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Seasonality of Rural Finance

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Abstract

Simultaneity of borrowing, withdrawal of savings, and loan defaults due to the pronounced seasonality of ag-riculture often leads to investment failure of rural financial institutions. Lack of borrowing leads to lack of in-come- and consumption-smoothing, and in turn, causes inefficient resource allocation by rural households. Financial institutions that are active in rural areas take different measures to address the covariate risks in in-termediation. For example, microfinance institutions have sought various measures such as supporting non-farm activities to diversify income, introducing seasonal loans, and bringing flexibility in loan repayments to reduce non-payments in lean seasons. This paper examines whether the financial inclusion policies of micro-finance institutions have successfully helped reduce the adverse effects of covariate risks. Analysis of household and program level data from Bangladesh suggests that despite the innovative measures taken by the MFIs to cope with the covariate risks, seasonality of income still affects seasonality of borrowing and invest-ment decisions of both the households and MFIs beyond and above what is caused normally by agricultural seasonality. Innovation is needed to promote, among other things, sectoral diversification of financial inter-mediation and to avert the extreme seasonality of rural income. Rural labor markets should be diversified enough to address the seasonality of income and consumption. Public policies guiding rural financial interme-diation must reflect such realities of rural economies.

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Seasonality of Rural Finance

1. Introduction

Rural credit markets are characterized by asymmetric information, covariate risks, and problems of enforcement of loan contracts (Stiglitz and Weiss 1981). Increasingly therefore, efforts are underway to reduce the role of asymmetric information by better managing borrower-level information and reduce loan default costs by enforcing loan contract using mechanisms such as peer pressure via group lending. But a covariate risk due to seasonality of agriculture is difficult to rein in through such mechanisms and hence, it contributes in part to the poor performance of rural financial intermediation (Binswanger and Rosenzweig 1986; Hoff and Stiglitz 1990; Yaron et al. 1997; Nagarajan and Meyer 2005). Covariate risks, unlike idiosyncratic risks, affect everyone in a community. For example, a significant portion of the rural labor force is subject to the seasonality of the crop cycle every year due to marked weather patterns and lack of insurance mechanism (Menon 2006). No wonder employment is highly responsive to the seasonality of labor markets in many agrarian economies (Ravallion 1990). Seasonality of food prices induced by seasonality of food production is found to affect calorie intake, especially among the urban poor (Kaminski et al, 2016).

The poor are highly vulnerable to seasonal changes, particularly because they are primarily engaged in agriculture that clearly depends on the climate (Pitt and Khandker 2002). A seasonal shock such as drought or flood can ruin crops, reduce their income, forcing them to withdraw savings, borrow or default loans (if they had borrowed). Also, the seasonality and synchronic timing of agriculture mean that if depositors and borrowers are both engaged in agriculture, depositors would want to withdraw

money exactly when borrowers would want to borrow—at the beginning of the production season. Similarly, depositors would want to make deposits exactly when borrowers would want to make repayments—after the harvest season.

A flexible and responsive credit market can be a boon to people vulnerable to seasonality. This is because when credit is available, households do not have to sell their products or assets at below the market price during the lean season, thereby avoiding income loss (Marcus, Porter and Harper 1999). Also, easy access to credit and the provision of emergency loans enable poor people to cope better with seasonal income and consumption fluctuations (Pitt and Khandker 2002; Marcus, Porter and Harper 1999; Montgomery 1996).

However, financial institutions themselves can be affected by seasonality, often making financial intermediation inaccessible to many, making both production and consumption inefficient. In such a situation, credit operation becomes a risky venture unless credit markets are flexible enough to diversify the risk of rural credit operation. This is because simultaneous borrowing, withdrawal of savings, or loan defaults reduce the volume of loanable funds and may, thus, lead to investment failure for rural financial institutions (RFIs), including traditional moneylenders. Seasonality of agriculture therefore remains a serious threat to the viability of RFIs. A financial institution must therefore diversify its portfolio to reduce the negative impacts of covariate risks in investment. The diversification strategy of a financial institution, among other factors, must include diversity in the activities financed, activity size, and areas of operation (e.g., rural versus urban areas).

