprising result, which contradicts the findings of Adams, 2005 and Taylor and Mora. It is often argued that the effect of labor migration on consumption goes beyond simple income increase, and that, for example, exposure to different goods and lifestyles through the family migrant causes a change in spending decisions of those remaining at home. However, we do not find evidence for this in the Tajik data. A possible explanation for this could be that Tajik labor migration is often seasonal, meaning that migrants frequently return home for longer stays, thus keeping strong ties with their families and hindering immersion into the culture of the host country.
Following the literature, shares are analyzed separately for food, non-food, medical, utilities and educational expenditures. This allows an (admittedly somewhat crude) distinction between short-term consumption (food and most non-food items) and more long-term spending, which might be regarded as investments. Education is the best example here. Medical expenditures could also be viewed as an investment into human health and therefore productivity. Utilities such as fuel for cooking and heating, as well as water and electricity, are probably best categorized as medium-term expenditures. Unfortunately, the consumption aggregate of the TLSS 2007, which is at the basis of this analysis, does not include expenditures on housing such as rent or home improvement, which should be counted as investments, and play an important role in the Central Asian context. The same is true for agricultural expenditures and the purchase of durable assets. Other than spending on housing, these last two categories can be constructed from the data. However, separate analysis of these shares yielded no significant effects. They are omitted here, since distributions are quite lumpy around zero, with the majority of households claiming no expenditures, which makes the results somewhat doubtful. The results are shown in table 1.8 below.

As already anticipated by the descriptive results, the effect of the migration dummy[17] on expenditure shares does not seem very prominent. The expected ef-

[17]As a robustness check, all regressions were repeated using remittances per capita, rather than the migration dummy as the treatment variable, as well as a broader migrant definition,

Table 1.8: Results of 2SLS regression on household expenditure shares

| | (1) share_food | (2) share_nonfood | (3) share_med | (4) share_housing | (5) share_educ |
|---|---|---|---|---|---|
| hh has migrant (d) | 0.145 | -0.0944** | 0.0451 | -0.0503 | -0.0474* |
| | (1.45) | (-2.38) | (1.58) | (-1.30) | (-1.87) |
| land per capita | 0.000183 | 0.000152 | -0.000411*** | -0.0000428 | 0.0000860 |
| | (0.43) | (0.43) | (-3.81) | (-0.25) | (0.45) |
| tajik (d) | 0.00577 | -0.00287 | -0.00531 | -0.000464 | 0.000745 |
| | (0.56) | (-0.40) | (-1.24) | (-0.11) | (0.15) |
| dep. ratio | 0.0159*** | -0.00985** | 0.00269 | -0.00419** | -0.00714*** |
| | (2.78) | (-2.36) | (1.50) | (-2.31) | (-3.03) |
| access to cash (d) | -0.0109 | 0.00935 | -0.00205 | 0.00486 | -0.00206 |
| | (-0.78) | (0.82) | (-0.23) | (1.09) | (-0.29) |
| altitude | -0.0000124 | 0.0000200*** | -0.00000954*** | 0.0000163*** | -0.00000134 |
| | (-1.39) | (3.59) | (-3.37) | (3.02) | (-0.39) |
| location (d) | -0.0167 | 0.0161** | 0.00483 | 0.00159 | 0.0128*** |
| | (-1.56) | (2.37) | (1.13) | (0.34) | (2.65) |
| head sec. (d) | -0.0196** | 0.0132** | -0.00125 | 0.00196 | 0.0107*** |
| | (-2.44) | (2.09) | (-0.36) | (0.51) | (3.32) |
| head age squ. | 0.00000251 | 0.0000162 | -0.0000109* | 0.00000617 | 0.00000114 |
| | (0.15) | (1.19) | (-1.72) | (0.86) | (0.16) |
| head age | 0.000182 | -0.00199 | 0.00124* | -0.000737 | -0.000134 |
| | (0.10) | (-1.36) | (1.81) | (-0.92) | (-0.17) |
| head unemp. (d) | -0.0176* | 0.000425 | 0.00805** | 0.00352 | 0.00677* |
| | (-1.90) | (0.07) | (2.27) | (0.87) | (1.91) |
| log total pc exp. | -0.131*** | 0.0707*** | 0.0166*** | 0.0118*** | 0.0341*** |
| | (-13.28) | (9.21) | (3.77) | (3.71) | (3.63) |
| log hhsize | -0.0683*** | 0.0381*** | 0.00739** | -0.00734** | 0.00872** |
| | (-6.95) | (5.88) | (2.00) | (-2.00) | (2.08) |
| cons | 1.454*** | -0.190*** | -0.0947*** | 0.0172 | -0.136** |
| | (21.35) | (-3.60) | (-3.39) | (0.74) | (-2.59) |
| First stage F-test | 82.87 | 82.87 | 82.87 | 82.87 | 85.22 |
| *N* | 4715 | 4715 | 4715 | 4715 | 3589 |

*t* statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

fects associated with an increase in wealth, namely a decrease in the expenditure share on food, as well as an increase in the other, less basic categories, cannot be observed. Quite on the contrary, there seem to be significant decreases for both non-food items and, most worryingly, education.[18]

Before we move on to further investigate the somewhat counterintuitive observed effects of migration on the different expenditure categories, we will have a brief look at the remaining covariates of the analysis. As would be expected, a high dependency ratio, meaning that few work-age household members have to support relatively many non-work-age individuals significantly increases the food expenditure share, while it reduces all others. The impact of altitude also holds few surprises, however, it is a little more complex. The very small, yet highly significant increase in the non-food share is most likely an artefact of insufficient deflation. As already mentioned, infrastructure strongly deteriorates with increasing altitude, meaning that goods are more expensive due to excessive transportation costs. While this effect is accounted for for food expenditures by using regional price deflators, we cannot fully control for them in the case of non-food items, since the deflators are based on food prices. The same could be true for the increased spendings on utility, however, here the harsher climate with noticeably colder winters could also add to costs. A decrease in medical expenditures can also be explained with lack of infrastructure in the highlands, which makes receiving medical help difficult and probably often leads to self-medication, rather than visiting a facility. All in all, altitude seems to matter, although the magnitude of the effect is quite small.

Whether a household is rural or urban has the expected effects on expenditure shares, however, they are only significant for non-food spending and education. If the household head has secondary or higher education, food expenditure shares are relatively lower, while an increase is observed for non-food, as well as education spending, which is intuitive.

The most puzzling effect is the one observed for an unemployed household head, which seems to lead to a decrease in food expenditure shares, as well as an increase

also including already returned, as well as non-remitting migrants. Results are always equal in sign and usually also in significance.

[18] To avoid excessive censoring around zero, expenditure shares for education were analyzed on the subsample of households with at least one school age child. "School age" here is defined as being between 7 and 17 years of age, which in 2007 was the mandatory school age in Tajikistan.

in spending on medication and education. One possible, yet somewhat unlikely, explanation could be that scarce funds are redirected into education, to avoid more household member unemployment in the long run. It could also be that causality is reversed, meaning that poor health leads to unemployment. Since this would bias the coefficient of the dummy indicating unemployment of the household head rather than the coefficient of interest (i.e. that of the migration dummy), it seems safe to ignore this possible endogeneity problem here.
The logarithm of total per capita expenditure is always highly significant and shows the expected sign. With increasing income, households tend to spend less of their resources on food, and more on the other categories. Some economies of scale can be observed for household size, namely for food and utilities, which is what one would expect.[19]

The question remains as to why so few effects of labor migration on expenditure shares can be found for low-skilled labor in Tajikistan, and why for some sub-categories there actually seems to be a negative impact. When looking at the results of Matthieu, 2011, who does an analysis of per capita expenditure levels for 2003 Tajik data using propensity score matching, one finds this effect at least partly repeated. Although he observes a significant and positive effect on per capita expenditures on short-term consumption (defined as food and non-food items), a significant negative effect of almost equal magnitude emerges for the remaining, more long-term consumption categories emerges, thus leading to an overall effect on expenditures somewhere close to zero.

This paper offers and tests two hypotheses as to why the impact of labor migration on expenditures seems so low. Firstly, as already outlined above, labor migration in Tajikistan possibly needs some time to become profitable for those remaining at home. Secondly, labor migration might cause a reduction in labor supply of those staying behind. In the following, these two possibilities are investigated.

[19]The huge and highly significant effect of the constant in the regression for food share is somewhat surprising. However, similiar results are obtained for the food share by Adams and Page, 2005 for Guatemala.

### 1.7.3 Long-term effects of migration

It is easy to imagine that sending a family member abroad to find work warrants some initial costs, which can be substantial, relative to family income. Also, establishing oneself as a worker in a foreign country can take some time, during which returns will be modest, and possibly even negative. Anecdotal evidence for this can be found in Kumo et al., 2011 and Ganguli, 2009, where interviews with Tajik migrant workers in Russia were conducted. Not only are costs of travel rather high, but legal issues, such as work permits also initially take up a lot of resources. Finding and keeping lucrative work may further be hindered by exploitation by employers, as well as harrassment of migrant workers through Russian officials, which seems to be quite common. So it is easy to imagine that the newly arrived migrant needs some time to install himself in a profitable working place. Also, since a substantial part of migration seems to be seasonal, travel frequency back and forth increases, which naturally also drives costs. A first, descriptive confirmation of this hypothesis is the t-test of the mean monthly amount remitted both by recent and more long-term migrants. "Recent" here is defined as having been away no longer than 5 months.[20] Table 1.9 shows significantly lower mean remittances for new migrants, thus lending first support to the time hypothesis.

Table 1.9: Mean comparison of remittances (in Tajik Somoni) between recent and long-term migrants

| recent migrant (<= 5 months) | long-term migrant (> 5 months) | mean difference | t-value |
|---|---|---|---|
| 85.56 | 296.2 | -210.64*** | -7.63 |
| *N* | 734 | | |

The t-test was repeated several times, gradually increasing the time span considered "recent". Differences between the two groups of migrants seem to disappear around a migration spell of 15 months. To further investigate this, the 2SLS analysis was repeated, using migration spell and migration spell squared (measured in months since departure) as endogenous variables, to see if initial negative effects might be reversed over time. Looking at the results in table 1.10, we see some

[20]To accomodate seasonal migration, migration spells include returns to home of up to 3 months).

confirmation of the time hypothesis (Since the estimates for the covariates other than the migration spell and its square are very similiar to those in table 1.8, a discussion of them is omitted here). The expenditure share for food first significantly increases, and then starts to slowly decrease with migration duration. Shares for utilities, on the other hand, show long-term growth after initial decrease. There also seems to exist a positive effect of migration time on medical expenditures, however, significance is quite weak here and can only be observed for the interaction term. The negative effect of migration on education expenditures apparently is not reversed over time, but actually exacerbated, which is cause for concern. A possible explanation could be negative signalling. Since most Tajik migrants work in low-skilled jobs abroad, although the majority of them has secondary eduction, this might send out the wrong message regarding the future usefulness of schooling. If even with higher education, working abroad on a construction site is the most lucrative option (which most likely could also be achieved without secondary education), spending money on more than basic schooling seems somewhat pointless. It also needs to be noted, however, that this effect is not robust to alternative estimation samples. If, for example, the definition of "school age" is broadened, this effect also reverses. From the present results it is therefore not possible to draw a final conclusion concerning the effect of migration on education spending. For all expenditure categories, the observed effects of the length of the migration spell are quite small, but it has to be kept in mind that duration is measured in months (ranging from 0 for non-migrant households to a maximum of 104). Finally, it goes without saying that longitudinal data are of course needed to fully gauge the intertemporal effects of labor migration on expenditures. Nevertheless, this analysis is a first step in the direction of analyzing such effects and gives some indication that the hypothesis of positive, but delayed effects of migration is valid.

### 1.7.4 Effects of migration on domestic labor supply

In addition to the time needed for labor migration to become profitable, reduced labor supply of those remaining at home, and therefore reduced domestic income, could also be a reason why we do not immediately observe the expected effects of migration on expenditures. One could think of two main reasons for remaining

Table 1.10: Time effect of migration on household expenditures

| | (1)<br>share_food | (2)<br>share_nonfood | (3)<br>share_med | (4)<br>share_housing | (5)<br>share_educ |
|---|---|---|---|---|---|
| land per capita | 0.000368 | 0.000190 | -0.000491*** | -0.000151 | 0.0000252 |
| | (0.90) | (0.56) | (-4.93) | (-0.88) | (0.14) |
| tajik (d) | 0.00298 | -0.00235 | -0.00505 | 0.000864 | 0.00150 |
| | (0.43) | (-0.41) | (-1.43) | (0.28) | (0.39) |
| dep. ratio | 0.0180*** | -0.00920** | 0.00159 | -0.00544** | -0.00746*** |
| | (3.26) | (-2.23) | (0.71) | (-2.45) | (-3.13) |
| access to cash (d) | -0.0116 | 0.00874 | -0.00135 | 0.00537 | -0.00228 |
| | (-0.96) | (0.79) | (-0.19) | (1.06) | (-0.32) |
| altitude | -0.0000172*** | 0.0000236*** | -0.0000114*** | 0.0000179*** | 0.000000211 |
| | (-3.02) | (5.05) | (-4.63) | (5.04) | (0.08) |
| location (d) | -0.0173** | 0.0187*** | 0.00274 | 0.00117 | 0.0134*** |
| | (-2.57) | (3.80) | (0.98) | (0.35) | (3.39) |
| head sec. (d) | -0.0160* | 0.0128* | -0.00181 | 0.000164 | 0.00973** |
| | (-1.86) | (1.94) | (-0.50) | (0.04) | (2.50) |
| head unemp (d) | -0.0184*** | -0.00129 | 0.00973*** | 0.00438 | 0.00694* |
| | (-2.64) | (-0.25) | (2.78) | (1.26) | (1.75) |
| head age sq. | 0.00000418 | 0.0000184 | -0.0000132** | 0.00000468 | 0.00000210 |
| | (0.28) | (1.53) | (-2.25) | (0.65) | (0.25) |
| head age | -0.000107 | -0.00220* | 0.00150** | -0.000526 | -0.000209 |
| | (-0.07) | (-1.71) | (2.32) | (-0.70) | (-0.22) |
| log pc total exp. | -0.134*** | 0.0716*** | 0.0166*** | 0.0131*** | 0.0354*** |
| | (-18.96) | (10.79) | (4.37) | (4.42) | (4.34) |
| log hh size | -0.0680*** | 0.0390*** | 0.00649* | -0.00777** | 0.00905** |
| | (-8.45) | (6.05) | (1.84) | (-2.51) | (2.09) |
| migration spell | 0.0129*** | -0.00237 | -0.00124 | -0.00615*** | -0.00321** |
| | (4.38) | (-1.01) | (-0.82) | (-3.31) | (-2.16) |
| migration spell sq | -0.000775** | -0.000151 | 0.000330* | 0.000451* | 0.000144 |
| | (-2.38) | (-0.60) | (1.64) | (1.89) | (1.13) |
| cons | 1.471*** | -0.197*** | -0.0929*** | 0.0101 | -0.141*** |
| | (26.53) | (-4.28) | (-3.52) | (0.41) | (-2.80) |
| First-stage F test | 49.8 | 49.8 | 49.8 | 49.8 | 41.02 |
| $N$ | 4715 | 4715 | 4715 | 4715 | 3589 |

$t$ statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

household members to supply less labor domestically. The first is that the household misjudges the new income situation by simply overestimating the expected returns from migration. Less labor is supplied, since it is assumed that future remittances will overcompensate the foregone domestic income. However, such irrational behaviour seems somewhat unlikely. A second, more rational hypothesis is that the reduction in work income is caused by a reshuffling of labor inside the household. Especially if the migrant was unemployed prior to departure (which seems to be the majority of cases, as can be seen in table1.4), most likely he or she was doing some unpaid task at home. A replacement now has to be found among family members, which might lead to a reduction in working hours offered. There is some support for this in the literature (see, among others, Amuedo-Dorantes and Pozo, 2006 and Funkhouser, 1992 for the Latin American context). A recent paper by Justino and Shemyakina, 2010, also confirms this finding for Tajikistan, observing a reduction in work hours for members of migrant households. The same is true for the findings of chapter 2, although it is unclear if the observed effect might be exacerbated by the financial crisis.
To see whether migration indeed has an adverse effect on labor market participation of household members at home, the above analysis from table 1.8 is repeated, using the log of last month's per capita work income[21] as dependent variable. Admittedly, the per capita work income can only serve as a rather crude proxy for labor supply, however, it is the best the data permit. Nevertheless, when looking at the results in table 1.11, the analysis confirms the findings of Justino and Shemyakina, who use more detailed data containing information on the hours worked of each household member.

A strong and highly significant negative effect of migration on domestic per capita income can be observed, which is consistent throughout all different specifications of migration (as already mentioned, only results using the above defined migration dummy are shown here). Thus the hypothesis of reduced labor supply due to migration is confirmed. (Another interesting result is the fact that apparently access to occasional additional funds is not enough to cause significant reduction in labor supply). Arable land per capita significantly reduces work in-

[21]Per capita figures are calculated excluding migrants currently abroad.

Table 1.11: Results of 2SLS regression on household pc income

| | log_dinc_pc |
|---|---|
| hh has migrant (d) | -2.734*** |
| | (-3.82) |
| land per capita | -0.0176*** |
| | (-4.28) |
| tajik (d) | 0.00174 |
| | (0.02) |
| dep. ratio | -0.375*** |
| | (-7.59) |
| access to cash (d) | 0.113 |
| | (0.68) |
| altitude | -0.000501*** |
| | (-5.83) |
| location (d) | 0.0776 |
| | (0.74) |
| head sec. (d) | 0.133 |
| | (1.26) |
| head age sq | 0.0000120 |
| | (0.08) |
| head age | 0.0240 |
| | (1.54) |
| head unemp. (d) | -1.481*** |
| | (-15.31) |
| log hh size | 0.152* |
| | (1.95) |
| cons | 3.083*** |
| | (7.73) |
| First-stage F test | 30.7 |
| $N$ | 4715 |

$t$ statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

come, which is straightforward, since the bigger the family plot, the more people are needed to farm it. As expected, a high dependency ratio, meaning that the household has relatively few work-age members, also decreases family work income. The same is true for an unemployed household head, which is strictly logical. (As a robustness check, this covariate was omitted from the analysis, however, this did not lead to any changes with regard to the effect of migration on household work income). The small, yet highly significant negative effect of altitude is also not surprising. As already mentioned many times, infrastructure and employment opportunities grow scarce with increasing altitude. Finally, the positive effect of household size is also to be expected: The more household members, the bigger the probability that some of them are of work-age and earning income.

A third possible cause for the observed effects of migration on expenditure (or the lack thereof) exists, which is also connected to labor supply. It could be that remittances are used to start up small enterprises at home. This has been observed for other countries (see, for example, Amuedo-Dorantes and Pozo, 2006 for Mexico, as well as Funkhouser, 1992 for Nicaragua). However, anecdotal evidence (see Mughal, 2007 and Olimova and Olimov, 2007), as well as the results from chapter 2 speak against this hypothesis for Tajikistan.[22] Unfortunately the TLSS 2007 data do not provide enough information to fully research this question, so this is left for further research.