Like other RFIs, MFIs in Bangladesh are subject to vulnerability caused by seasonal fluctuations or climate changes and crop failures. Seasonality therefore would pose a big challenge to the spread of institutional finance such as microfinance in areas centered in rain-fed agriculture, areas that include some of the poorest regions of South Asia and Africa (Morduch 1999). Yet, microfinance programs have flourished in many parts of the world in the recent past, including areas highly vulnerable to seasonality.

For example, Bangladesh alone, as of 2012, had more than 750 registered MFIs reaching more than 30 million members, mostly in rural areas (InM and CDF 2011).

In fact, microcredit members are found to have a better coping capacity in lean seasons, increasing with the length of membership and loan size (Khandker and Mahmud 2012). Microfinance participation improves the ability of the rural households to withstand aggregate shocks such as seasonality of crop cycle that causes changes in seasonal consumption. This happens because credit provides the borrowers with an opportunity that is unlikely to co-vary with seasonal shocks, considering both consumption smoothing and loans used in income generation activities (through non-agricultural activities) (Menon 2006; Mustafa et. al. 1996; Pitt and Khandker 2002).

Microfinance seems a powerful tool against seasonal hardship, at least by allowing to smooth income and reduce vulnerability (Morduch 1999). To protect lenders from covariate risk, MFIs may rely on strict weekly loan repayment schedules for loan repayments. The weekly repayment schedule practiced in Bangladesh perhaps increases the ability of MFIs to withstand the negative consequences of seasonal shocks. MFIs in Bangladesh provide credit mostly to support nonfarm activities to reduce the severity of negative consequences of seasonality of agriculture, which also helps borrowers diversify income. But it is also well known that rural nonfarm activities are geared largely toward serving a local economy dominated by agriculture. While it is known that microfinance helps reduce seasonality of income and consumption (Pitt and Khandker 2002), it has not been yet rigorously investigated whether such features of microfinance (e.g., peer pressure, reliance on nonfarm activity, and weekly loan repayment) have helped MFIs and their borrowers avoid the pitfalls of covariate risks caused by agriculture seasonality.

The objective of this paper is to examine whether credit institutions are managing covariate risks effectively so that seasonality does not really matter in terms of outreach and operational efficiency.[1] More specifically, the paper first explores if there is a pattern of seasonality in household borrowing from MFIs, in particular, in terms of loan disbursement, savings mobilized, and loan recoveries. The paper then estimates if seasonality of income also matters in household borrowing beyond and above the seasonality of borrowing. The paper also estimates whether the seasonality of MFI investment portfolio (e.g., loan disbursement) affects MFI income portfolio such as loan outstanding, savings mobilization, and loan recovery beyond and above the seasonality of these outcomes caused by agriculture seasonality.

2. Seasonality of agriculture in Bangladesh

Seasonality in income and consumption is a reality in an agrarian economy such as Bangladesh. As a result, rural people are more sensitive to seasonal variations than urban people. Also rural people, because of the poor infrastructure, find it difficult to cope with seasonal changes. Agriculture contributes to more than 25 percent of Bangladesh's GDP and 45 percent of the rural employment. To demonstrate how agriculture affects the seasonality of rural livelihoods, we need to consider the timing of the plantation and harvesting of major crops such as rice. Rice is the dominant crop in Bangladesh: in 2009, for example, the area under cultivation of rice was 75 percent of the agricultural land, followed by the land for potato and wheat cultivation (with 3 percent of agricultural land for each) (BBS 2011). As in the Southeast Asian countries, rice production in Bangladesh makes major contribution to the reduction of hunger and poverty, and to the economy as a whole (Basak 2010).

There are three major rice crop seasons in Bangladesh: *Aus*, *Aman* and *Boro*. In 2009, the area under cultivation of *Aus*, *Aman* and *Boro* was 7 percent, 43 percent and 35 percent, respectively (BBS 2011). The *Aman* rice has the largest share in crops, and hence, its production and harvesting have the

[1] By outreach we mean an easy accessibility of financial instruments such as credit, savings, and insurance, while by operational efficiency we mean financial institutions are operating at a cost effective way (i.e., not losing money for lending, for example).

largest impact on agricultural employment, income and prices. As the use of high yielding varieties and irrigation technologies has spread, *Boro* crop production has been increasing in recent years (Jalil and Kabir 2008). With the cultivation of *Boro*, the early summer lean period (April-May) has significantly reduced. But the autumn lean season (after the plantation of the *Aman* crop) still affects almost all parts of the country, especially the northwest region of Bangladesh – due to the dearth of alternative sources of employment (Rahman and Hossain 1991).

The lean season for the rural poor is traditionally the months just before the *Aman* harvest (locally known as *Monga*) when rural consumption reaches its lowest annual level (Khandker 2012; Khandker and Mahmud 2012; Menon 2006). On the other hand, food availability is highest during the months just after the *Aman* harvest (November-December), and also during May-June, just after the harvest of *Boro* rice (Chowdhury 1989). Cultivation of *Boro* takes place in March-May (Banglapedia 2003) which contributes more than 55 percent to the total rice production during 2008-09 (Basak 2010). Figure 1 presents the distribution of months by four seasons.

During September-November, no variety of paddy is sown or transplanted, and none is harvested. As noted earlier, the agriculture sector in Bangladesh constitutes only one-fifth of the GDP, yet almost half of the labor force comes from this sector. About 8.93 million households (31.1 percent) depend on agricultural labor, and 13 percent of them are landless (BBS 2008). Most of these people are engaged in rice cultivation. So the two aforementioned periods (November-December and May-June) definitely affect their living and livelihood.

The *Aman* harvest during November-December creates the greatest demand for agricultural labor. Labor demand is also relatively high in January when the transplantation of Boro HYV takes place. Labor demand is lowest during September-October, just before the harvesting of *Aman* rice (Muqtada 1975; Hossain 1990). Thus, the strong seasonality of crop production in Bangladesh is bound to affect

the income, consumption and asset management behavior (Khandker 2012; Khandker and Mahmud 2012; Pitt and Khandker 2002).

3. Seasonality in household borrowing and income: Descriptive evidence

Using Household Income and Expenditure Surveys (HIES) of 2000 and 2005, Khandker (2012) demonstrates that seasonality is pronounced in household consumption and income, and that income seasonality affects significantly the seasonality of consumption and poverty beyond and above seasonal variations in consumption and poverty. This phenomenon is most acute in the Northwest region of Bangladesh (Khandker and Mahmud 2012). Findings also indicate that seasonal variations severely affect poor people who mainly live on agricultural income, and microcredit has so far played a good role in mitigating seasonal hardship. Seasonality still matters, however. Using the 2010 HIES data, Khandker and Samad (2016) show that although the severity of seasonal hunger has declined, consumption and poverty are still influenced by the seasonality of income caused by the agriculture cycle.

In order to explore the seasonality of household borrowing and income, we use panel data collected by the World Bank with help of Bangladesh Institute of Development Studies (BIDS) in 1998/99 and Institute of Microfinance (InM) in 2010/11 (see Khandker and Samad 2014 for a detailed description of the data set).[2] Using these data we can divide the borrowing sources into three categories (microcredit, formal or commercial, and informal) and the whole year into four seasons (*Boro*, *Aus*, *Monga* and *Aman*). Figure 2 shows the trend in the amount of loans from each source and aggregate loans from all sources combined across four seasons during 1998/99. As the figure shows, the aggregate loans from all sources is the lowest during the *Monga* season. As for the individual sources, the pattern is more pronounced for microcredit and informal sources than for formal sources.[3] As shown in Figure 3, the

[2] While the panel surveys also include data from 1991/92, we could not use them because they are not suitable for calculating season-specific income that would be consistent with incomes calculated from 1998/99 and 2010/11 data. So, the analysis of this paper is restricted to 1998/99 and 2010/11 survey data only. Nevertheless, using the 1991/92 along with the 1998/99 and 2010/11 panel surveys, our results on the seasonality of income and borrowing still hold.