## 1.8 Conclusion

In this chapter, I tried to shed some light on the impact of low-skilled labor migration on household expenditure shares. Results suggest that the impact is rather small. Consumption patterns in Tajikistan apparently are not influenced by migration per se, but by a change in disposable household income. There seem to exist two effects, working in combination, which cause the expected positive effects of migration on expenditure to appear less prominently. Tajik migrants just starting work abroad usually need some time to install themselves in profitable positions,

[22]Note however, that the results from chapter 2 are observed during the financial crisis. It is therefore unclear whether they can be generalized to hold also for non-crisis times.

which can be seen in the continuous increase in average remittances sent home over time. At the same time, labor supply in the family decreases, most likely due to a reshuffling of responsibilities inside the household. Since the majority of migrant workers were unemployed prior to their departure, their place at home will have to be filled by some other household member, who will then have less time to supply to the labor market. The combination of these two effects leads to the observed initial deterioration in household expenditure patterns, with rising food shares and decreasing shares for non-food items, education and utilities, which are usually associated with lesser wealth. However, with increasing length of the migration spell, these findings at least partly reverse to yield the expected results, namely more money spend on medical services and utilities (which could be counted as medium term or investment-type expenditures), while the expenditure share on food decreases. The long-term effect of migration on education remains unclear. Results actually indicate a worrying decrease over time, however, they are somewhat sensible to the sample, and vary with the chosen definition of "school age". Further research using longitudinal data is needed to explore the intertemporal effects of migration in general, and with respect to education in particular. In addition to this it would also be interesting to repeat the analysis with more comprehensive expenditure categories, including, for example, money spend on home improvement, which plays an important role in the Central Asian context. Also, the role remittances play in investment into start ups would be an interesting topic for further investigation.

# Chapter 2

# Employment and the financial crisis in Tajikistan

## 2.1 Introduction

Since the economic crisis hit in fall 2008 the world has seen one of the worst economic turmoils in history, including both developed and developing countries.

There is scant information available concerning the impact of the economic crisis on transition economies. This is especially true for the former Soviet Union economies in Central Asia. As one of the poorest regions in the world, Central Asia was dramatically hit by the financial crisis (ICG, 2010, UNDP, 2010b, Lukashova and Makenbaeva, 2009). As remittance-dependent countries, not only did these countries experience decreasing remittance inflows, there were also tremendous changes in domestic labor markets (ILO, 2010, Tiongson et al., 2010). However, the datasets necessary for more in-depths investigation are scarce, since panel data are necessary to examine dynamics of the financial crisis in the labor market.

In the case of Tajikistan, we can draw on unique panel data, using the 2007 and 2009 Tajik Living Standards Measurement Surveys (henceforth TLSS 2007 & 2009) to examine individual labor market and household migrant decisions[1] in

[1] As could already been seen in chapter 1, labor migration plays an important role in the Tajik

Tajikistan before and during the crisis.

The core questions this chapter tries to answer are: Does the recent financial crisis indeed affect labor market outcomes in Tajikistan via reduced employment in the main exporting sectors? If yes, how is this shock absorbed? By the informal sector, by increased labor migration, or both?

In order to answer these questions, a detailed analysis of the labor market outcomes before and during the crisis is conducted. Specifically, this paper examines the flows from wage employment, self-employment and being inactive or unemployed in the Tajik labor market during the crisis. The analysis focuses on labor market and migration transitions between the end of 2007 and 2009 by estimating Markov chain-style transition probability matrices for different subgroups. The determinants of these transitions are investigated, taking into account factors on the individual, as well as on the household level. To our knowledge, this paper is the first to attempt such an analysis for a Commonwealth of Independent States (CIS) nation. It is also the first to use a heterogeneous exposure variable (namely pre-crisis sector of work) to try to capture the impact of the crisis on labor market decisions.

We find that pre-crisis work in the manufacturing sector, which was hit the hardest by the crisis in terms of employment, has a significant negative effect on staying in wage employment. The agricultural sector, although also affected by the crisis, shows no such effect. While we see no evidence of the informal sector absorbing labor, migration abroad might be a (predominantly rural) mitigation strategy in times of crisis.

The remainder of this paper is organized as follows. The next section introduces some background on Tajikistan's economy, labor market and migration. In the third section, some theory and previous empirical results on labor market outcomes during crises are presented. In the fourth section, we describe the dataset. Our methodology is explained in section five. Results are presented and discussed in the sixth section, while section seven concludes.

context.

## 2.2 Background on Tajikistan

### 2.2.1 Economic transition

Although Tajikistan enjoyed economic growth between 2005 and 2008, it remained the poorest state in Central Asia, with more than half of its population living below the national poverty line in 2008. As already mentioned in chapter 1, Tajikistan has limited natural resources, and only about 7% of the land is arable. This fact, in combination with a less than smooth transition from a planned to a market economy, has led to increased pressure on the national economy and the domestic labor market. Since independence in 1991, decreasing production by, and closure of, state-owned companies led to massive job losses and a long period of economic contraction (ILO, 2008). Between 1992 and 1997, the country's economy was further weakened by a devastating civil war.

Due to the dire job situation at home, large numbers of Tajiks choose labor migration to other countries, predominantly to Russia, which makes Tajikistan one of the top remittances receiving countries when considering the proportion of remittances to GDP. In chapter 1 it was shown that around 65% of all migrants in 2007 were unemployed before leaving the country, thus indicating that poor labor prospects at home spur migration. Without large emigration flows mainly toward Russia, in 2006, unofficially, unemployment in Tajikistan was estimated to be as high as 40%, and in rural areas it was estimated to exceed 60%(FRD, 2007).

There is severe gender-segmentation in the labor force, with women working in the lower-paid sectors of agriculture, education, and health care (JICA, 2008). There is also an overall decreasing level of involvement of women in the formal labor force. While in 2003, 70% of men and 45% of women were in the workforce, in 2008 the figures had shifted to 58% and 31% respectively (ADB, 2010).

### 2.2.2 Tajikistan during the financial crisis

A sharp reduction in workers' remittances, mainly due to economic difficulties in Russia, along with weak demand for Tajikistan's main export commodities of aluminum and cotton were the major factors slowing Tajik GDP growth by more than half in 2009. The local currency, the Tajik Somoni, depreciated by about 22% against the US dollar in the first half of 2009 due to a large drop in foreign exchange receipts from remittances and exports. Industrial production, making up about 30% of GDP, contracted by 6.3% (ADB, 2010). This led to a noticeable decline in employment in both the manufacturing and the agricultural sector during the crisis (see figures 3.1 and 3.2 in the appendix). (Employment in the non-producing sector, however, remained relatively untouched and also showed some growth, as can be seen in figure 3.3 in the appendix).

## 2.3 The impact of crises on labor market outcomes: Some theory and empirical evidence

What are the possible effects of an external shock such as the recent financial crisis on labor market outcomes? Standard macro-economic labor market theory suggests that in a two-sector model, labor leaving the formal sector is absorbed by the informal one, which is assumed to be a less desirable, makeshift workplace, which will eventually disappear with sufficient growth of the economy. It is more or less viewed as a substitute for a non-existing social security net in times of employment difficulties. Some empirical evidence for such dynamics exists, (see, for an example of a transition economy, the article by Dimova et al., 2005 on Bulgaria) however, recent literature suggests that such a generalization of the informal sector might not be adequate. There rather seem to exist at least two sub-groups or tiers, one with work prospects comparable to the formal sector, where individuals choose to work voluntarily, and a second one which has the initially assumed subsistence quality and only serves as a transitory stage from unemployment into formal sector employment. (see, for example Fields, 2005, Bosch and Maloney, 2010). In this case, the shock absorbing function during crises should only be observable in the lower tier of the informal sector. Unfortunately, the data do not allow us to sufficiently test for this, since sector information is limited and the informal sector has to be proxied by self employment, which is somewhat rough, and most likely encorporates the upper, rather than the lower tier.

An additional strategy to avoid unemployment or labor force exit, which is espe-

cially relevant in the Tajik context, is labor migration. Going abroad to find work could not only mitigate personal employment problems, but possibly also help finance the labor force exit or temporary unemployment of other family members remaining at home. Empirical evidence for this exists for Tajikistan for non-crisis times (see, among others, Justino and Shemyakina, 2010, as well as chapter 1), as well as for the recent crisis, were both Danzer and Ivaschenko, 2010 and Ivakhnyuk, 2009b show an increase in Tajik labor migration in their descriptive analyses of the TLSS 2007 and 2009. This is an interesting finding when taking into account that due to economic difficulties in the main country of destination, Russia, migration legislation was noticeable toughened during the financial crisis, reducing both legal job opportunities and wages for foreign migrants (see Lukashova and Makenbaeva, 2009 in their study on the impact of the financial crisis on the Kyrgyz Republic). Nevertheless migration increased, since harsher conditions abroad still are perceived as more favourable than the situation at home in Tajikistan (Ganguli, 2009).
Another question of interest ist whether shocks have gender-specific effects on labor market outcomes. Although in Tajikistan the majority of the workforce is male, this aspect nevertheless warrants some investigation. Some empiricial evidence for transition economies already exists, see, for example Blunch and Sulla, 2011, who show that females are disadvantaged in the Serbian labor market in terms of moving out of the two undesirable states, unemployment and economic inactivity, relative to males during the first year of the recent financial crisis.

## 2.4 Data

For our empirical analysis we use two waves from the Tajikistan Living Standard Survey (TLSS), which is representative at the national, as well as the rural and urban levels. The sampling frame is based on the 2000 Census of Tajikistan. The questionnaires for the 2007 and 2009 surveys are comparable and were designed as panel data on the individual level. The surveys were prepared by the World Bank in collaboration with UNICEF and carried out by the National Committee for Statistics (former Goskomstat, now Tajstat). The surveys include data on the socio-demographic composition of the household, labor market activities, the health and education of individuals, transfers to the household from various sources and a very detailed module on migrants.

Well before the financial crisis, the first wave was collected between September and November 2007, which includes a total of 4,500 households. In late 2009 (October and November), a randomly drawn subsample of these households (totaling to 1,503 households) was reinterviewed. The subsample again was chosen to be representative at the national, as well as rural and urban levels. We restrict our sample to all working age men and women between 18[2] and 65 years of age. After strictly balancing the panel, we are left with 3,264 individuals (or 1,465 households) for each year.[3]

## 2.5 Methodology

As previously mentioned, labor migration plays an important role in Tajikistan. In our analysis we assume the decision to migrate abroad for work to be different from the labor market decisions at home, which is why we examine them separately. First, we investigate the labor market decisions of individuals in the domestic labor market. Then, we analyze the household decision to send a migrant abroad.

### 2.5.1 Analysis of labor market outcomes at home

The analysis of labor market outcomes other than migration abroad is conducted at the individual level, assuming that this is where domestic labor decisions are made. However, it must be assumed that the family decision to send a migrant away will also influence the remaining individuals' work decisions. Not only must the costs of sending someone abroad be covered, but family members also have to replace the missing person's labor. If some family members have sufficiently lucrative jobs, labor migration might not be necessary at all. On the other hand,

[2] Although the questionnaires define working age to start as early as 14, we found that the majority of those individuals are still at school, which leads to an overly inflation of the "inactive" category. We therefore define working age as being older than 17, which during the period in question was the maximum mandatory school age in Tajikistan.

[3] Note that the balancing does not affect the representativeness of the sample, since the composition of households (on the basis of which the sampling was done) remains almost unchanged by the removal of the inconsistent individuals.

the inflow of remittances surely influences the labor supply decisions of those left at home, possibly leading to less employment, or a shift to more risky, capital-intensive forms of work, such as start-ups. (There exist different theories and findings on the effect of remittances on labor supply in the literature. See, among others, Justino and Shemyakina, 2010 for a recent analysis of the situation in Tajikistan, as well as Amuedo-Dorantes and Pozo, 2006 and Funkhouser, 1992 for the Latin American context. Chapter 1 also finds tentative evidence for a reduction of labor supply caused by migration.) There clearly exists an endogeneity problem, which is caused by reversed causality. To correct for this, we include only those working age individuals from migrant households, who resumed their current work after the migrant was sent abroad, thus avoiding the reverse influence.[4]

The main goal of this chapter is to shed light on the influence of the financial crisis on labor market outcomes in Tajikistan. An impact evaluation in the true sense of the word is not possible, since the counterfactual situation with an absence of the crisis obviously can neither be observed, nor proxied by a control group, as the crisis hit worldwide. We therefore resort to a heterogeneous exposure approach (compare Kis-Katos and Sparrow, 2011, as well as Edmonds et al., 2007), making use of the fact that the crisis strongly affected employment in the manufacturing and the agricultural sector, whereas the non-producing sector was left relatively unharmed (and even experienced slight growth during the crisis, see figure 3.3). We thus use the pre-crisis (i.e. 2007) sector of employment of each wage employed working age individual as a measure of individual exposure to the crisis. Due to data limitations, the definition of "manufacturing" is somewhat broad. It includes all activities in the producing sector, other than agricultural. High-level engineering and management positions are excluded.[5] The agricultural sector in our definition also includes fishery and forestry (both of which are rather irrelevant categories for Tajikistan), and excludes subsistence agriculture.

[4]In the case of households with more than 1 migrant, the migrant with the longest ongoing migration spell is used as a reference. Although this can be critizied, we do not think that it has a significant influence on our results, since in our sample only 5 households with multiple migrants have migrants with different lengths of migration spells.

[5]This is not likely to have a strong influence on results, since the percentage of such high-level positions in the sample is very low.

In our analysis of the domestic labor market, we look at four labor market outcomes, namely "inactive", "unemployed",[6] "wage-employed" and "self-employed", where the last category also serves as a proxy for the informal sector. As already mentioned, this is a rather rough and possibly incomplete definition, which most likely only captures the more desirable upper tier of the informal sector. However, the data do not permit a true distinction between the two. With the help of multinomial probit regressions, we estimate the transition probabilities[7] of moving between these four states before (2007) and after the onset of the crisis (2009).
In the multinomial probit model it is assumed that the utility an individual $i$ derives from choosing alternative or category $k$ is a latent variable $y^*_{ik}$ described by

$$y^*_{ik} = \boldsymbol{x}'_i \boldsymbol{\beta}_k + \epsilon_{ik}$$

Category $k$ is chosen if $y^*_{ik}$ is highest for $k$, i.e.

$$y_i = \begin{cases} 1 \; if \; y^*_{i1} \geq y^*_{i2}, \ldots.., y^*_{ik} \\ 2 \; if \; y^*_{i2} \geq y^*_{i1}, y^*_{i3} \ldots.., y^*_{ik} \\ \ldots \\ k \text{ otherwise} \end{cases}$$

Other than with the multinomial logit model, the error terms $\epsilon_{ik}$ are assumed to be multivariate normally distributed and are allowed to be correlated across

[6]Since only very few work-age individuals actually claimed to be unemployed in the official sense of the term, i.e. without employment but looking for work, we included into this category all people currently out of work for reasons other than housework, military service, schooling or health problems.

[7]The concept of transition probability matrices is taken from the analysis of Markov chains. In our context, however, we only observe two time-periods, with an external shock (i.e. the financial crisis) between them. Therefore our interest is not to estimate the parameters of a Markov chain, but to descriptively investigate the transition between 2007 and 2009.

categories:

$$\epsilon = MND\,(0, \Sigma),\ with\,\Sigma = \begin{pmatrix} 1 & \rho & \cdots & \rho \\ \rho & 1 & \cdots & \rho \\ & & \ddots & \\ \rho & \rho & \cdots & 1 \end{pmatrix}$$

Thus the assumption of independence of irrelevant alternatives (IIA), which can cause problems when using a multinomial logit, is avoided.[8]

The multinomial probit regression is run on the 2009 labor outcomes, divided into different subsamples determined by the labor outcome of the individual in 2007. In other words, this means that the first subsample consists of the 2009 outcomes of those who were inactive in 2007 (with "inactive" being the base category against which the other outcomes are evaluated). The second subsample consists of the 2009 outcomes of those who were unemployed in 2007 (with "unemployed" being the base category against which the other outcomes are evaluated), and so forth. The transition probabilities $p_{lm}$ are then estimated as the predicted probability of choosing state $k$ over the base category.
To accomodate the complexity of the labor supply decision, a number of individual, as well as household level covariates are included in the estimation. The following model was fitted:

$$\begin{aligned} labor\ status\ in\ 2009 &= \alpha + \beta_1\, age + \beta_2\, age^2 + \beta_3\, gender + \\ \beta_4\, know\ Russian &+ \beta_5\, secondary\ education + \beta_6\, dep.\ ratio + \\ \beta_7\, location &+ \beta_8\, altitude + \beta_9\, manufac.\ sector\ 07 + \\ \beta_{10}\, agric.\ sector\ 07 &+ \beta_{11}\, hh\ head + \beta_{12}\, migrant\ dummy + \\ \beta_{13}\, perc.\ wage\ 07 &+ \epsilon \end{aligned}$$

[8]Tests have indicated that IIA might be problematic for the data at hand.

On the individual level, age (also entering as a squared term), gender, as well as whether the person knows Russian and has secondary education are included as covariates. In addition to this, we add our exposure measure to crisis, namely whether the individual was working in the manufacturing or agricultural sector prior to the crisis in 2007. These two variables can only be meaningfully included into the regression on the subset of those wage-employed in 2007, since it is unlikely that the informal sector (proxied by self-employment) has enterprises big enough to feel the drop in exports caused by the crisis. It is also to be assumed that most private enterprises are either non-producing (mostly trading), or only producing for the local market (e.g. small bakeries, etc.). The reference category for the two sector dummies is employment in the non-producing (i.e. the service) sector.
Household level covariates include the location of the household (whether it is urban or rural), as well as the altitude. With regard to intra-household characteristics, we control for the dependency ratio (measured as the ratio of non-working age to working age household members), the percentage of wage employed family members in 2007 and whether the household currently has a migrant. It should be noted that "migrant" here is defined as being away, working and remitting either in cash, in kind or both (which is identical to the definition in chapter 1).

In addition to the multinomial probit, transition probabilities are also calculated using a straightforward and simple count method. Since this method is much less data intensive than the multinomial probit, it is possible to run seperate analyses by gender, age group and income quintiles. The method used is outlined below:

With $k$ states in both years, the transition probability matrix has the dimension $k$ x $k$ where the element $p_{lm}$, denoting the probability to move from state $l$ to state $m$ is given by:

$$p_{lm} = \frac{n_{lm}}{\sum_m n_{lm}}$$

with $n_{lm}$ denoting the number of individuals who were in state $l$ in 2007 and moved to state $m$ in 2009. The denominator is the sum over all individuals who were in state $l$ in 2007.

### 2.5.2 Analysis of labor migration

As already mentioned above, the decision to migrate abroad is assumed to take place at the household level, so we estimate the probability of having at least one migrant currently abroad and remitting in the household.[9] The following model is fitted:[10]

$$\begin{aligned}
hh\,has\,migrant &= \alpha_m + \beta_{m1}\,dep.\,ratio + \\
\beta_{m2}\,location &+ \beta_{m3}\,altitude + \beta_{m4}\,age\,of\,hh\,head + \\
\beta_{m5}\,age\,of\,hh\,head^2 &+ \beta_{m6}\,sec.edu\,of\,hh\,head + \\
\beta_{m7}\,perc.\,of\,migrant\,hhs &+ \beta_{m8}\,perc.\,of\,hh\,memb.\,manufac.\,sector\,07 + \\
\beta_{m9}\,perc.\,of\,hh\,memb.\,agric.\,sector\,07 &+ \beta_{m10}\,add.\,cash + \\
\beta_{m11}\,land\,pc. &+ \beta_{m12}\,tajik + \epsilon
\end{aligned}$$

Again we include location, altitude and the dependency ratio as covariates. Household-head specific variables are age (and its square term), as well as secondary education. The household-level equivalent of the exposure variable is the percentage of household members working in the manufacturing and the agricultural sector in 2007. We also include the intra-cluster percentage of households with migrants (excluding the current household), as it can be shown that such networks are important pull factors for migration in the Tajik context (see, for example, Carrington and Vishwanath, 1996, Bauer et al., 2002, Woodruff and

[9] Unfortunately, additional descriptive analyses of labor migration on the individual level are not possible, since the data do not allow for tracking of migrants between the two years. Only individuals who were present in Tajikistan for both survey interviews can be tracked, thus limiting the possibilities of analysis.