[3] This is not surprising, given that formal financial institutions lend little but mobilize more from their rural branches.

pattern in 2010/11 is similar to that in 1998/99 with two exceptions: (i) there are two minima - one in the *Aus* season and the other during the *Monga*, and (ii) the seasonal differences across sources are less pronounced.[4]

We see a similar pattern in the seasonality in per capita income when income is expressed as a ratio of seasonal income to average income per season (Figure 4).[5] The seasonal share of income is the lowest during *Monga* season in 1998/99, while it also dips considerably during the *Aus* season, similar to the pattern observed for borrowing during 2010/11. Income seasonality is more pronounced overall during 1998/99, compared to that during 2010/11, indicating that income seasonality has decreased over time.[6] These trends show that households are most likely credit-constrained if there is a need for loans during the lean season (*Monga*) to smooth consumption, and it is possible that seasonality of income has driven the seasonality of borrowing. The real challenge therefore is to establish such causality, that is, if seasonality of income caused by seasonality of agriculture also affects the seasonality of borrowing beyond and above what is normally seen in the seasonal patterns of borrowing as discussed in this section. We check the statistical significance in the seasonal differences between amounts of loans taken in the lean season and average loans taken over other seasons. We also do the same for the seasonal distribution of per capita income. As shown in Table 1, we reject the null hypothesis of no difference in seasonal shares of income between *Monga* and non-*Monga* seasons at the five percent level for both years. The null hypothesis of equality in borrowing between *Monga* and non-*Monga* seasons is however rejected for microcredit and informal sources in 2010/11, but not in 1998/99.

[4] Our findings on the seasonality of borrowing by rural households are consistent with those of Hashemi (1997), Rahman and Hossain (1991) and Shonchoy (2014).

[5] Using our data the income seasonality can only be observed from crop income. Because the survey collected household crop income for each crop that the household cultivates, which is usually harvested during a specific season of the year, it is possible to calculate season-specific crop income for the household. For simplicity, incomes from non-seasonal crops and non-crop activities were distributed evenly across four seasons. Unlike income, however, household consumption expenditure cannot be distributed across seasons using our data because consumption questions were asked for the whole year.

[6] Indeed seasonality of income, consumption and poverty is found less pronounced in recent years than in the past (Khandker 2012; Khandker and Samad 2016).

4. Seasonality in financial intermediation of MFIs: Descriptive evidence

Household borrowing and its seasonal pattern are very likely a reflection of both demand for and supply of loans. If household borrowing is lowest during *Monga* season, for example, even though the demand for loans for smoothing income and consumption is high, this is perhaps due in part to the supply of loans being lowest during *Monga* season, compared to other seasons. So we ought to verify whether there is a seasonality of rural financial intermediation. We use the data on MFIs supported by a microfinance wholesale agency to verify this as they are readily available on a monthly basis than that of formal financial institutions. This also makes sense as MFIs are largely engaged in rural financial intermediation in Bangladesh. The question is, do MFIs suffer from the seasonality of agriculture?

Palli Karma-Sahayak Foundation (PKSF), an apex organization for Bangladeshi microfinance institutions (MFIs), finances various programs of 262 MFIs—called Partner Organizations (POs) of PKSF (PKSF 2011). These POs are scattered all over the country and are part of the 750 registered MFIs in Bangladesh.[7] The analysis of the 262 PKSF POs captures well the microfinance sector of Bangladesh. PKSF lends to POs at a subsidized rate of interest, while POs lend to household borrowers at market rates and repay PKSF from revenues generated.[8]

We use monthly data from all five major projects of the 262 POs from FY2004-05 to FY2010-11 (see the discussion of program level data in Appendix A). The monthly data over the seven years help establish a seasonal trend of MFI portfolio. If there are any distinct seasonal patterns (persistent upward or downward movements) in indicators in most years, we can say that seasonality is at play for financial intermediation. We present the monthly distribution of loan disbursement, loans recovered, and other indicators of program performance.