[10] See chapter 1 for the theoretical motivation of this model.

Zenteno, 2007, McKenzie and Rapoport, 2010, as well as the results from chapter 1). Furthermore, a dummy indicating whether the household has access to temporary external funding (e.g. from friends or relatives outside the household) is included. In chapter 1 it is shown that this is also an important determinant of migration, since it helps covering one-time costs associated with sending someone abroad to find work. Finally, the arable land per capita (both owned and rented) enters the regression equation, since a relatively big plot warrants more household members to farm it, and should therefore lead to a reduction of the propensity to migrate.

## 2.6 Results

### 2.6.1 Results for labor market outcomes at home

#### Descriptives

Table 2.1 shows the percentages of different labor market outcomes for both 2007 and 2009, statistical significance between the two years is tested using a two-sample t-test. The first panel combines the figures for both men and women, and shows a significant increase in the percentage of unemployment, as well as a significant decrease in inactiveness. The straightforward interpretation of the latter would be that the crisis forces more previously "dormant" individuals to enter the labor market and try to earn income, while the situation there has deteriorated, which is indicated by the increase in unemployment. Furhermore, there is a significant decrease in wage employment. No difference between the years can be seen for self employment, and the other changes are somewhat small.

When looking at panels 2 and 3, which display the percentages for men and women respectively, it becomes clear that the increase in unemployment is mainly driven by men, which makes sense when considering that the percentage of women in the labor force is traditionally low in Tajikistan (JICA, 2008). However, the comparatively few women that do work seem to account for the decrease in wage employment, which gives rise to the assumption that the crisis might have had a

Table 2.1: Employment in the different categories in 2007 and 2009

| | 2007 | N | 2009 | N | 09-07 Sign. |
|---|---|---|---|---|---|
| *All* | | | | | |
| inactive | 0.40 | 1311 | 0.37 | 1190 | -0.03*** |
| unemployed | 0.06 | 209 | 0.12 | 402 | 0.06*** |
| wage employed | 0.37 | 1171 | 0.33 | 1075 | -0.04** |
| self-employed | 0.17 | 535 | 0.18 | 555 | 0.01 |
| *Men* | | | | | |
| inactive | 0.18 | 291 | 0.11 | 171 | -0.07*** |
| unemployed | 0.09 | 159 | 0.21 | 323 | 0.12*** |
| wage employed | 0.51 | 766 | 0.47 | 716 | -0.03 |
| self-employed | 0.22 | 328 | 0.21 | 330 | 0.02 |
| *Women* | | | | | |
| inactive | 0.60 | 1020 | 0.60 | 1019 | 0.00 |
| unemployed | 0.02 | 50 | 0.04 | 79 | 0.02*** |
| wage employed | 0.25 | 405 | 0.21 | 359 | -0.04** |
| self-employed | 0.13 | 207 | 0.15 | 225 | 0.02 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

stronger, negative effect on employed women than on employed men.

**Estimation of transition probabilities**

First, transition probabilities are calculated using the simple count method outlined above. Table 2.2 shows the transition matrices for the full sample and for men and women, respectively.[11]

Our results indicate that inactiveness is a fairly persistent state: 62% of those inactive before the onset of the crisis in 2007 remain so in 2009. As expected, this effect is stronger for females than for males.

60% of those wage-employed in 2007 manage to keep this employment status in 2009. For females this percentage is a bit lower, while for males it is slightly higher, however, the difference is rather small. Only 14% move from wage employment to self employment during the crisis, which can be seen as first evidence against a shock absorbing function of the informal sector.

[11]Since the sample is quite small, some cell populations are rather low. Resulting estimates should be treated with caution.

Table 2.2: Transition probabilities for domestic labor outcomes

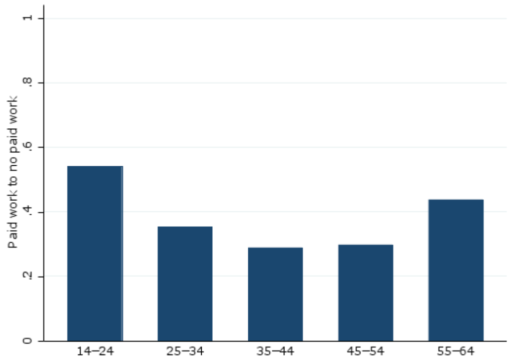
| | inactive | N | unemployed | N | wage | N | self empl | N |
|---|---|---|---|---|---|---|---|---|
| *All* | | | | | | | | |
| inactive | 0.62 | 659 | 0.10 | 102 | 0.13 | 133 | 0.14 | 13 |
| unemployed | 0.16 | 27 | 0.32 | 43 | 0.31 | 49 | 0.21 | 37 |
| wage employed | 0.14 | 128 | 0.11 | 100 | 0.60 | 592 | 0.14 | 145 |
| self-employed | 0.22 | 98 | 0.11 | 48 | 0.31 | 136 | 0.35 | 149 |
| *Men* | | | | | | | | |
| inactive | 0.33 | 82 | 0.27 | 61 | 0.24 | 55 | 0.14 | 35 |
| unemployed | 0.06 | 7 | 0.36 | 39 | 0.37 | 45 | 0.21 | 27 |
| wage employed | 0.06 | 36 | 0.15 | 91 | 0.61 | 400 | 0.17 | 114 |
| self-employed | 0.03 | 10 | 0.15 | 39 | 0.42 | 112 | 0.39 | 102 |
| *Women* | | | | | | | | |
| inactive | 0.71 | 577 | 0.05 | 41 | 0.10 | 78 | 0.14 | 102 |
| unemployed | 0.51 | 20 | 0.17 | 4 | 0.10 | 4 | 0.22 | 10 |
| wage employed | 0.31 | 92 | 0.03 | 9 | 0.57 | 192 | 0.09 | 31 |
| self-employed | 0.50 | 88 | 0.06 | 9 | 0.14 | 24 | 0.31 | 47 |

The most unstable state actually seems to be self-employment, with transition probabilities out of paid work (i.e. into either inactiveness or unemployment) at around 33% in total. Here it is noteworthy that the transition from self employment into inactiveness is especially high for women (50%), while it is only 3% for men (note here, however, that results might be less stable due to the small cell population of only 10 individuals). Also, the probability to move from unemployment into inactiveness is quite substantial for women. This could mean that due to the crisis, women otherwise willing to work decide to rather take on the traditional role of a housekeeper, since the jobmarket has become too tight.

To investigate the influence of age and wealth (measured as per capita expenditure quintiles in 2007) on the transition probabilities, outcome categories had to be reduced to no paid work (i.e. inactiveness or unemployment) or paid work (meaning either wage employed or self-employed), due to insufficient cell populations. The results can be seen in Figures 2.1 and 2.2.

The characteristic, u-shaped relation between age and employment presents itself clearly. Very young people, as well as those close to retirement, have a

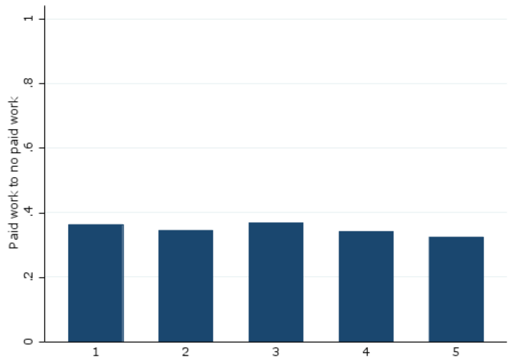
Figure 2.1: Transition probabilities by age




noticeably higher probability of moving from paid work into unemployment, inactiveness or unpaid work in 2009. This is a very common result, which can be observed in many countries, and it is unclear whether it should be attributed to the financial crisis.

Further, we also calculate transition probabilities for the different expenditure quintiles in 2007. As seen in Figure 2.2, the results show no noticeable differences, suggesting that the effects of the economic turmoil were not just limited to poor families.

Figure 2.2: Transition probabilities by expenditure quintile




In a second step, we run a multinomial probit regression estimating the transition probabilities, including explanatory variables on the individual, household and community levels in 2007, as explained in the previous section.

The resulting transition probabilities are quite similar to those obtained using the simple count method. Tables 2.3 to 2.6 show the transition probabilities, as well as the marginal effects of the covariates.[12]

Table 2.3: Multinomial Probit Model: Labor outcomes in 2009 if inactive in 2007

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | inactive | unemployed | wage employed | self-employed |
| age | -0.001 | -0.000 | -0.000 | 0.001* |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| sex (d) | -0.342*** | 0.152*** | 0.109*** | 0.081** |
| | (0.039) | (0.022) | (0.028) | (0.032) |
| knowing Russian (d) | 0.021 | 0.007 | 0.003 | -0.031 |
| | (0.031) | (0.019) | (0.023) | (0.026) |
| sec. educ. (d) | 0.058 | 0.014 | -0.025 | -0.046 |
| | (0.036) | (0.021) | (0.024) | (0.028) |
| dep. ratio | 0.019 | -0.008 | -0.017 | 0.007 |
| | (0.031) | (0.027) | (0.020) | (0.022) |
| location (d) | 0.105*** | -0.000 | -0.065*** | -0.040 |
| | (0.034) | (0.018) | (0.023) | (0.028) |
| altitude | -0.000 | 0.00006*** | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| perc. wage empl. 07 | -0.013 | 0.008 | 0.033 | -0.028 |
| | (0.045) | (0.026) | (0.033) | (0.036) |
| head of hh (d) | -0.119** | 0.030 | 0.082** | 0.007 |
| | (0.055) | (0.034) | (0.038) | (0.043) |
| hh has migrant (d) | 0.105* | -0.009 | -0.093** | -0.003 |
| | (0.062) | (0.032) | (0.042) | (0.046) |
| Predicted probabilities | .63 | .10 | .13 | .14 |
| *N* | 1249 | 1249 | 1249 | 1249 |

Marginal effects, s.e.'s in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As expected, the sector of the individual's employment prior to the crisis influences 2009 labor status outcomes. Previous work in the manufacturing sector has the anticipated significant negative effect on remaining in wage employment,

[12]Standard errors adjusted for clustering at the household level are shown in parentheses.

Table 2.4: Multinomial Probit Model: Labor outcomes in 2009 if unemployed in 2007

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | inactive | unemployed | wage employed | self-employed |
| age | 0.007* | -0.017*** | 0.002 | 0.008*** |
| | (0.003) | (0.006) | (0.005) | (0.003) |
| sex (d) | -0.290*** | 0.162 | 0.178* | -0.050 |
| | (0.050) | (0.120) | (0.103) | (0.070) |
| knowing Russian (d) | 0.104** | -0.043 | 0.038 | -0.099* |
| | (0.049) | (0.098) | (0.084) | (0.060) |
| sec. educ. (d) | 0.178** | 0.059 | -0.180* | -0.057 |
| | (0.085) | (0.096) | (0.100) | (0.080) |
| dep. ratio | -0.052 | 0.049 | 0.032 | -0.029 |
| | (0.057) | (0.079) | (0.065) | (0.055) |
| location (d) | 0.010 | -0.058 | 0.017 | 0.030 |
| | (0.043) | (0.081) | (0.076) | (0.061) |
| altitude | -0.000 | -0.000 | 0.000 | 0.00008** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| perc. wage empl. 07 | 0.073 | 0.035 | 0.265** | -0.373*** |
| | (0.075) | (0.131) | (0.115) | (0.118) |
| head of hh (d) | -0.152* | 0.165 | 0.088 | -0.102 |
| | (0.092) | (0.129) | (0.110) | (0.088) |
| hh has migrant (d) | -0.081 | 0.326*** | 0.007 | -0.252*** |
| | (0.061) | (0.087) | (0.101) | (0.081) |
| Predicted probabilities | .15 | .34 | .32 | .19 |
| $N$ | 203 | 203 | 203 | 203 |

Marginal effects, s.e.'s in parentheses

(d) for discrete change of dummy variable from 0 to 1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: Multinomial Probit Model: Labor outcomes in 2009 if wage-employed in 2007

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | inactive | unemployed | wage employed | self-employed |
| age | 0.006*** | -0.002** | -0.002 | -0.001 |
| | (0.001) | (0.001) | (0.002) | (0.001) |
| sex (d) | -0.173*** | 0.166*** | -0.038 | 0.045 |
| | (0.026) | (0.032) | (0.045) | (0.033) |
| knowing Russian (d) | -0.056** | -0.001 | 0.012 | 0.045 |
| | (0.024) | (0.023) | (0.038) | (0.030) |
| sec. educ. (d) | -0.020 | 0.003 | 0.089* | -0.072** |
| | (0.028) | (0.027) | (0.046) | (0.031) |
| dep. ratio | 0.016 | -0.071*** | 0.067** | -0.013 |
| | (0.019) | (0.023) | (0.033) | (0.023) |
| location (d) | -0.003 | 0.065*** | -0.024 | -0.038 |
| | (0.025) | (0.021) | (0.039) | (0.029) |
| altitude | -0.000 | -0.000 | 0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| manufac. sector 07 | -0.025 | 0.090*** | -0.107*** | 0.041 |
| | (0.028) | (0.021) | (0.039) | (0.027) |
| agricultural sector 07 | 0.025 | 0.008 | -0.060 | 0.028 |
| | (0.028) | (0.030) | (0.045) | (0.033) |
| perc. wage empl. 07 | -0.016 | 0.016 | -0.009 | 0.009 |
| | (0.034) | (0.037) | (0.054) | (0.038) |
| head of hh (d) | -0.050 | -0.053* | 0.091** | 0.012 |
| | (0.033) | (0.027) | (0.046) | (0.034) |
| hh has migrant (d) | -0.023 | 0.124*** | -0.104 | 0.003 |
| | (0.045) | (0.032) | (0.067) | (0.049) |
| Predicted probabilities | .15 | .12 | .59 | .14 |
| $N$ | 1127 | 1127 | 1127 | 1127 |

Marginal effects, s.e.'s in parentheses

(d) for discrete change of dummy variable from 0 to 1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: Multinomial Probit Model: Labor outcomes in 2009 if self-employed in 2007

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | inactive | unemployed | wage employed | self-employed |
| age | 0.004*** | -0.004*** | -0.004* | 0.003 |
| | (0.002) | (0.001) | (0.002) | (0.003) |
| sex (d) | -0.355*** | 0.121*** | 0.168*** | 0.066 |
| | (0.038) | (0.034) | (0.047) | (0.057) |
| knowing Russian (d) | -0.029 | 0.017 | 0.063 | -0.051 |
| | (0.035) | (0.030) | (0.048) | (0.055) |
| sec. educ. (d) | 0.082** | 0.002 | -0.054 | -0.029 |
| | (0.037) | (0.043) | (0.052) | (0.058) |
| dep. ratio | 0.046* | -0.106*** | 0.052 | 0.007 |
| | (0.026) | (0.034) | (0.039) | (0.044) |
| location (d) | -0.011 | -0.000 | -0.147*** | 0.159*** |
| | (0.038) | (0.030) | (0.052) | (0.051) |
| altitude | 0.0001*** | 0.0001*** | -0.0001** | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| perc. wage empl. 07 | 0.061 | -0.013 | 0.049 | -0.097 |
| | (0.053) | (0.067) | (0.092) | (0.098) |
| head of hh (d) | -0.005 | -0.052 | 0.064 | -0.006 |
| | (0.047) | (0.037) | (0.059) | (0.070) |
| hh has migrant (d) | -0.049 | 0.088* | -0.058 | 0.019 |
| | (0.058) | (0.048) | (0.075) | (0.086) |
| Predicted probabilities | .22 | .13 | .30 | .35 |
| *N* | 514 | 514 | 514 | 514 |

Marginal effects, s.e.'s in parentheses

(d) for discrete change of dummy variable from 0 to 1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and increases the chance of becoming unemployed. There is no evidence that the informal sector (proxied by self employment) functions as a shock absorber for the formally wage employed in times of crisis. The probability of moving from wage employment into self employment is not significantly influenced by the exposure variable. In contrast, no effect of previous wage employment in the agricultural sector can be observed. It is to be assumed that the agricultural sector is less dependent on export and therefore world market development than the manufacturing sector, since domestic demand will be comparatively stronger, even during crisis.

With regard to migration, the analysis yields some interesting results. Having a migrant in the family clearly seems to lead to a reduction in labor supply by the remaining household members. The probability of staying out of the work force is increased by migration, the same is true for unemployment. Also, chances of moving from paid work into unemployment increase. Other than Amuedo-Dorantes and Pozo, 2006 for Mexico, as well as Funkhouser, 1992 for Nicaragua, we find a decrease in both wage employment and self employment, which does not confirm the hypothesis that remittances are used to finance start-ups and thus lead to an increase in informal sector labor supply. It therefore looks as if labor migration indeed is a mitigation strategy in times of crisis, which is used to finance temporary unemployment, as well as labor market exit of the remaining household members. However, the effect seen here is not clearly attributable to the crisis. Justino and Shemyakina, 2010, as well as chapter 1 show that even in pre-crisis times, labor migration in Tajikistan leads to a decrease in domestic labor supply, the most likely reasons for this being a reshuffling of intra-household tasks. This seems especially likely if one takes into account that the majority of migrants were unemployed prior to their departuer (see Olimova and Bosc, 2003, as well as 1.4 in chapter 1), and therefore most likely did household work that now someone else has to do. Considering the fact that labor migration is a predominantly rural phenomenon in Tajikistan, this becomes even more apparent, since family plots have to be farmed.

The percentage of working age household members wage-employed in 2007 (excluding the current individual) shows the expected pull factor only on the small subsample of the previously unemployed, where it leads to a significant increase

in the probability of moving into wage-employment, as well as a decrease in the chances of becoming self-employed. It does make sense to assume that finding a job in a company or with the government is easier if some family member already has his or her foot in the door. As expected, age (after accounting for its possibly nonlinear relationship with the outcome) generally seems to increase the probability of moving into or staying in inactiveness, while it decreases the chances of becoming unemployed, as could already be seen in the previous analysis (figure 2.1). Being male has a clear positive effect on the probability of moving into or staying in paid labor or unemployment, as well as a decreasing effect on inactiveness. This is straightforward, considering traditional patterns in Tajikistan, where the labor force mainly consist of men. The role of knowing Russian, however, is unclear. Mostly, coefficients are not significant, which is surprising, since proficiency in Russian is a proxy for higher education and should be associated with better work prospects. One of the few times where the coefficient is significant, it indicates a positive effect on the possibility of going from unemployment into inactiveness. This could be an indicator of wealth-induced labor force exit in times of crisis, meaning that comparatively better educated (and therefore most likely more wealthy) individuals chose to stop looking for paid work when the job market gets too tight. Similar results are found for the impact of secondary education. While it has a positive impact on staying in wage employment, the exit from less stable self employment, as well as unemployment into inactiveness is also positively influenced by having at least secondary education.
The dependency ratio within a household (measured as the relation of non-workage to workage household members) has a positive impact on the probability of staying in wage employment, possibly due to increased pressure to provide for the remaining family members. The same can be observed for being the head of the household. It is noteworthy that this effect cannot be seen for self employment, which suggests that the formal sector is preferred by most individuals in Tajikistan.

The impact of altitude on labor market outcomes is quite small and usually not significant. However, for the subsample of those self-employed in 2007, a negative effect on becoming or staying in paid labor, both wage and self-employed, can be observed. While of course poor infrastructure in the highlands is a possible explanation, it remains unclear why this should mainly affect the previously self-employed. This could be due to predominance of the informal sector over wage employment in the highlands, however, the data do not give evidence for this. Living in an urban area has a negative effect on being wage employed, while it seems to positively influence the chances of working in one's own business. As already assumed above, a possible explanation might be that finding a wage-paying job in agriculture, which is not an option in an urban setting, might be comparatively easier.

### 2.6.2 Results for labor migration

#### Descriptives

Table 2.7 compares percentages of households without, with one, or with more than one labor migrant both before and after the crisis, revealing a significant overall increase in migrants.

This is in line with the literature (see Marat, 2009, Ganguli, 2009, Danzer and Ivaschenko, 2010).

Table 2.7: Number of migrants per household in 2007 and 2009

| | 2007 | N | 2009 | N | 09-07 Sign. |
|---|---|---|---|---|---|
| *No of migr* | | | | | |
| zero | 0.745 | 3703 | 0.655 | 982 | -0.091 *** |
| one | 0.196 | 896 | 0.248 | 365 | 0.052 *** |
| two and more | 0.059 | 261 | 0.097 | 148 | 0.038 *** |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As already discussed in the previous section, a possible explanation for this development could be that households are trying to cope with the crisis at home by sending family members abroad to work (see, for example, Brown et al., 2008). One point needs further investigation: The overwhelming majority of Tajik work migrants goes to find employment in Russia. However, the Russian economy was actually hit even harder by the crisis than the Tajik one, with GDP growth not just slowing down but temporarily even turning negative. So it has to be assumed (and this was indeed the case), that restrictions were placed on labor immigration to Russia, as well as wages earned by migrants. Nevertheless the data suggest an increase of labor migration to Russia during the crisis. A possible explanation for this is that even a Russia deeply in crisis still offers more work opportunities than a less affected Tajikistan (see, for example, Ganguli, 2009). Another reason might be the reduced wages received abroad, which make sending more migrants necessary in order to achieve an acceptable amount of remittances. As already mentioned, Russia tightened regulations for labor migrants (Ivakhnyuk, 2009a), making it more difficult for Tajik migrant workers to find work and earn enough money. The results in table 2.8 give tentative evidence for this, showing a rather small, yet significant increase in pre-arranged jobs (to better cope with stricter labor market regulations), as well as in expulsions from the host country due to legal issues (involving work permits, etc.).

Table 2.8: Possible indicators for restriction of labor migration in the host country

| | 2007 | 2009 | 09-07 Sign. |
|---|---|---|---|
| *Job pre-arranged* | | | |
| Yes | 0.155 | 0.236 | 0.080 *** |
| No | 0.845 | 0.764 | |
| *Kicked out* | | | |
| Yes | 0.027 | 0.098 | 0.071 *** |
| No | 0.973 | 0.902 | |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Estimation of determinants of migration**

Table 2.9 gives the marginal effects of the probit analysis, as explained in section 2.5.2.

With regard to our exposure variables we see an interesting result: Other than in the previous analysis of individual domestic labor market outcomes, we now observe a significant positive effect on migration of previous employment in the agricultural sector, while the manufacturing sector has an insignificant coefficent. This result is easily explained if one takes into account that labor migration in Tajikistan traditionally is predominantly rural, with only around 19% of migrant

Table 2.9: Probit model: Determinants of labor migration in 2009

| | HH has at least one migrant |
|---|---|
| head age | 0.00108 |
| | (1.19) |
| land per capita | -0.000894 |
| | (-0.88) |
| head sec. (d) | -0.00963 |
| | (-0.38) |
| head unemp (d) | 0.0573*** |
| | (2.88) |
| dep. ratio | -0.137*** |
| | (-6.37) |
| tajik (d) | -0.00617 |
| | (-0.40) |
| location (d) | -0.0147 |
| | (-0.94) |
| altitude | 0.0000250*** |
| | (4.12) |
| perc. manufac. 07 | -0.0264 |
| | (-0.48) |
| perc. agric. 07 | 0.106*** |
| | (2.94) |
| migrant hh cluster perc. | 0.173*** |
| | (2.95) |
| access to cash (d) | 0.0526** |
| | (2.04) |
| $N$ | 1465 |

$t$ statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

households living in urban areas in 2007. Therefore it makes sense that rural households are more prone to using migration as a mitigation strategy for the crisis. Although this percentage increases to 26% in 2009, the difference is not statistically significant on conventional levels, so it remains unclear whether due to the crisis more urban households consider it necessary to send someone to work abroad.

The results for the remaining covariates are quite similar to those observed in table 2.9 in chapter 1. The dependency ratio has a negative and significant effect on the probability of sending a migrant abroad, which makes sense, since this means that relatively few working age people (and therefore potential migrants) are present in the family. Altitude has a significant, yet again very small positive effect, which is also intuitive, since high-altitude areas in Tajikistan are generally poorer and offer less employment possibilities than lower regions. The network variable, giving the intra-cluster percentage of migrant households is again highly significant and positive in sign. Also, having access to additional funds has the expected, positive and significant impact. If the household head is unemployed, this increases the probability to send a migrant, most likely due to financial pressure. No significant effects are observed for the household head's age, or location. The effect of the location dummy, however, is most likely captured in the agricultural sector exposure variable. If it is left out, location becomes significant again, with the expected negative sign (meaning that rural households have a higher propensity to migrate). Other than in chapter 1 we also find no significant influence of household head education.

A remaining question which is not investigated in this chapter is whether migration actually improves the living conditions of those staying behind. Analyzing the pre-crisis TLSS 2007 chapter 1 finds a positive, yet rather small effect on consumption patterns, which, however, only starts to show after some time. It looks as if labor supply reduction, mainly caused by having to fill the gap of leaving migrants, along with initially poor earning prospects for newcomers abroad are to blame for this effect. During the financial crisis, this effect should be further exacerbated by wage decreases in the host countries, as well as increased legal difficulties due to tightened labor regulations for migrants. Further research on the effects of migration, especially during the times of crisis is needed to reach a conclusion here.

## 2.7 Conclusion

Does the recent financial crisis impact employment patterns in Tajikistan? Our aim was to make a first attempt at resolving this question by analyzing the effects of the financial crisis in 2008/2009 on the Tajik labor market, using TLSS panel data from 2007 and 2009. Keeping in mind that our analysis does not have the methodological rigor of an impact analysis that is able to truly identify causality, our results nevertheless give some interesting clues about possible effects of the crisis on labor market outcomes. Using pre-crisis employment in the manufacturing and the agricultural sector as exposure variables to the crisis we see a significant negative effect of prior work in manufacturing on wage employment. This cannot be observed for the agricultural sector, possibly because even in times of crisis domestic demand can make up for some of the losses in export. Also, with Tajikistan being a predominantly rural country, the agricultural sector is comparatively more developed and therefore should offer more flexible employment opportunities, whereas manufacturing is rather specialized and heavily depends on exports. Although this can often be observed for other countries, we find no evidence for the informal sector (proxied by self employment) absorbing labor during the crisis. No significant move from wage employment to the informal sector can be seen in our results, the same holds for moving there from inactiveness or unemployment. We further find that labor migration, which has always been prominent in Tajikistan and seems to have increased during the crisis, could be a way to finance crisis-induced labor market exit, as well as temporary unemployment. If the family has a remitting migrant, the remaining work-age household members are more likely to become unemployed or leave the labor force, and less likely to re-enter paid work (both wage and self-employed). When looking at the determinants of labor migration we also find evidence for an increase during crisis. However, since migration in Tajikistan is a predominantly rural phenomenon, only the impact of former employment in the agricultural sector is significant and positive on the propensity to have a migrant. It remains to be clarified whether this coping strategy is actually successful, since Russia, the main destination of Tajik labor migrants, was hit even harder by the financial crisis in terms of GDP growth. Also, as can be seen in chapter 1, there seems to be a delay in positive effects of migration on expenditure patterns.

Although traditionally in Tajikistan the labor force is predominantly male, the few women who do work seem to have been hit comparatively harder by the crisis, with high transition probabilities into inactiveness from all other categories, as well as a small, but significant reduction in wage employment from 2007 to 2009. With regard to the relationship between age and work, the data show the characteristic u-shape, meaning that the relatively young, as well as those close to retirement age are at more risk of moving out of the labor force or into unemployment. A question unanswered by our analysis is whether the impact of the financial crisis on labor market outcomes carries through to household well-being via a change in income. Unfortunately the data at hand do not permit a satisfactory investigation of this interesting topic. This is left for further research with more comprehensive income data.

# Chapter 3

# A sensitivity check of the recursive bivariate probit model under various misspecifications with and without a valid instrument

## 3.1 Introduction

Estimating the impact of an endogenous treatment is a central problem, not only in empirical economics, but also in many other disciplines. A number of approaches exist to deal with endogeneity, when randomization of treatment prior to analysis is not an option. Many of these methods rely on some form of an exclusion restriction for model identification, meaning that the researcher has to find a variable which is highly correlated with treatment (relevance), and at the same time not directly related to the outcome of interest (exogeneity). While the first requirement is easily tested, the second cannot be objectively verified in any satisfactory way, which means that it is left to the persuasive powers of the researcher to defend his approach and the resulting estimates. A way to avoid this is the so-called identification by functional form, where, as the name suggests, model identification is obtained through functional form assumptions rather than exclusion restrictions. An example for this is the (recursive) bivariate probit model, which is the model of choice if the impact of a binary treatment, such as receiving a micro credit, on a binary outcome, such as school enrolment, is investigated. Although maximum likelihood estimation yields consistent estimates when the model is correctly specified (meaning that errors come from the assumed bivariate normal distribution), robustness of the estimates in the face of misspecifications is often unclear. Another question is whether the effect of such misspecifications could be remedied by a valid instrument, or possibly even worsened by the use of a faulty (endogenous) one. While there already exists some research on sensitivity to wrong distribution assumptions of the errors (see Angrist, 1991, Bhattacharya et al., 2006, Monfardini and Radice, 2008 and, most recently, Chiburis et al., 2011), the question of the effect of both valid and endogenous exclusion restrictions on the resulting estimates has not yet been investigated. This chapter intents to fill this gap and analyzes the sensitivity of the recursive bivariate probit estimator, at first without an exclusion restriction, to different misspecifications of the error distribution, using a Monte Carlo simulation framework. In a second step, a valid exclusion restriction is added to the estimation to see to what extend (if at all) appropriate instruments can "make up" for non-normal error distributions. Finally, the model is estimated using a faulty (endogenous) instrument. The aim is to give some guidance for the practitioner, who usually has no way of knowing whether his exclusion restrictions are valid or not, and is therefore confronted with the decision of either relying on the functional form assumption and estimating impact without an instrument, or including an instrument, at the risk of worsening the results due to violations of the (untestable) exogeneity condition.

The remainder of the chapter proceeds as follows: In section two, the recursive bivariate probit model is introduced. Section three then describes the set up of the simulation, while results are presented in section four. Section five concludes.

## 3.2 The recursive bivariate probit model

### General specification of the bivariate probit model

In the bivariate probit model, two equations with binary outcomes and correlated error terms are estimated simultaneously. The general specification is (see Greene, 2003):

$$\begin{aligned} y_{1i}^* &= \boldsymbol{\beta}_1' \boldsymbol{x}_{1i} + \epsilon_{1i}, \quad y_{1i} = 1 \quad \text{if } y_{1i}^* > 0\,,\, 0 \text{ otherwise} \\ y_{2i}^* &= \boldsymbol{\beta}_2' \boldsymbol{x}_{2i} + \epsilon_{2i}, \quad y_{2i} = 1 \quad \text{if } y_{2i}^* > 0\,,\, 0 \text{ otherwise} \end{aligned}$$

where $\boldsymbol{x}_{1i}, \boldsymbol{x}_{2i}$ are vectors of covariates, and $\boldsymbol{\beta}_1, \boldsymbol{\beta}_2$ are the corresponding coefficient vectors.

$y_{1i}^*, y_{2i}^*$ are the unobserved latent variables determining the observed binary outcomes $y_{1i}, y_{2i}$. Errors are assumed to come from a bivariate normal distribution and to be indentically and independently distributed, i.e.

$$\begin{pmatrix} \epsilon_{1i} \\ \epsilon_{2i} \end{pmatrix} \sim IIDN \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right).$$

### Estimation

This model is estimated using maximum likelihood. The recursive bivariate probit is a slightly different version of the above specified model, where the left-hand variable of the first equation is used as an explanatory variable in the second one:

$$\begin{aligned} y_{1i}^* &= \boldsymbol{\beta}_1' \boldsymbol{x}_{1i} + \epsilon_{1i}, \qquad\qquad y_{1i} = 1 \quad \text{if } y_{1i}^* > 0\,,\, 0 \text{ otherwise} \\ y_{2i}^* &= \boldsymbol{\beta}_2' \boldsymbol{x}_{2i} + \gamma y_{1i} + \epsilon_{2i}, \quad y_{2i} = 1 \quad \text{if } y_{2i}^* > 0\,,\, 0 \text{ otherwise} \end{aligned}$$

The log-likelihood is given by (Maddala, 1983, with some notational changes)

$$l(\beta) = \sum_{i=1}^{N} \left[ d_{11} ln P_i^{11} + d_{10} ln P_i^{10} + d_{01} ln P_i^{01} + d_{00} ln P_i^{00} \right],$$

where

$$\begin{aligned}
d_{11} &= y_{1i}y_{2i},\ d_{10} = y_{1i}(1-y_{2i}),\ d_{01} = (1-y_{1i})y_{2i},\ d_{00} = (1-y_{1i})(1-y_{2i}) \\
P_i^{11} &= Prob(y_{1i}=1,\ y_{2i}=1|x_{1i}, x_{2i}) = \Phi_{i2}(\boldsymbol{\beta}_1^{'}\boldsymbol{x}_{1i},\ \gamma + \boldsymbol{\beta}_2^{'}\boldsymbol{x}_{2i},\ \rho) \\
P_i^{10} &= \Phi_{i2}(\boldsymbol{\beta}_1^{'}\boldsymbol{x}_{1i},\ -\gamma - \boldsymbol{\beta}_2^{'}\boldsymbol{x}_{2i},\ -\rho) \\
P_i^{01} &= \Phi_{i2}(-\boldsymbol{\beta}_1^{'}\boldsymbol{x}_{1i},\ \boldsymbol{\beta}_2^{'}\boldsymbol{x}_{2i},\ -\rho) \\
P_i^{00} &= \Phi_{i2}(-\boldsymbol{\beta}_1^{'}\boldsymbol{x}_{1i},\ -\boldsymbol{\beta}_2^{'}\boldsymbol{x}_{2i},\ \rho),
\end{aligned}$$

and $\Phi_{i2}(.,.,\rho)$ is the cdf of the bivariate normal distribution of the error terms.

#### Endogeneity problem and approaches

This recursive specification is useful when modelling a binary outcome ($y_{2i}$), which is influenced by a binary treatment ($y_{1i}$), e.g. the impact of having received a microcredit on whether children are enrolled in school, or a binary measure of life satisfaction. The regressor $y_{1i}$ is clearly endogenous, which follows from the fact that $Corr[\epsilon_{1i}, \epsilon_{2i}|\mathbf{x}_{1i}, \mathbf{x}_{2i}] = \rho \neq 0$. To guarantee identification in this case, usually such models are estimated using at least one exclusion restriction, $z_i$ (also called instrument), which is included only in the regressor vector of the first equation. These exclusion restrictions are required to be exogenous, meaning that $Cov(z_i, \epsilon_{2i}) = 0$.

The two common approaches of dealing with this problem are the bivariate probit model introduced above, as well as the (linear) two-stage IV estimator. However, when comparing the two (for a detailed comparison see Chiburis et al., 2011), the bivariate probit model exhibits some advantages over the IV estimator. Firstly, bivariate probit estimation is more flexible with regard to the different treatment effects, which it can consistently estimate. In the evaluation literature, three main treatment effects are used, namely the average treatment effect (ATE), the average treatment effect on the treated (ATT) and the local average treatment effect (LATE). They are defined as shown below:

$$\begin{aligned} ATE &= E[Y_1] - E[Y_0] \\ ATT &= E[Y_1|T=1] - E[Y_0|T=1] \\ LATE &= \frac{E[Y|Z=1] - E[Y|Z=0]}{E[T|Z=1] - E[T|Z=0]} \end{aligned}$$

where $Y_1$ is our outcome variable $y_{2i}$ if treatment was received (i.e. $y_{1i} = 1$), and $Y_0$ is the control case without treatment. $T$ indicates reception of treatment (meaning that it is equal to 1 if $y_{1i} = 1$ and zero otherwise), and $Z$ is a valid (binary) exclusion restriction as defined above. As can be seen, the ATE measures impact of treatment as an average over the entire population, while the ATT averages only over treated individuals. The LATE further differentiates the population according to treatment received based on the value of the instrumental variable.

While the IV approach can only consistently estimate the LATE, the (correctly specified) bivariate probit model yields consistent estimates for all three effects. (see Chiburis et al., 2011 for details on the relationship between the raw coefficients of the model and the different treatment effects). In addition to that, when comparing the variances of LATE estimates between IV and the bivariate probit, the bivariate probit estimator is generally more efficient.[1]
Another advantage of the bivariate probit approach, which is in the focus of this chapter, is the possibility of estimating treatment impact without a valid exclusion restriction.

For some time a valid exclusion restriction was considered the only feasible way of estimating the impact of endogenous treatment, also when the bivariate probit model was used, following Maddala, 1983. However, as Wilde, 2000 shows, Mad-

[1] Angrist, 1991 reaches a different conclusion here for some cases, however, this is most likely due to the fact that he compares two different effects, namely the ATE estimated by the bivariate probit and the LATE, estimated by the IV approach. Also, Chiburis et al., 2011 show that the bivariate probit estimator is more efficient as soon as additional covariates are included in the model.

dala's argumentation of lacking identification is only valid for a constant regressor. As soon as there is variation in the regressors, identification is given even without an exclusion restriction, as long as the regressor matrix is of full rank and the errors follow a bivariate normal distribution. Wilde shows this for the simple case of moving from a constant to a binary regressor. The same reasoning is also found in Greene, 2003. It can be shown analytically that identification by functional form yields consistent estimates of the model coefficients if errors indeed follow a bivariate normal distribution. The question remains as to how sensitive estimation is to violations of the distribution assumptions, and whether misspecifications can be remedied by including a valid instrument, or possibly further exacerbated by including a faulty (endogenous) one. In the following section, the simulation setup to investigate these questions will be explained.

## 3.3 Simulation setup

### 3.3.1 Model structure

To test the performance of the recursive bivariate probit estimator in the presence of various distributional misspecifications, a Monte Carlo simulation setup is used. To investigate the research questions stated earlier, two different underlying models generating data are tested, as will be outlined in more detail below. Note that all simulations will be run twice. The first time, all covariates $x$ are drawn from identical, independend standard normal distributions with $\mu = 0$ and $\sigma^2 = 1$, meaning that there is no correlation between covariates. In a second run, this assumption is relaxed and the $x$s are generated using a trivariate normal distribution such that

$$\begin{pmatrix} x_{1i} \\ x_{2i} \\ x_{3i} \end{pmatrix} \sim IIDN \left( \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0.1 & -0.03 \\ 0.1 & 1 & 0.05 \\ -0.03 & 0.05 & 1 \end{bmatrix} \right).$$

The reason for this is that in estimations with real data, covariates are likely to have at least a small degree of correlation between them, which then in turn affects model estimates when important explanatory variables are left out (omitted variable bias). Also, all simulations are done twice, once for a (more idealistic) sample size of 6000, and once for a more restricted data situation with only 500 observations.