[7] In 2010, Bangladesh Microfinance Statistics reported around 750 MFIs. Instead of PKSF data on its sectoral level portfolio, it would have been better if PO level data were available for analysis. Unfortunately, PO level data are not available.
[8] Subsidizing funds for on-lending by POs by PKSF along with the grants for institutional development of MFIs has helped promote the viability of microfinance institutions in Bangladesh (see Khandker, Khalily and Samad 2016).

Figure 5 presents the monthly variation in program-level disbursement and loans recovered, adjusted by the number of borrowers, for all five major credit categories of MFIs for the data periods of 2004-2011. A higher level of disbursement per borrower indicates a credit deepening, while a higher level of loan recovery implies success of microfinance institutions. We find a seasonal pattern in loan disbursement and recovery – low in February, high in the middle of the year and low again during September to November. The gap between the amount disbursed and recovered is, however, the highest in February and lowest in June and December—the months when MFIs fix up accounts and publish reports. Both indicators reach their global minima during September-November, which is the *Monga* season.

The seasonal pattern in lending and loan recovery also shows there is a seasonality of financial intermediation even with MFIs active in rural areas. Figure 6 presents the seasonal distribution of recovered loan as a percentage of loans outstanding. A large amount in recovered loans as a percentage of outstanding loans means a high loan repayment rate for the borrowers. The loan recovery rate as a percentage of loans outstanding varies from 10 to 20 percent. There is a cyclical pattern in the indicator and it drops during the lean months of February-March and September-November. Table 7 presents the loan recovery rate by month, which shows similar seasonal patterns over time.

Figure 8 presents average monthly savings mobilized by MFIs, mostly from members. Savings per member is an indicator of the financial strength of a financial institution. High savings enable an MFI to lend and invest more from its own stock without needing to borrow. Interestingly, savings accrued to MFIs from members also drop during February-March and September-November, a pattern similar to the seasonality of household income and consumption.

We also examine the overall performance of MFIs measured in terms of loan defaults to PKSF as a result of seasonality of agriculture. In every month, there is some 'recoverable' loan amount that the POs owe to PKSF. If an organization fails to repay the recoverable amount in a month, that amount is

considered 'overdue' and the partner organization is considered 'default'. We calculate the MFI default rate for different loan categories.

Figure 9 shows the average percentage of default MFIs. The percentage of default MFIs vary from 7 to 18 percent in a year. The default rate is the lowest in June when MFIs clear their accounts with PKSF. Because of the pronounced seasonality as observed earlier, the MFIs default is highest percentage during February-March and again during September-November. As borrower-level loan recovery rates are lower during these two lean seasons, MFIs are likely to default more during lean periods in repaying loans to PKSF. Hence, seasonality of agriculture may affect MFI performance.

We examine if the loan variables vary significantly between the lean seasons and non-lean seasons (Table 2). As we can see, the differences in monthly averages of disbursement per borrower, recovered loan per borrower, net savings per borrower, loan recovery rate, and the share of defaulting POs between *Boro* lean season (February-March) and the other seasons are not statistically significant. However, monthly disbursement, loan recovered, and savings mobilized do drop during *Monga* season (September-November) even if we consider *Boro* lean season as normal season. This does not imply that *Boro* lean season does not affect microfinance operation. Indeed, combining *Boro* with *Monga* seasons gives the highest statistical significance for the differences in means for recovered loan and the number of defaulting POs.

So we find that like rural households, seasonality of agriculture seems to influence financial intermediation of MFIs in terms of lending, recovery, and savings mobilized. But, as we know, MFIs have succeeded in arresting high loan default cost of rural lending which otherwise plagues formal financial institutions. Part of the MFI success rests on innovative program design such as enforcing loan contract via group lending and the weekly loan recovery mechanism. The question is whether group-based MFI lending with weekly payment schedule and rural nonfarm lending is a safeguard against the covariate risk caused by the seasonality of agriculture. That is, whether seasonal variations as observed

with MFI portfolio and household borrowing are not the effects of covariate risk induced by agricultural seasonality.