**Model 1, containing an exclusion restriction**

For model 1 data are generated as outlined below:

$$\begin{aligned} y_{1i}^* &= \alpha_1 + \beta_{11}x_{1i} + \beta_{12}x_{2i} + \delta_1 x_{3i} + \epsilon_{1i}, & y_{1i} = 1 \quad \text{if } y_{1i}^* > 0\,,\, 0 \text{ otherwise} \\ y_{2i}^* &= \alpha_2 + \beta_{21}x_{1i} + \beta_{22}x_{2i} + \gamma y_{1i} + \epsilon_{2i}, & y_{2i} = 1 \quad \text{if } y_{2i}^* > 0\,,\, 0 \text{ otherwise} \end{aligned}$$

Here the data generating process contains a true instrument, namely $x_3$. Model 1 is estimated twice, once in the correct specification shown above, and once incorrectly (under)specified, not making use of the valid instrument:

$$\begin{aligned} y_{1i}^* &= \alpha_1 + \beta_{11}x_{1i} + \beta_{12}x_{2i} + \epsilon_{1i}, & y_{1i} = 1 \quad \text{if } y_{1i}^* > 0\,,\, 0 \text{ otherwise} \\ y_{2i}^* &= \alpha_2 + \beta_{21}x_{1i} + \beta_{22}x_{2i} + \gamma y_{1i} + \epsilon_{2i}, & y_{2i} = 1 \quad \text{if } y_{2i}^* > 0\,,\, 0 \text{ otherwise} \end{aligned}$$

**Model 2, not containing an exclusion restriction**

In addition to model 1, data are also generated using the following model:

$$\begin{aligned} y_{1i}^* &= \alpha_1 + \beta_{11}x_{1i} + \beta_{12}x_{2i} + \delta_1 x_{3i} + \epsilon_{1i}, & y_{1i} = 1 \quad \text{if } y_{1i}^* > 0\,,\, 0 \text{ otherwise} \\ y_{2i}^* &= \alpha_2 + \beta_{21}x_{1i} + \beta_{22}x_{2i} + \delta_2 x_{3i} + \gamma y_{1i} + \epsilon_{2i}, & y_{2i} = 1 \quad \text{if } y_{2i}^* > 0\,,\, 0 \text{ otherwise} \end{aligned}$$

As can be seen, the true underlying model does not contain an exclusion restriction. To simulate an endogenous instrument, the model is wrongly specified for the estimation, falsely treating $x_3$ as an exclusion restriction:

$$
\begin{aligned}
y_{1i}^* &= \alpha_1 + \beta_{11}x_{1i} + \beta_{12}x_{2i} + \delta_1 x_{3i} + \epsilon_{1i}, \quad y_{1i} = 1 \quad \text{if } y_{1i}^* > 0 \text{ , 0 otherwise} \\
y_{2i}^* &= \alpha_2 + \beta_{21}x_{1i} + \beta_{22}x_{2i} + \gamma y_{1i} + \epsilon_{2i}, \quad y_{2i} = 1 \quad \text{if } y_{2i}^* > 0 \text{ , 0 otherwise}
\end{aligned}
$$

Here $x_3$ is clearly endogenous.

### 3.3.2 Different bivariate error distributions

To test the sensitivity of the estimation of the raw coefficient $\gamma$ (which is crucial in deriving the aforementioned treatment effects) to misspecifications of the error-term distribution, data are generated using errors from various bivariate non-normal distributions. To increase flexibility, errors were generated using copulas.

**Copulas** Copulas are a very convenient and flexible tool to facilitate random draws from multivariate probability distributions. Using a copula, one can construct a multivariate distribution by specifying marginal univariate distributions, and choosing a particular copula to provide a correlation structure between variables. A copula therefore gives the possibility to seperate the marginal distribution from the correlation structure. The marginal distributions of the respective variables need not be the same, thus allowing combinations of different marginals within one multivariate distribution.
More formally, a copula is a multivariate distribution, where all marginals follow a uniform distribution. For an n-dimensional random vector $U$ on the unit cube, a copula $C$ is defined as (Yan, 2007 with slight notational changes):

$$C(u_1, ....., u_n) = Pr(U_1 \leq u_1, ....., U_n \leq u_n)$$

Since by making use of the so-called probability integral transformation, any continuous random variable can be transformed to be uniformly distributed by being plugged into its respective CDF, copulas can be used to provide multivariate dependence structures seperately from the marginal distributions. Sklar's theorem shows the relationship between an n-dimensional multivariate distribution function $F$ with margins $F_1, ....., F_n$ and an n-dimensional copula $C$:

$$F(x_1, .....x_n) = C\left(F_1(x_1), ....., F_n(x_n)\right)$$

The flexibility of copulas, which makes it possible to combine any marginal distribution with a chosen correlation structure becomes apparent when Sklar's theorem is reversed. Let $F_i^{-1}$ denote the inverse of $F_i$, the CDF of the ith margin. By making use of the so-called inversion method, a uniformly distributed variable can be transformed into any distribution $F$ by plugging it into its inverse $F^{-1}$:

$$C(u_1, ....., u_n) = F\left(F_1^{-1}(u_1), ....., F_n^{-1}(u_n)\right)$$

The choice of the multivariate CDF $F$ depends on the taste of the researcher. In the current chapter, a Gaussian copula is used, meaning that $F$ is the CDF of a bivariate normal distribution.
It needs to be kept in mind that due to the two-step non-linear transformation process of the variables (first they are converted to be uniformly distributed, then they are transformed to the respective marginals needed), the correlation structure between the random variables is no longer linear, and $\rho$ can therefore not be measured meaningfully by the linear correlation coefficient. However, this should not affect the validity of the results, since with real-life data correlation might also be non-linear.

To make the sensitivity analysis as comprehensive as possible, error distributions both close to the normal distribution, as well as those quite far away from it were used for the simulations. The bivariate t-distribution (df = 3) was chosen for its heavy tails, as well as the bivariate lognormal distribution for its skewness. Also, a combination of the two (meaning that $\epsilon_1 \sim t$ and $\epsilon_2 \sim lognorm$) was analyzed. All distributions were centered and scaled to have $\mu = 0$ and $\sigma = 1$. The extend of endogeneity (i.e. $\rho_1$) was varied, using $\rho = +/-0.01, 0.25, 0.5, 0.75, 0.9$[2]

[2]Note that for reasons related to programming, the parameter $\rho$ was defined as $+/-\frac{10}{1000}, \frac{10}{40}, \frac{10}{20}, \frac{10}{13}, \frac{10}{11}$, which leads to slightly bigger values for the last two specifications (i.e. 0.77 and 0.91 instead of 0.75 and 0.9)

The density plots in figures 3.4-3.7 give a visual idea of the shapes of the various error distributions.

### 3.3.3 Different response frequencies of $y_1$ and $y_2$

In addition to varying the error distributions, different frequencies of the outcomes $y_1$ and $y_2$ are used. Five different versions were generated:[3]

1. A balanced distribution of both outcomes, where $y_1$ and $y_2$ are equal to 1 in about 50 % of the observations (DGP1).
2. $y_1$ is mostly zero (around 75 %), and $y_2$ is mostly 1 (around 75 %) (DGP2).
3. $y_1$ is mostly 1 (around 75%), and $y_2$ is mostly 0 (around 75%) (DGP3).
4. Both $y_1$ and $y_2$ are mostly 0 (around 75%) (DGP4).
5. Both $y_1$ and $y_2$ are mostly 1 (around 75%) (DGP5).

All of these five DGPs where simulated with all 4 different error distributions and for both models. Note that error distributions other than the bivariate normal, as well as different degrees of correlation, $\rho$, lead to slight shifts in the distributions of outcomes $y_{1i}$ and $y_{2i}$. However, the general direction remains true throughout the different $\rho$s and error distributions. It was also assured that cell population for all combinations of $y_1$ and $y_2$ never falls below 1 %, since this would cause severe bias, as well as convergence problems for the estimation. Also, the absolute value of $\gamma$, the coefficient in question, always equals 1.2, so that the magnitude of the MSE can be easily interpreted and compared across simulations.

### 3.3.4 Measuring performance

Since the true data generating process is known, the mean squared error can be calculated and compared among different erroneous distributional assumptions and

[3]Differences in probabilities for $y_1$ and $y_2$ where achieved by varying the constants $\alpha_1$ and $\alpha_2$, as well as, to a lesser extend, the coefficients of the $x$ covariates. The absolute value of the coefficient of interest, $\gamma$, remains unchanged at 1.2 for comparison across estimations.

therefore be used as measure of quality for the estimation. Making use of the fact that

$$MSE(\hat{\gamma}) = E\left[(\hat{\gamma} - \gamma)^2\right] = Var(\hat{\gamma}) + (Bias(\hat{\gamma}, \gamma))^2 \,,$$

the MSE is then further decomposed into variance and bias.

## 3.4 Results

The figures on pages 75-79 in the appendix show the simulation results for uncorrelated covariates and a sample of 6000 observations. The first column contains estimations without an instrument. In the second column, results for a valid instrument are shown, while in the last column the instrument is endogenous. The MSE is decomposed into squared bias and variance as shown above, where the blue dots denote the MSE, and the red dots indicate the mean squared bias. The difference between the two dots for each value of $\rho$ (which is denoted on the x-axis) can therefore be interpreted as the mean variance. The most prominent finding emerging is that the effect of non-normal errors varies quite strongly with the response frequencies of $y_1$ and $y_2$. While in general results can be considered best for the balanced case (i.e. DGP 1), bias as well as variance are substantial for the more extreme DGPs. Both results are consistent with those of Chiburis, Das and Lokshin. For the unbalanced DGPs it can be observed that skewness seems to be a much bigger problem than high kurtosis, or a combination of both. A puzzling exception is DGP 3, which yields surprisingly good results for the lognormal error distribution, while it has worst bias (and also convergence problems) for the normally distributed errors. However, keeping in mind that the true coefficient has an absolute value of 1.2, the size of the bias is generally unacceptable[4] if errors follow a highly skewed distribution.

Another somewhat counterintuitive finding is the excellent performance of the esti-

[4]The question of which magnitude of bias can still be considered acceptable is somewhat philosophical. In the present simulation, where the absolute value of the true parameter of interest, $\gamma$, is 1.2, a mean squared bias of 0.2 corresponds to a mean difference of around 0.45 between the average over the estimates and the true parameter, which in most applications would probably already be considered too high.

mator for normal errors, if most $y_1$ are equal to zero and most $y_2 = 1$ (i.e. DGP2). While this constellation leads to severe bias if errors are lognormally distributed, results for the normal case are even better in terms of both bias and variance than for the balanced case of DGP1. While no clear patterns emerge when looking at the results for the t-distribution and the mixed distribution, it seems that the variance in the case of normally distributed errors is highest for error correlation around zero. Most likely this is due to the fact that the estimator is based on the assumption that $\rho \neq 0$, meaning that it less efficient for cases where correlation actually is almost non-existent. Note that this only affects efficiency, while bias remains low throughout the different magnitudes of $\rho$. The opposite can be observed for lognormally distributed errors. Here both variance and bias increase with higher correlation. However, this pattern seems to be specific for DGP1. For DGPs 4 and 5, a clear increase in both bias and variance with $\rho$ can be seen, while this relationship is reversed for DGP2.

The results also suggest that an exclusion restriction can in some cases indeed improve the estimation in the face of non-normal errors, however, the improvement is quite subtle, with the mean squared bias remaining above acceptable levels in most cases. Although a full comparison between model 1 (no instrument and valid instrument) and 2 (endogenous instrument) is not possible, due to the different underlying data generating processes, using an endogenous instrument does not seem to seriously worsen results both in terms of bias and variance. The only case where a noticeable (yet still comparatively small) increase in bias can be observed is when errors are normally distributed. Apart from this, there actually might be situations, most noticeably for DGPs 4 and 5, where the inclusion of even an endogenous instrument improves estimation for non-normal errors both in terms of variance and bias, compared to a model specification without exclusion restriction. It is, however, unclear to what extend this is an artefact of comparing the different underlying models 1 and 2, and again, bias remains quite high.

Since for real-life data there most likely exists some sort of correlation between the covariates, the simulation was repeated drawing $x_{1i}, x_{2i}$ and $x_{3i}$ from a trivariate normal distribution, as outlined in the previous section. Letting covariates be correlated allows for possible omitted variable bias, which was not accounted for in the above simulation. Although this makes the results from the two models less comparable, it nevertheless comes closer to reality, since usually covariates in a model are at least slightly correlated with each other. Interestingly enough, however, results are almost identical to the uncorrelated case (see figures on pages 85-89 in the appendix).[5]

Finally, the simulation was repeated using a more realistic sample size of 500. Since the bivariate probit estimator is a maximum-likelihood estimator, consistency is approached asymptotically only for comparatively large sample sizes. Some evidence for this can already be seen for the simulation with uncorrelated covariates (see the figures on pages 80-84 in the appendix). While the overall conclusions for the case of 6000 observations still more or less hold, bias as well as variance increases on average. Even for normally distributed errors, bias seems inacceptably large, leading to the conclusion that a bivariate probit analysis should only be performed with sufficiently large samples. Just which sample size is "sufficiently large" again is a relative question, which also highly depends on the number of parameters to be estimated and cannot be generally answered by this chapter.

Overall, results show that departures from normality can have substantial effects on the estimates. Therefore, the use of a test for normality is recommended. There exists a score test by Murphy (see Murphy, 2007, as well as Chiburis, 2010 for details), which detects skewness and kurtosis, and which was included in the simulation. While the test was quite powerful for the large sample size, power noticeable decreased for the small sample, leading to wrong assumptions of normality.

## 3.5 Conclusion

In this chapter the sensitivity of the (recursive) bivariate probit estimator to various misspecifications of the error terms was tested via Monte Carlo simulation. Results suggest that departures from normality lead to a noticeable increase in bias, especially if the error distribution is highly skewed. Unfortunately, no truly

[5]This is possibly due to the rather low correlation assumed here. Further simulations with varying degrees of correlation between the regressors are needed to fully investigate this aspect. However, it needs to be kept in mind that high correlations between regressors lead to estimation problems in their own right, such as multicollinearity, which are additional to the identification problems investigated here.

reliable test for normality exists in this case. While Murphy's score test, which was used in this simulation, yields quite reliable results for the bigger sample size, it is unclear how variations in sample size and number of model covariates will affect its power. Results for the small sample of 500 observations already suggest a noticeable deterioration. Also, the frequencies of the two outcome variables $y_1$ and $y_2$ play a crucial role in combination with the error term distribution. It was also shown that the inclusion of a valid instrument in general is no sufficient remedy for misspecified errors, although in some cases bias can be reduced somewhat. Since exogeneity of an instrument is not testable the question arises whether the harm of including a faulty (endogenous) instrument could outweigh the potential (yet small) benefits of using a correct one. While an endogenous instrument noticeably increases bias if the error distribution is normal, if the marginal distribution of outcomes is such that both $y_1$ and $y_2$ have a low probability of occuring (i.e. DGP4), the inclusion even of a faulty instrument could somewhat reduce bias if errors are non-normal. Nevertheless, the general rules of thumb for the practitioner which can be derived from this simulation are:

- Normality of errors is crucial. If errors appear to be non-normal, results should be treated with great caution, or the analyst should resort to a different type of analysis. To test for normality of errors, Murphy's score test is recommended with all warranted caution.[6]

- The response frequencies of the two binary outcomes play an important role. All departures from a balanced distribution (i.e. DGP1) can lead to severe bias, if the distribution is non-normal.

- If errors can be assumed to be normal, rely on identification by functional form, rather than increasing bias by including a possibly endogenous instrument.

[6]It should be noted that normality of errors does not fully determine the functional form of the two equations of the bivariate probit, but only determines linearity in $\epsilon_1$, since with bivariate normal errors $E(\epsilon_2|\epsilon_1) = \frac{\sigma_{12}}{\sigma_1^2}\epsilon_1$ (where $\sigma_{12} = Cov(\epsilon_1, \epsilon_2)$). This means that it does not secure the researcher against possible misspecifications of the other effects in the model. This, however, is a general problem which is beyond the scope of this chapter.

- Sample size is important. In the case of two to three continuous covariates, sample size should probably be bigger than 500. It needs to be kept in mind that the power of the recommended Murphy's score test for normality of the errors also decreases with smaller sample size, thus exacerbating the problem.

# Appendix

Figure 3.1: Employment in the manufacturing sector 2007-2009

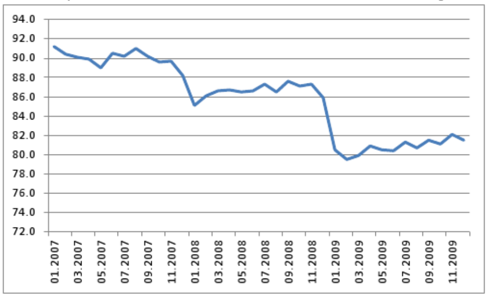



Figure 3.2: Employment in the agricultural sector 2007-2009

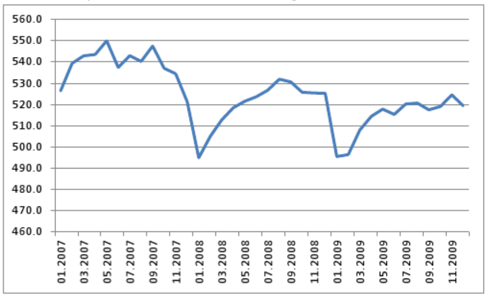



Figure 3.3: Employment in the non-production sector 2007-2009

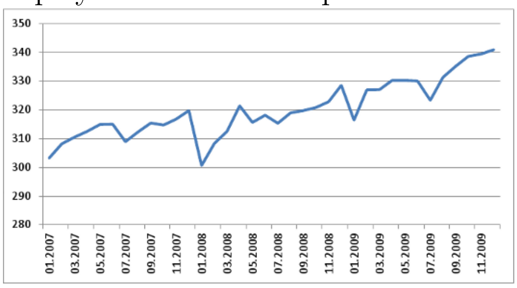


Figure 3.4: Bivariate normal distribution

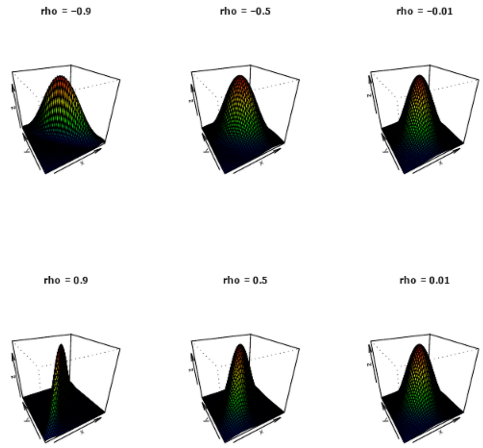



Figure 3.5: Bivariate t distribution

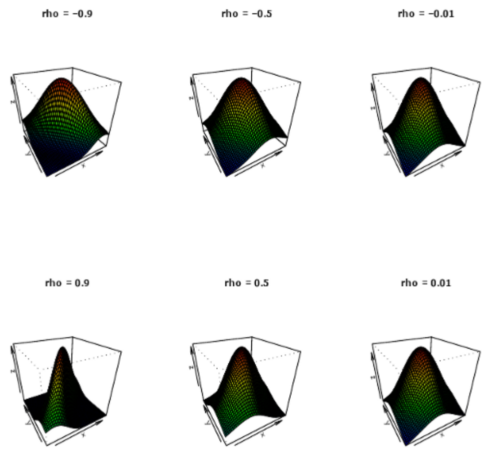


Figure 3.6: Bivariate lognormal distribution

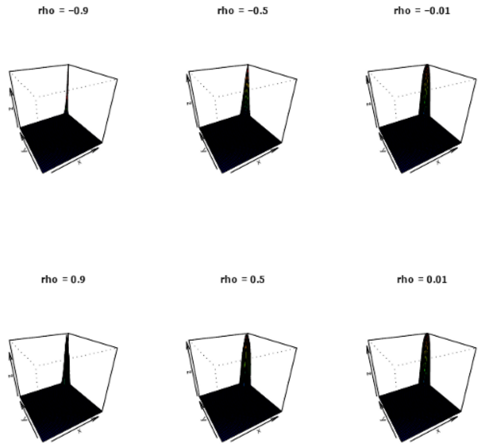
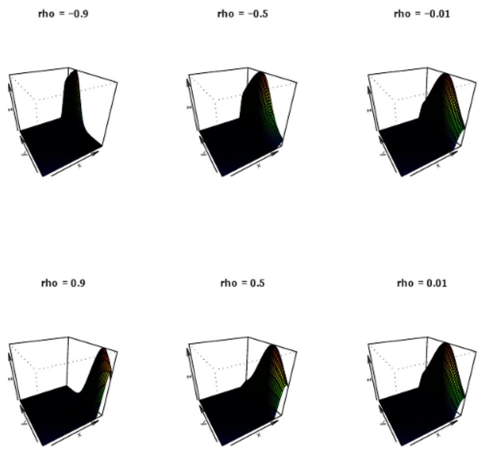
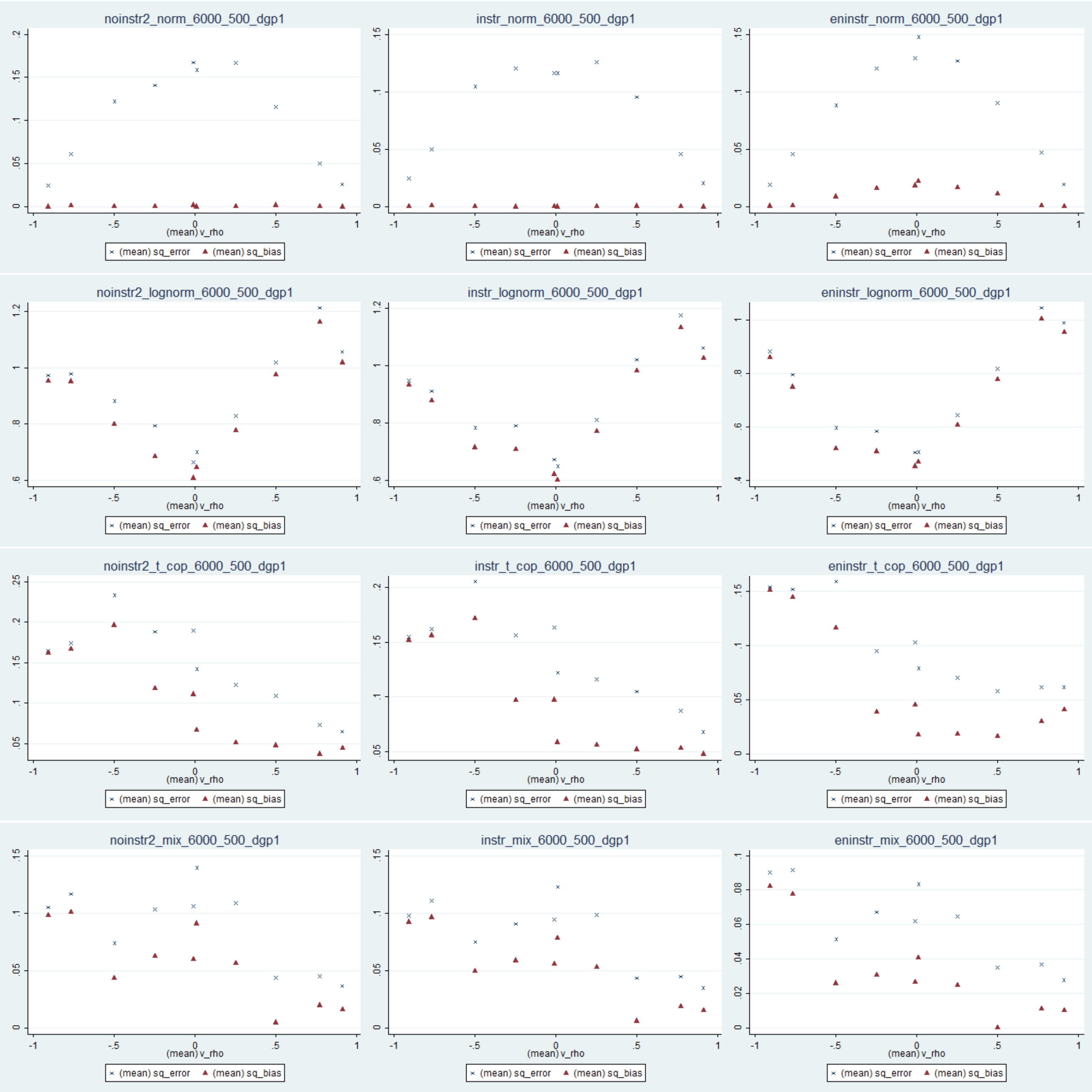



Figure 3.7: Bivariate lognormal-t distribution



# DGP1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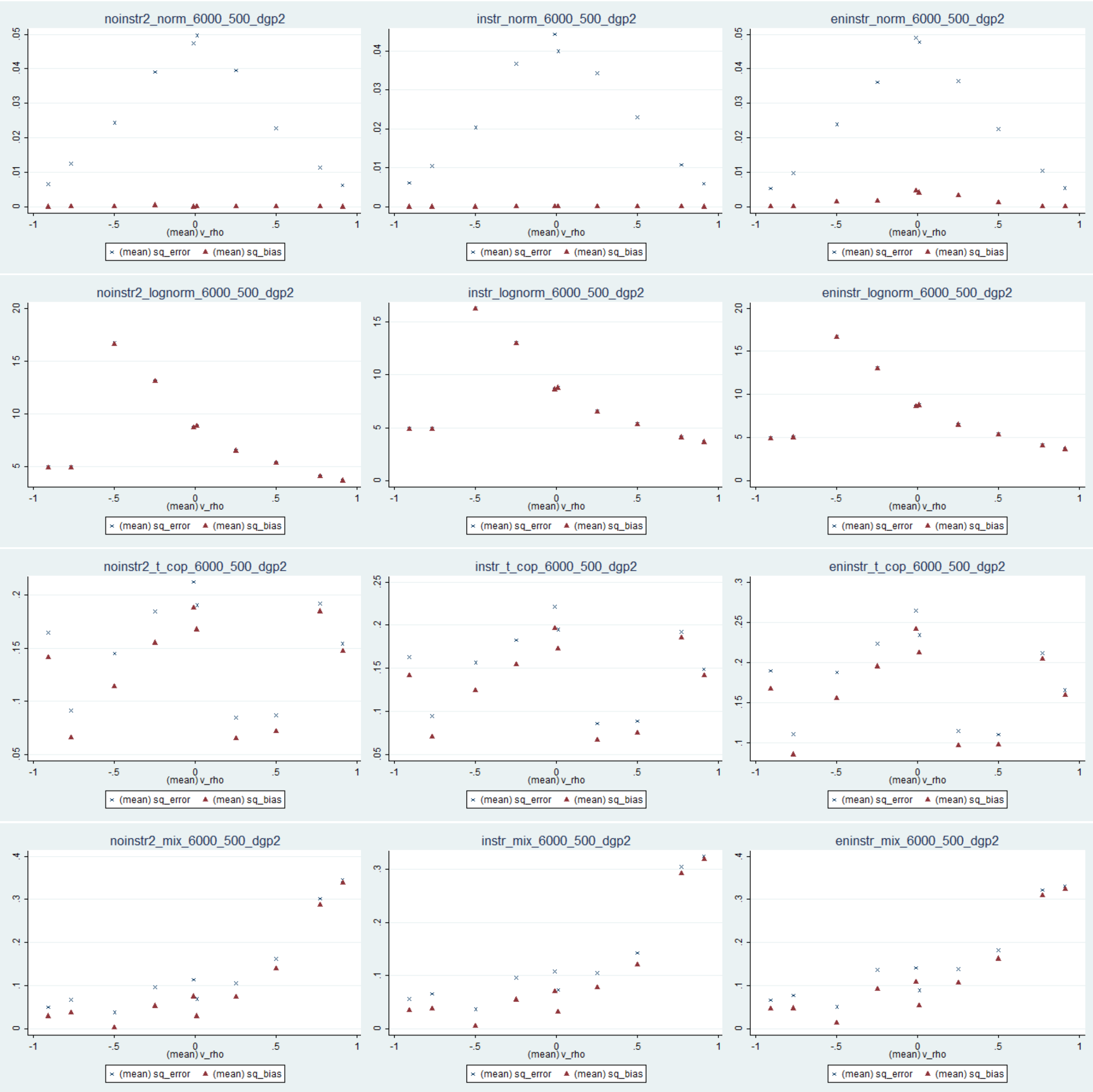
(mean) sq_bias

# DGP2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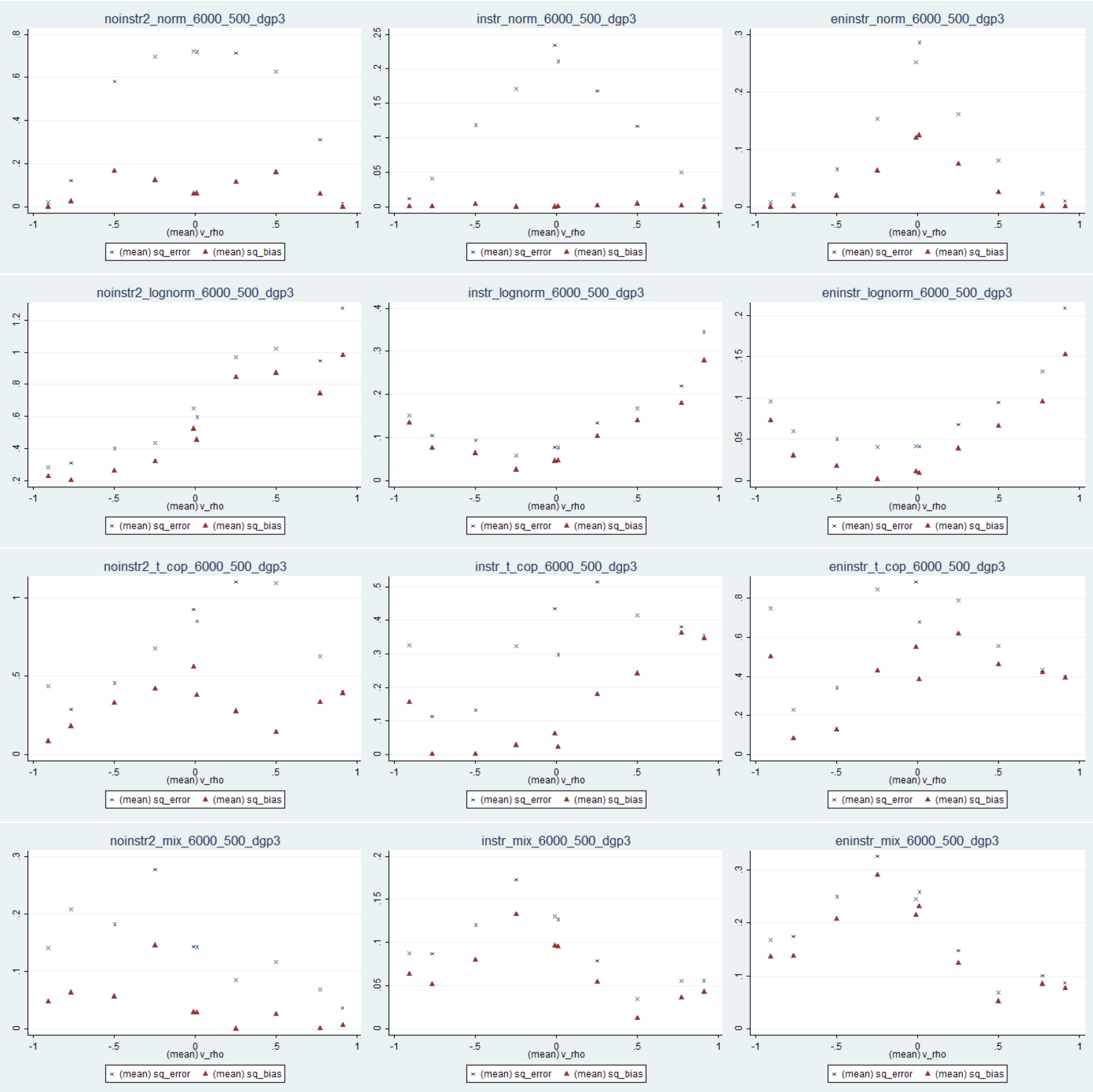
(mean) sq_bias

# DGP3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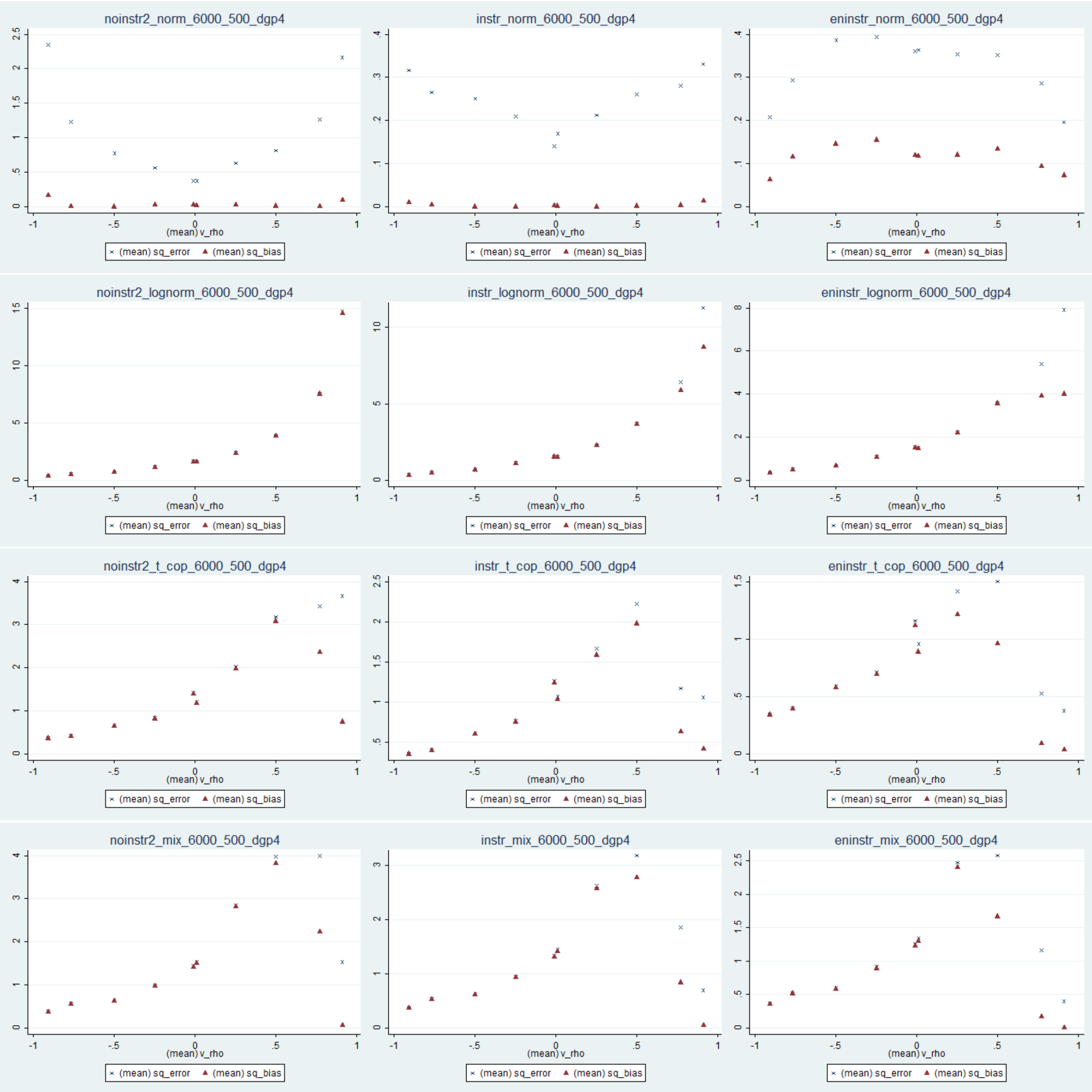
(mean) sq_error
(mean) sq_bias