5. Test of the seasonality of household borrowing

To test seasonality of household borrowing, we follow a model of seasonality of household consumption and investment behavior in a rural setting. Rural households face seasonality in income that is likely to affect consumption and investment in a particular season if they fail to smooth income and consumption through income diversification, borrowing or interfamily transfers (Paxson 1993; Khandker 2012). In other words, seasonality in income may not matter much for consumption smoothing in a lean season if households are able to borrow from credit agencies or relatives and friends. So it is not seasonality of agriculture per se that matters; what matters is whether households have a means (e.g., a coping mechanism such as borrowing) to withstand seasonality of agriculture.

We hypothesize that seasonality of income influences the demand for credit for income or consumption smoothing, and thus, when households seek to borrow money from local credit markets, including MFIs, credit rationing may trigger pronounced seasonality of income or consumption. Income seasonality may affect seasonality of borrowing beyond and above what is caused by agricultural seasonality.

Consider borrowing B_{ijs} (of a household i in village j in season s during a one year period) would depend on average per capita annual income (Y), as well as its seasonal shares (y), along with other variables such as prices, preferences, and local area characteristics similar to consumption models articulated in the literature (Deaton 1997; Khandker 2012; Kazianga and Udry 2006; Paxson 1993). We consider the following borrowing equation in semi-logarithmic form, for which seasonal borrowing, among other variables, is determined by per capita annual income (Y) and its seasonal shares (y):

$$lnB_{ijst} = \alpha\tau_{st} + \beta_1 lnY_{ijt} + \beta_2 y_{ijst} + \gamma X_{ijt} + T_t + \mu_{ij} + \eta_j + \xi_s + \varepsilon_{ijst} \qquad (1)$$

where X_{ijst} is a vector of household- and village-level characteristics, including prices, influencing consumption and income; τ_{st} is a dummy variable representing the seasons and T_t is the dummy for the survey year; α, β, and γ are unknown parameters to be estimated; and ε_{ijst} is a zero-mean disturbance term representing the unmeasured determinants of B_{ijst} that vary across households. Borrowing is also affected by unobserved household- and village-level heterogeneity represented by the error terms μ_{ij} and η_j, respectively, as well as unobserved season-specific heterogeneity (ξ_s).

Here β_1 measures the response of borrowing to average annual income, while β_2 measures the response to seasonal income. β_1 can be positive or negative depending on the role of credit in household income and other decision-making; it is positive if credit is seen as a production input meaning higher income demands higher amount of borrowing, while it is negative if credit is seen as a consumption input, meaning households with higher income do not need to borrow to meet a certain level of consumption. β_1 can also be zero, implying that demand for credit is completely inelastic with respect to income.

In contrast, β_2 can be positive, negative, or zero. If $\beta_2 = 0$, income seasonality is not an issue and seasonal income does not track seasonal borrowing, perhaps because a household has the ability to smooth income through self-insurance and other means such as remittance to compensate for losses in income during a part icular season. This case illustrates a perfect consumption or income smoothing model. However, it is also possible that the demand for credit to smooth income or consumption does not respond at all if the supply for credit is perfectly unresponsive to the seasonal demand for credit in which case $\beta_2=0$.

On the other hand, β_2 is positive when seasonal borrowing responds positively to seasonal income drops. Credit demand may fall because a drop in income does not permit higher use of credit in production. Also the demand for credit may decline if credit is imperfect for income or consumption smoothing. In contrast, β_2 is negative when credit demand increases in response to a shortfall in seasonal

income. This happens when credit is demanded for income smoothing in a particular season when seasonal income falls short of average yearly income. In either case, credit is sensitive to seasonal variations of income above and beyond what is caused by agricultural seasonality.

The relative response of borrowing with respect to average and seasonal income may shed light on the role of seasonality of income in the demand for credit. $\beta_1<\beta_2$, implies income seasonality matters more for the demand for credit (i.e., credit is more sensitive to seasonal than average income). On the other hand, $\beta_1>\beta_2$, implies demand for credit is more responsive to average than seasonal variations of income.