# DGP4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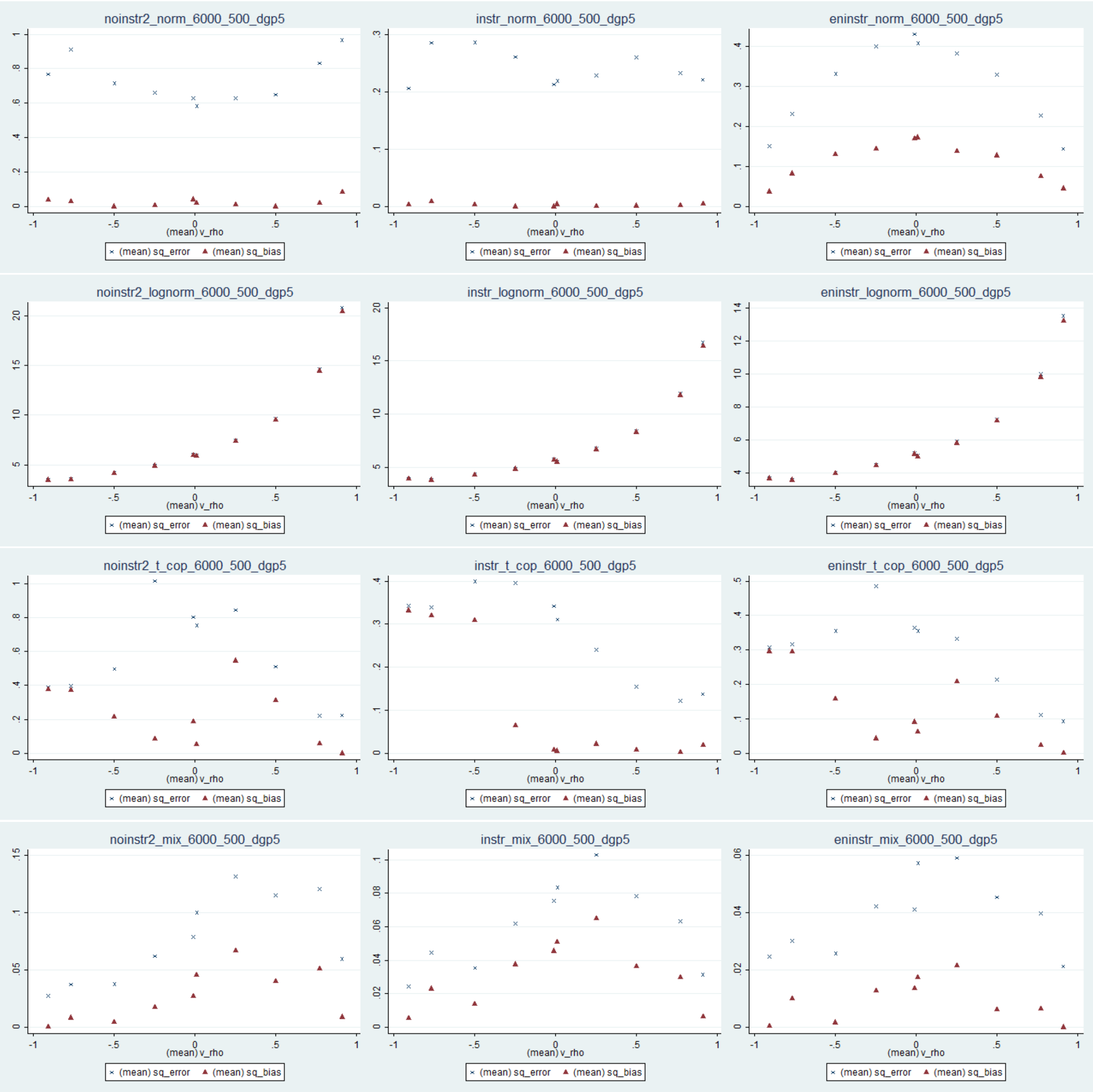
(mean) sq_bias

# DGP5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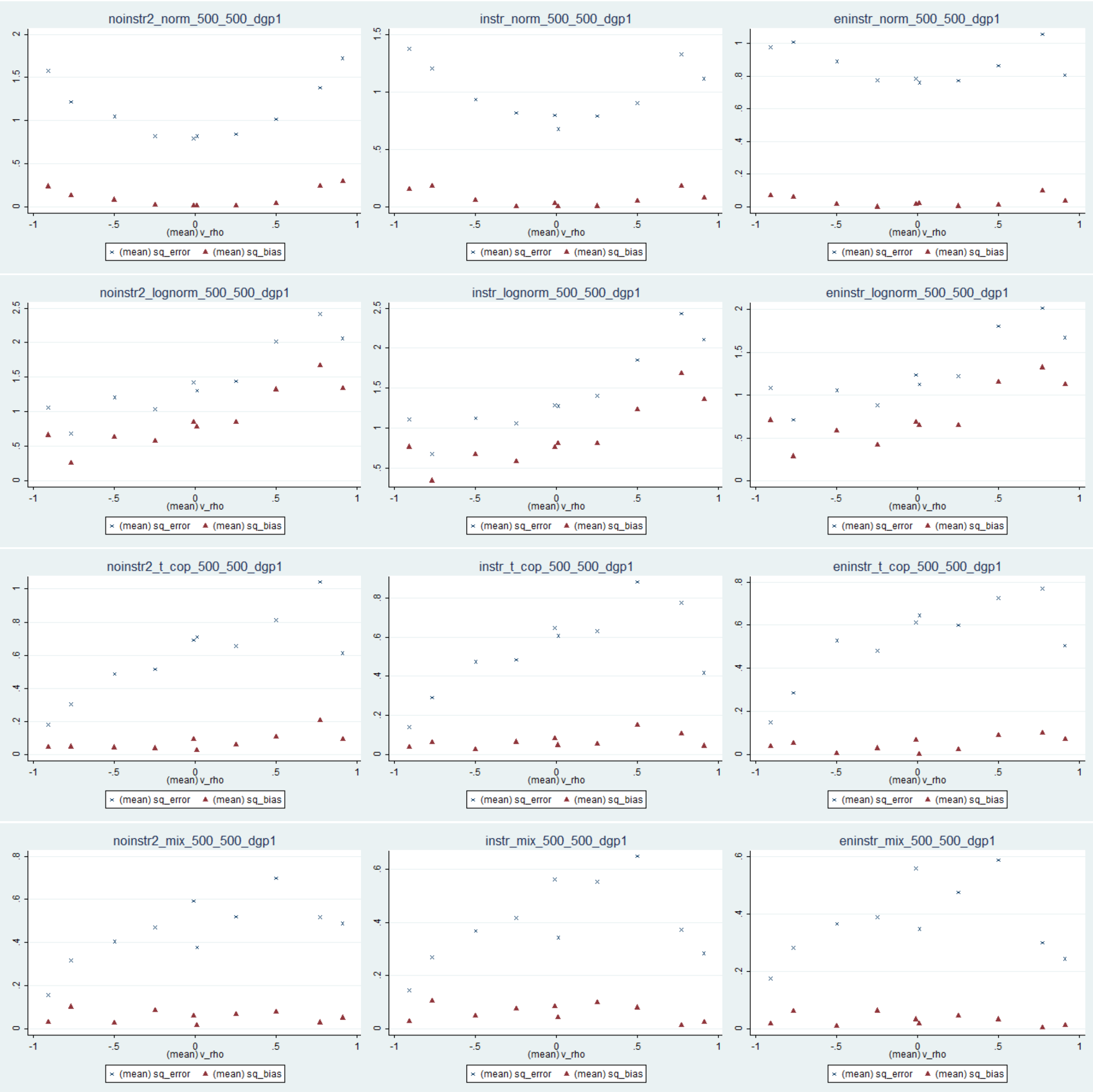
(mean) sq_error
(mean) sq_bias

# DGP1, 500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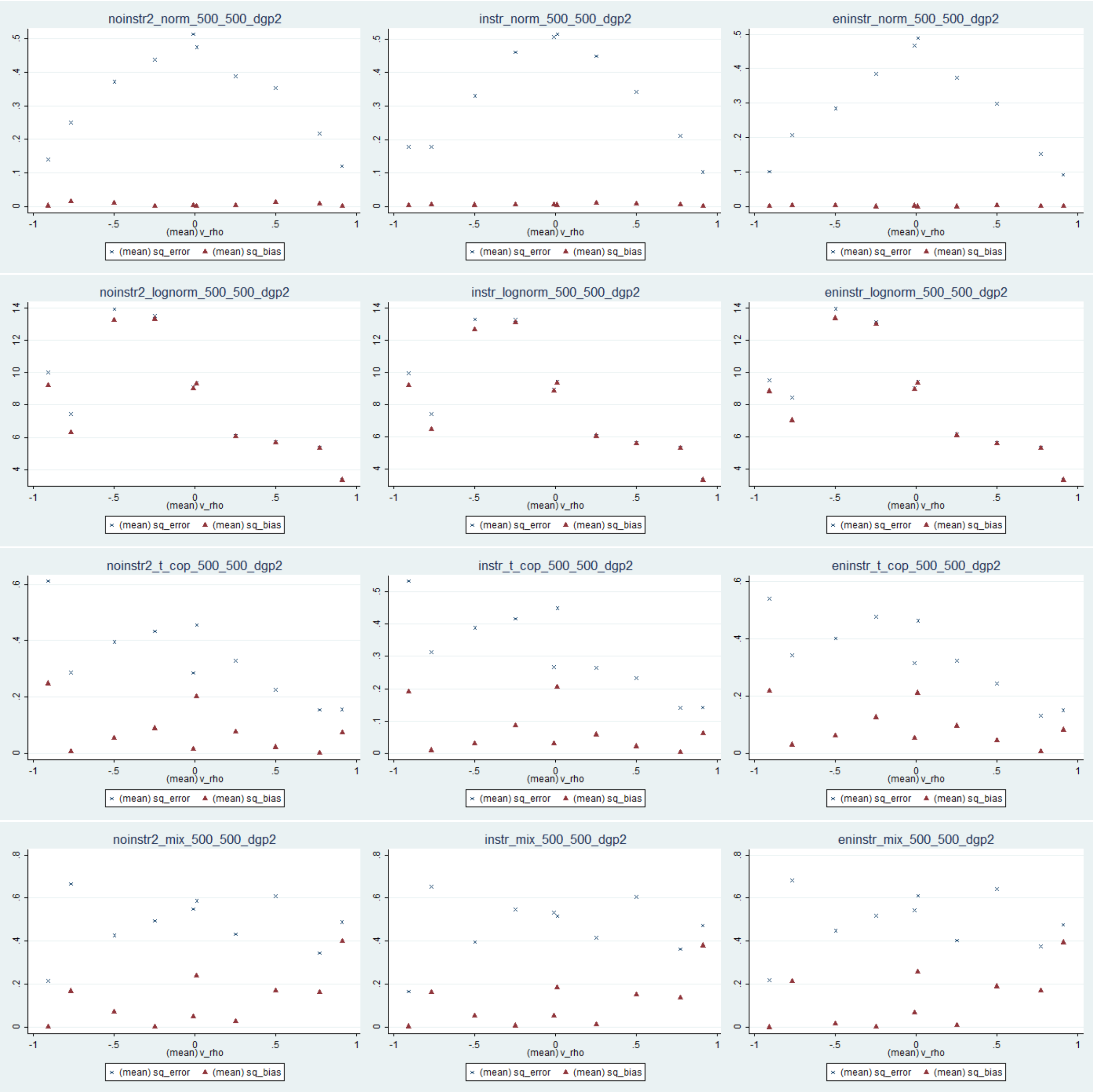
# DGP2, 500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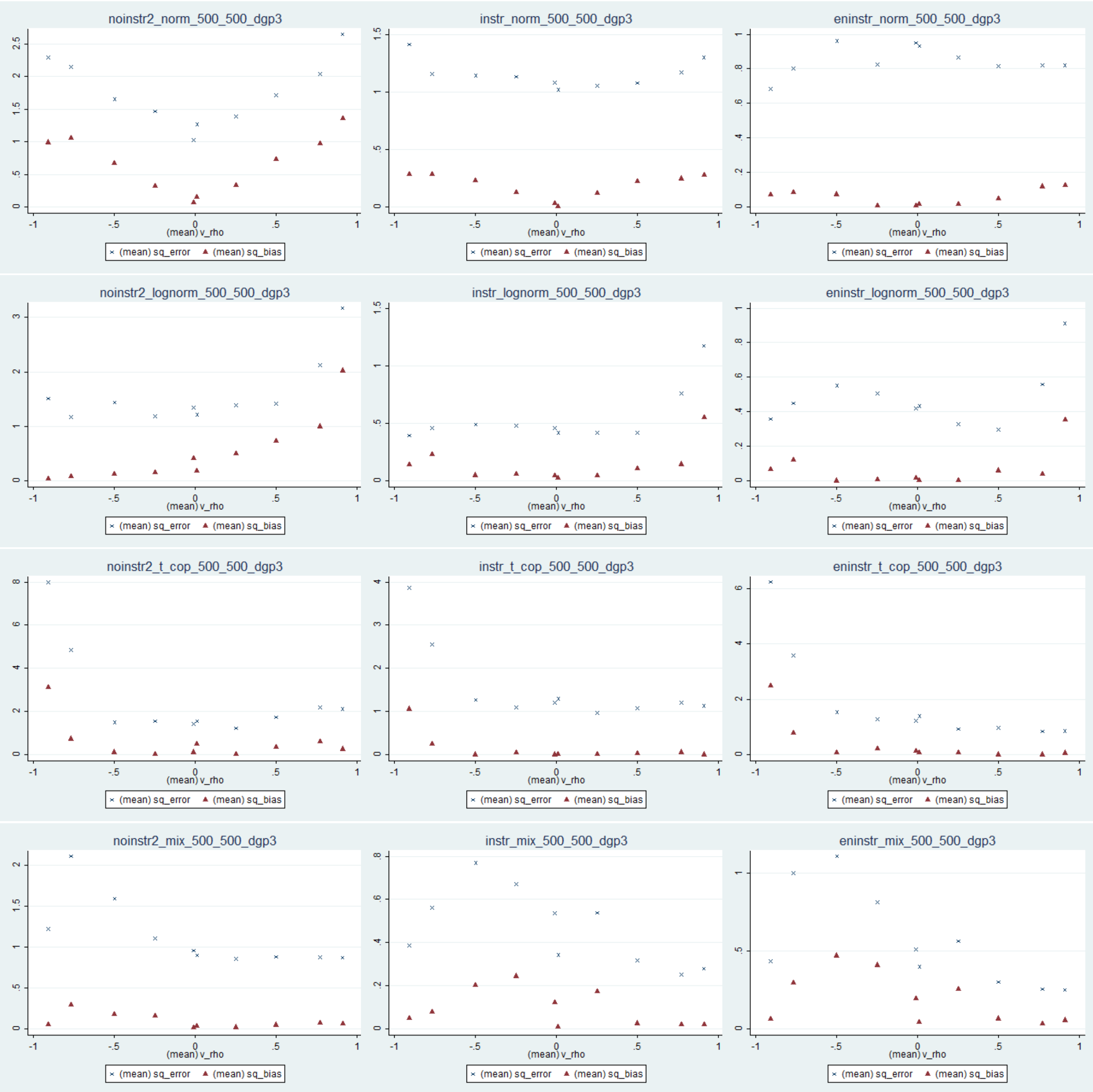
(mean) sq_bias

# DGP3, 500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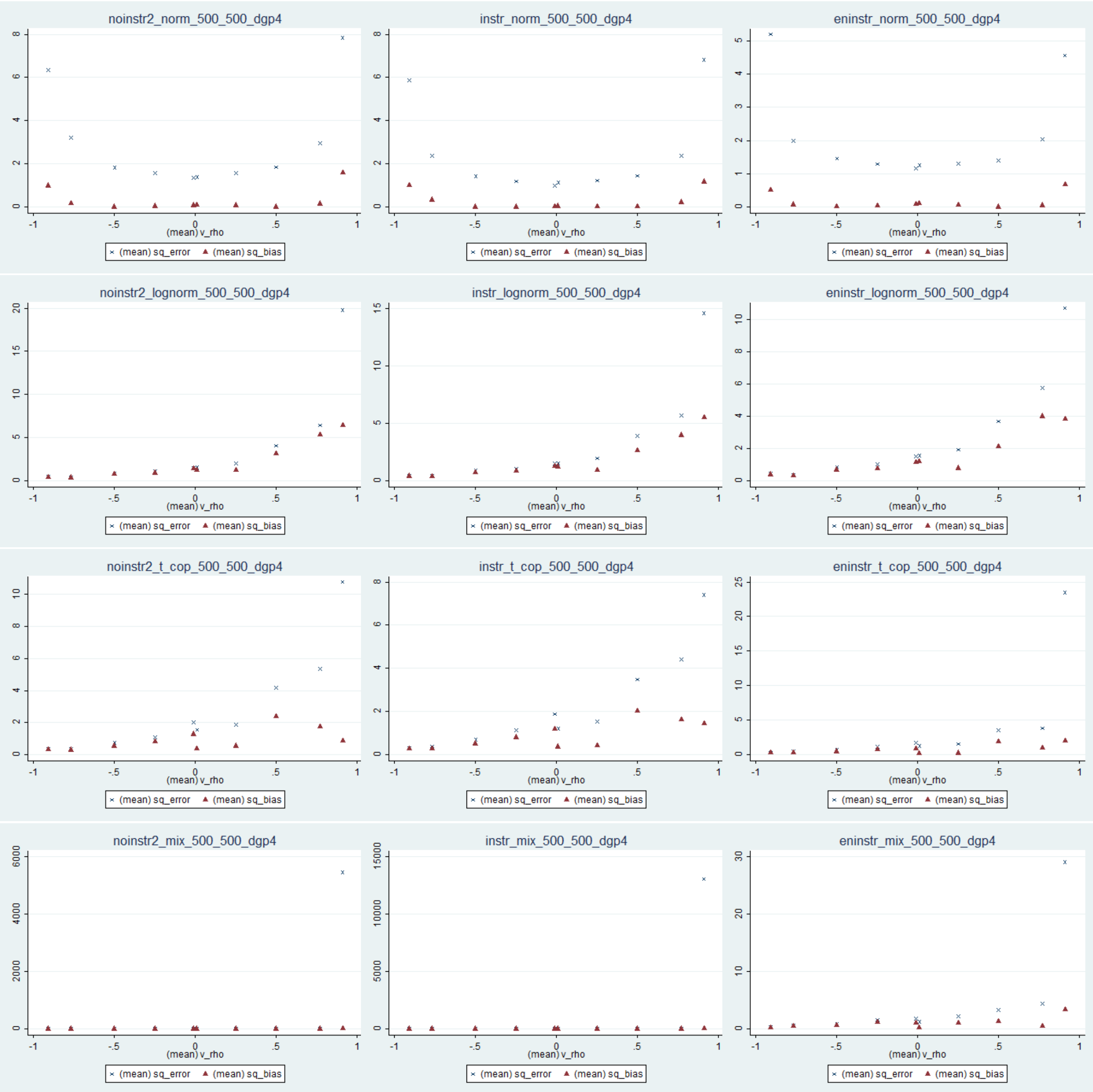
(mean) sq_bias

# DGP4, 500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eninstr_mix_500_500_dgp4
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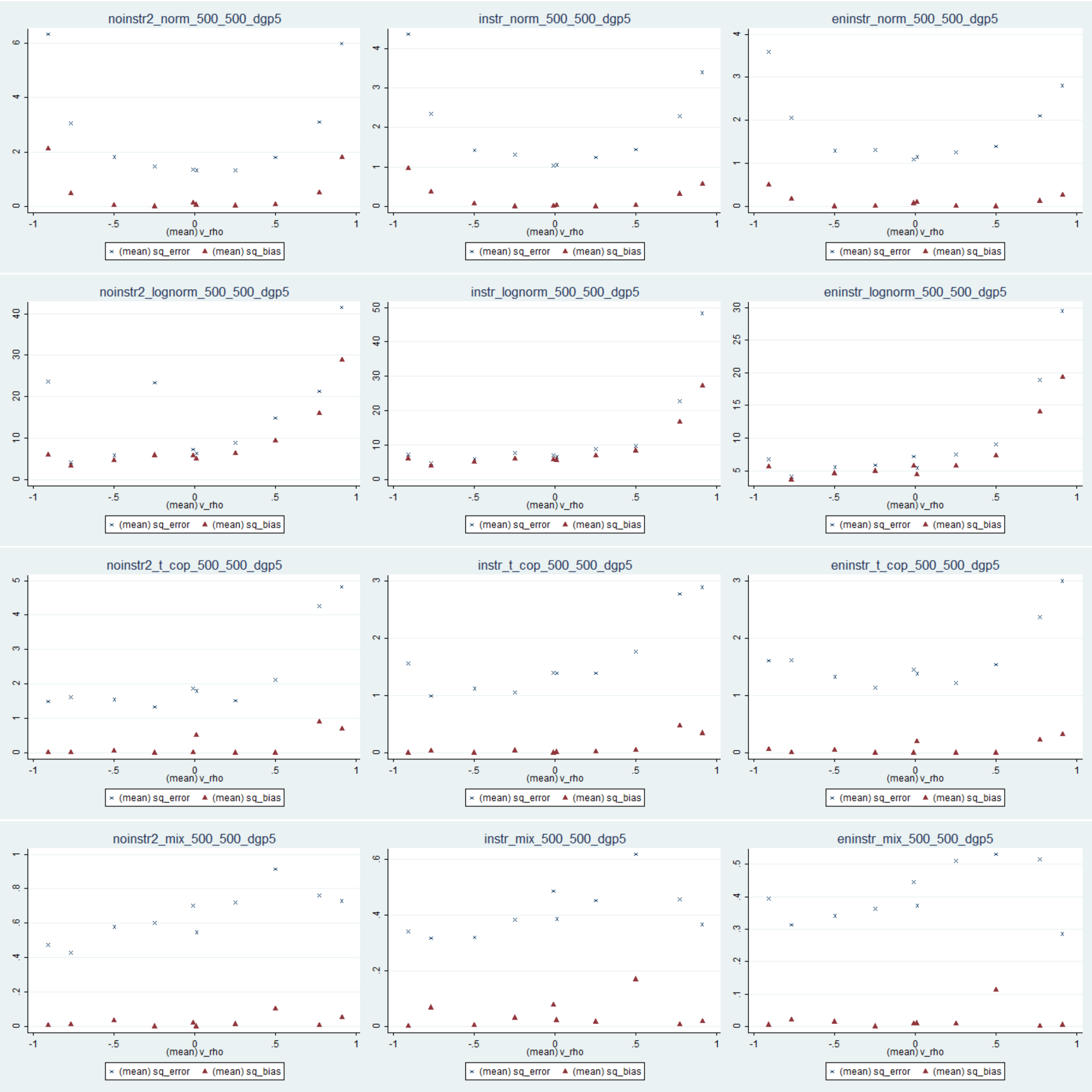
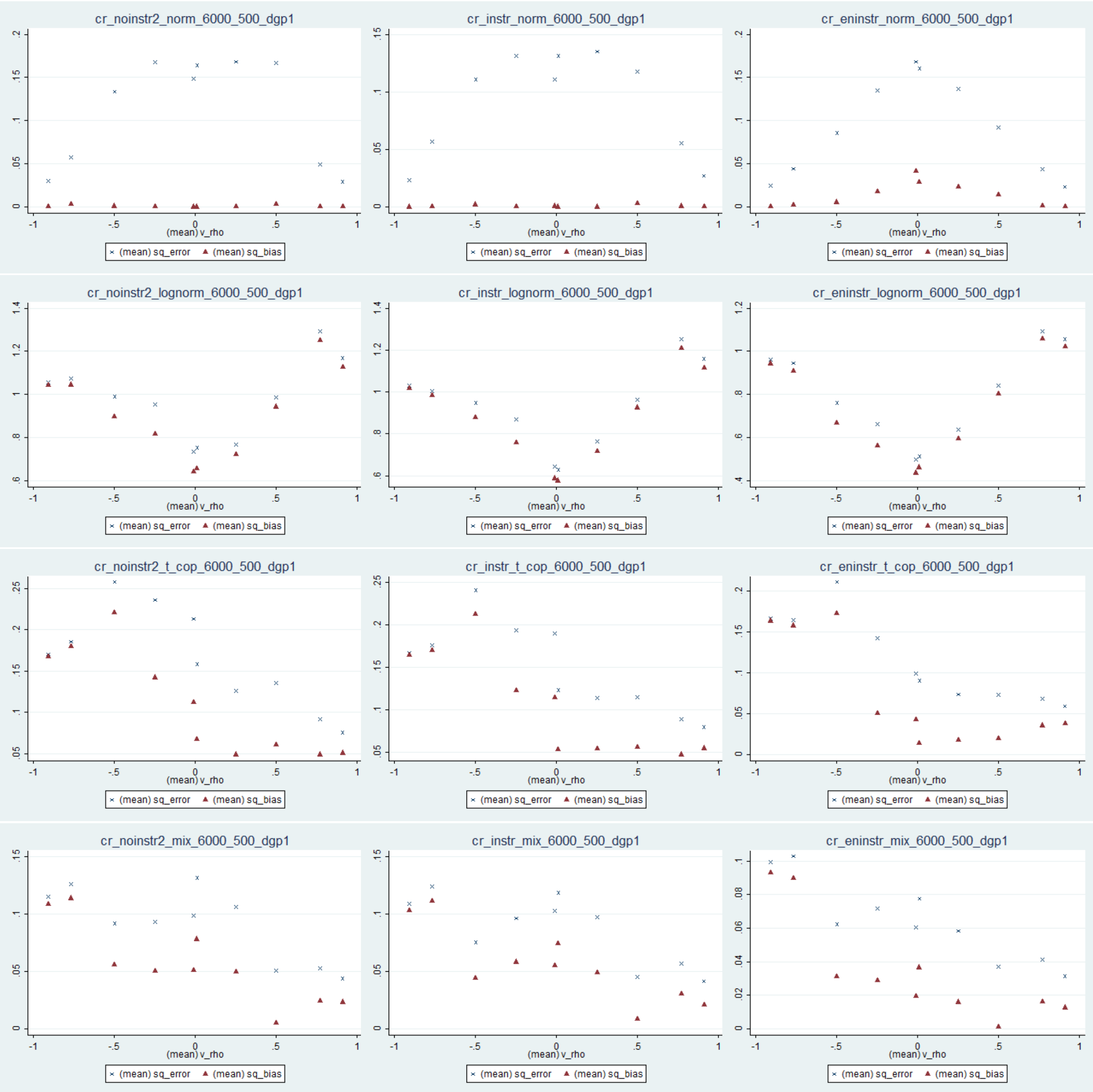
(mean) sq_bias

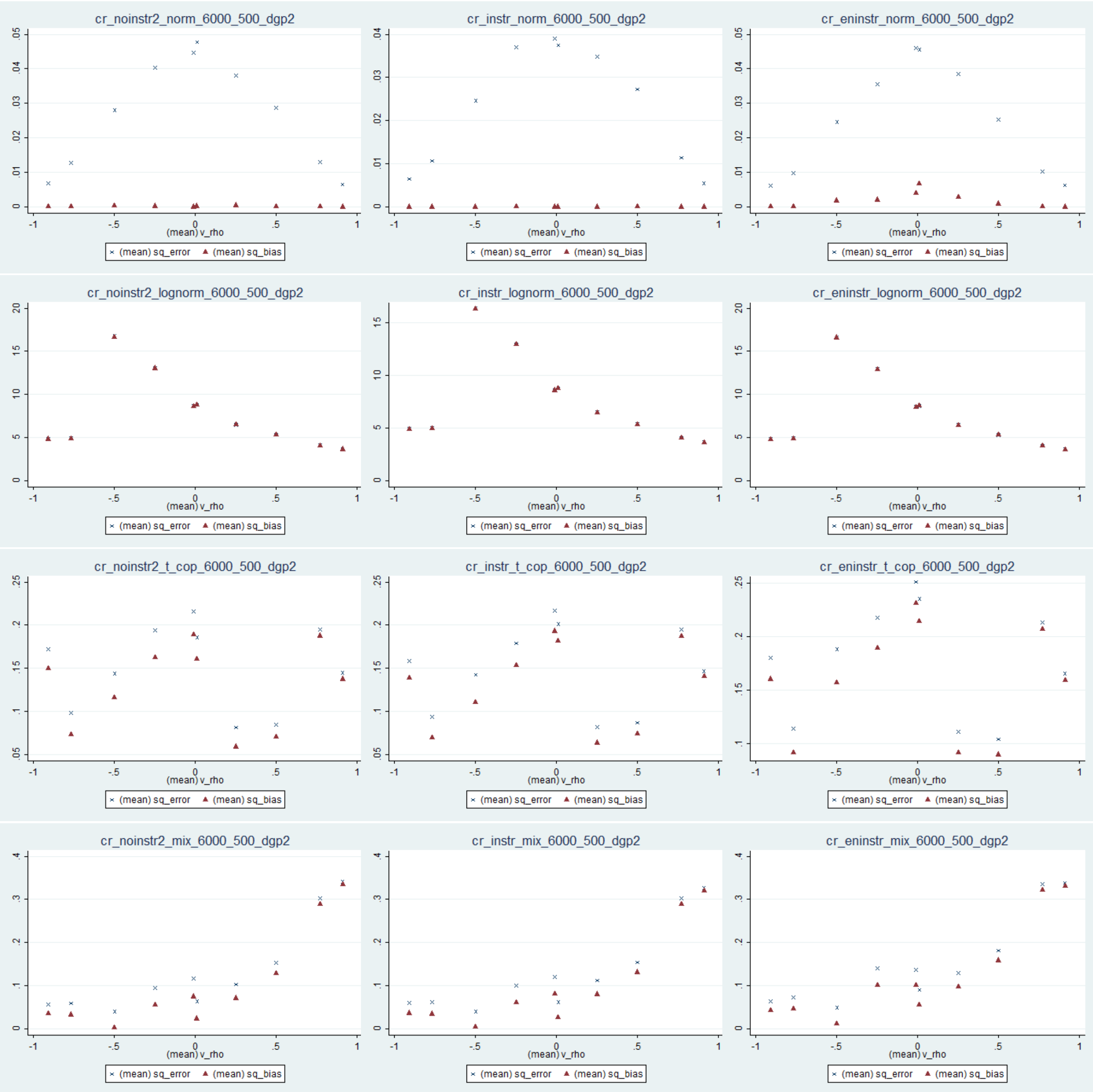
# DGP5, 500


noinstr2_norm_500_500_dgp5
instr_norm_500_500_dgp5
eninstr_norm_500_500_dgp5
noinstr2_lognorm_500_500_dgp5
instr_lognorm_500_500_dgp5
eninstr_lognorm_500_500_dgp5
noinstr2_t_cop_500_500_dgp5
instr_t_cop_500_500_dgp5
eninstr_t_cop_500_500_dgp5
noinstr2_mix_500_500_dgp5
instr_mix_500_500_dgp5
eninstr_mix_500_500_dgp5
(mean) v_rho
(mean) sq_error
(mean) sq_bias

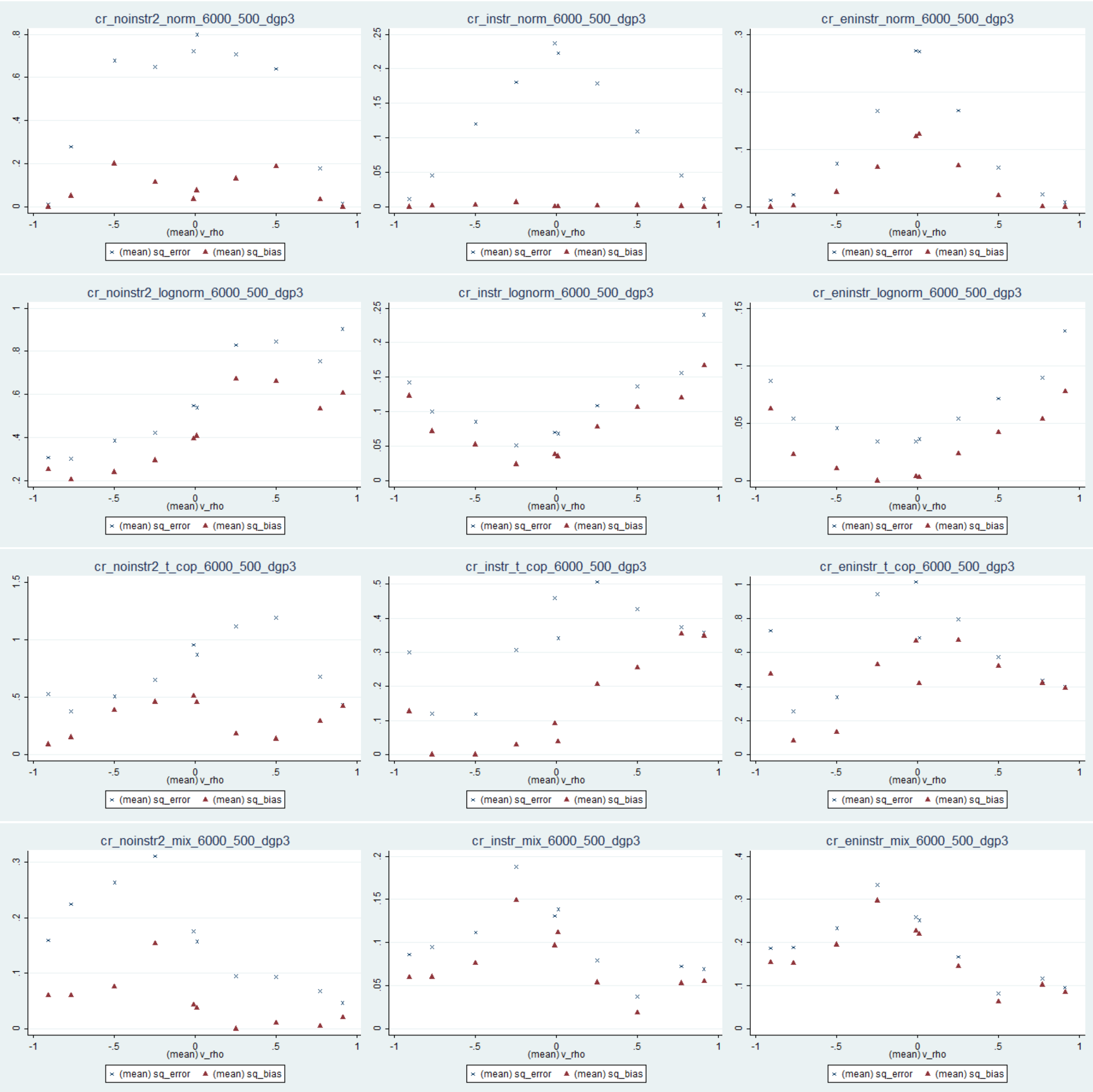
# DGP1, 6000, correlated $x_i$s



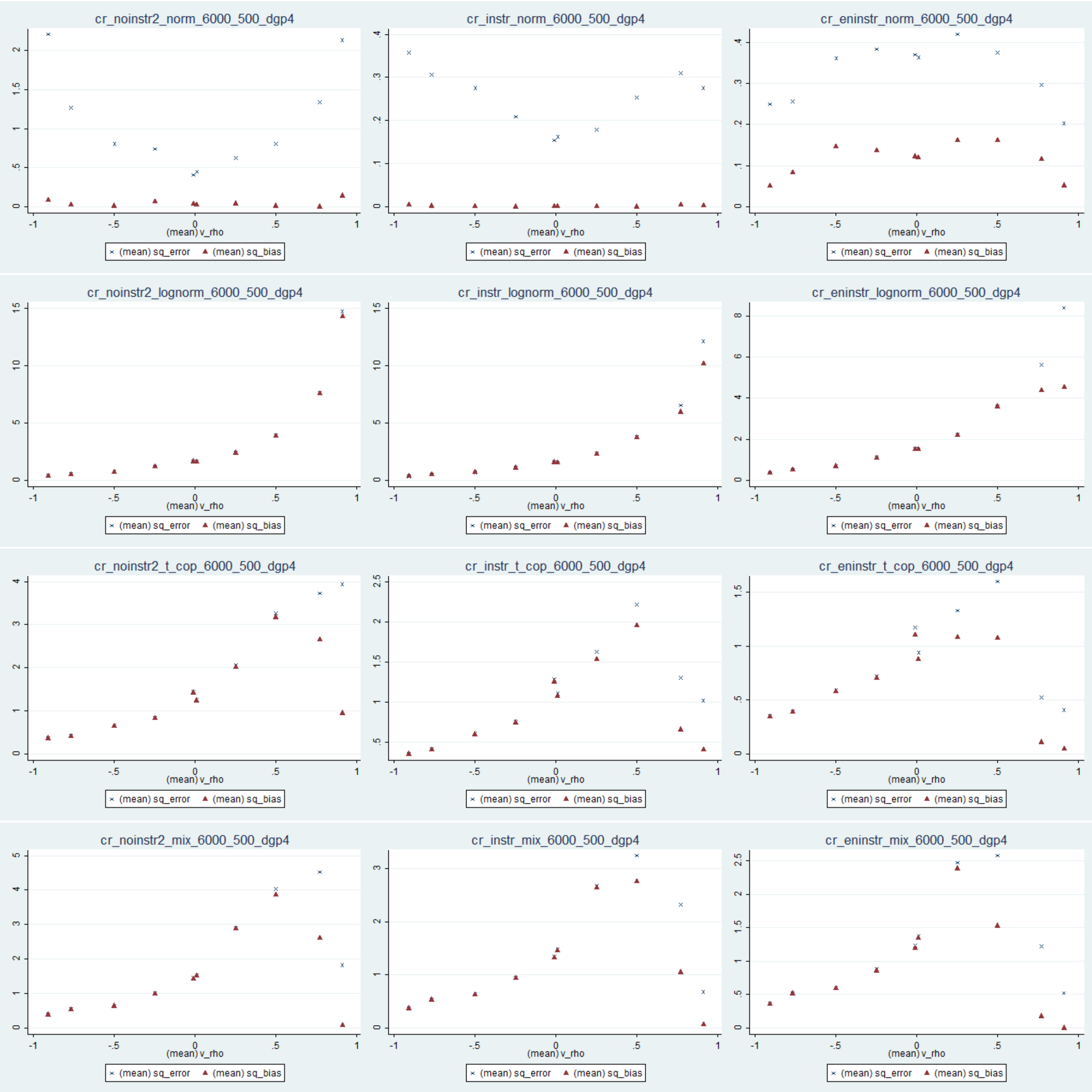
# DGP2, 6000, correlated $x_i$s



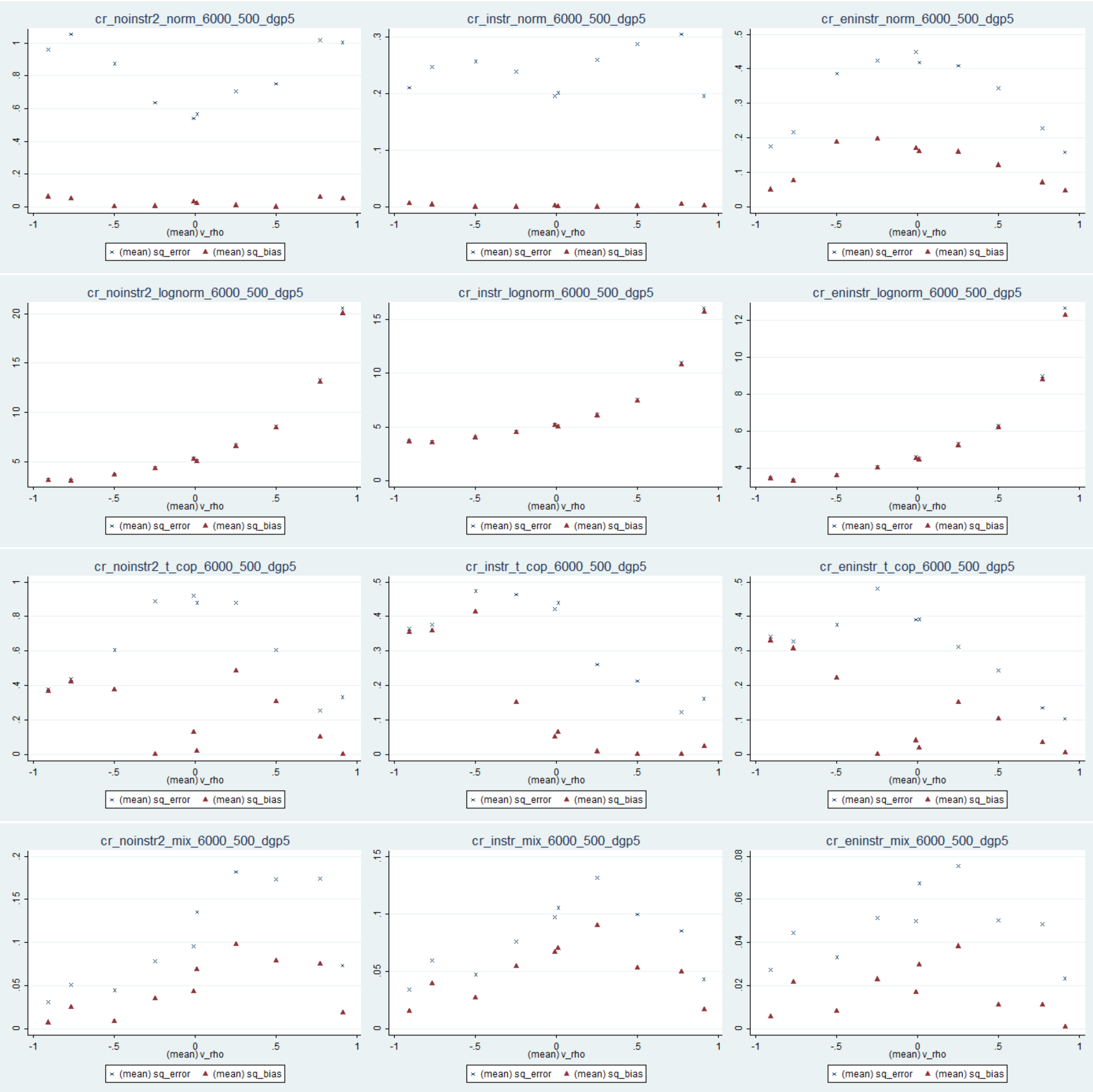
# DGP3, 6000, correlated $x_i$s



# DGP4, 6000, correlated $x_i$s



# DGP5, 6000, correlated $x_i$s



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