Estimation of equation (1) may be problematic because income and borrowing are jointly affected by common unobserved factors, such as the household and village heterogeneity represented by the error terms μ and η, respectively. More specifically, measurement errors in consumption, borrowing, and income are correlated, which may bias the estimated coefficients (Deaton 1997; Ravallion and Chaudhuri 1997). If unobserved errors are time invariant (as we have assumed here), we apply household-level fixed effect (FE) method to the panel data (two period of repeated samples of households over 1998/99 and 2010/11) to address potential bias caused by heterogeneity.[9]

The FE estimated coefficients of the borrowing equation (1) showing the effects of average and seasonal incomes are presented in Table 3a. The borrowing equation is estimated separately for the three sources of borrowing as well as for aggregate borrowing. Regressors include demand-side variables influencing credit demand such as prices, assets (both physical and human), and non-financial infrastructures such as availability of roads and electricity. Regressors also include supply-side variables influencing

[9]If heterogeneity is time varying, one way to resolve potential bias due to time varying heterogeneity is to use the instrumental variable (IV) within the FE method. However, suitable instruments are not available. But, as the bias due to time-varying heterogeneity is downward, this is yet an evidence of seasonality of borrowing beyond and above what is caused by crop cycle if we find the test of significance of the coefficient of seasonal income at even 10 percent level.

credit demand such as the presence of banks and microfinance organizations. Besides, we include seasonal dummies representing seasonality of agriculture, directly affecting the demand for credit.

The results confirm that crop income seasonality does affect the seasonality of borrowing beyond and above what is influenced by agricultural seasonality as well as by credit supply variables such as the presence of banks and MFIs in the village. Overall seasonal borrowing is more sensitive to seasonality of income than average income itself. Therefore, seasonal borrowing (estimated on a monthly basis) is strongly and positively related to per capita average income (also estimated as the monthly average). This is true for overall and micro-credit sources. For example, a 10 percent increase in per capita average income increases the demand for seasonal borrowing by 1.29 percent overall and 0.92 percent for microcredit loans. However, unlike microcredit, the demand for formal or informal credit is not sensitive to average income.

More importantly, seasonal variations in income (represented by the ratio of monthly income in a season to year-round average of monthly income) are found as a significant determinant of the seasonal demand for credit. This is equally true for all three sources of credit. Seasonality of borrowing is more sensitive to seasonality of income for microcredit and informal sources than for formal sources. If, for example, this ratio increases by one percentage point in a season, the borrowing amount in the season will decline by 0.35 percent overall, 0.14 percent for microcredit, 0.08 percent for formal credit and 0.14 percent for informal sources of credit. That decline implies a very strong relationship between seasonal income and seasonal demand for credit.

The statistically significant coefficient of the year dummy in Table 3a indicates that seasonal credit demand grew autonomously by 148 percent in real terms between 1998/99 and 2010/11 for microcredit sources. Results also suggest that the seasonal demand for credit is higher in any season than

in the *Monga* season, suggesting that borrowing is highly depressed in the *Monga* season when credit demand is the highest. Credit demand is also found to respond positively to the availability of credit through credit agencies in the village. Supply of microcredit is higher in villages with higher number of MFIs working. Villages with a commercial bank network seem to have higher incidence of borrowing from informal sources, suggesting that developed villages have higher demand for credit that sometimes come from informal lenders rather than formal lenders.

The equations for borrowing (that is, microcredit, formal, informal and aggregate borrowing), the results of which are presented in Table 3a, are estimated independently, assuming that their error terms are not correlated. However, if the error terms are correlated (or 'contemporaneously correlated'), the equations should be estimated jointly to get more efficient estimates. Such equations are called 'seemingly unrelated regression equations' or SURE, and the estimator for this problem is called SUR estimator, proposed by Zellner (see Zellner 1962; 1963).[10] Table 3b reports findings based on SUR estimator.[11] The effects of average seasonal income and share of actual seasonal income in average income are stronger based on SUR estimation. For example, a 10-percent increase in per capita average income raises the borrowing from microcredit lenders by almost 2 percent, and a one percentage point increase in the share of seasonal income is associated with 0.06 percent increase in microcredit borrowing. As for the independent effects of the seasons, except for microcredit borrowing, the borrowing from other sources seems to be affected by all three non-Monga seasons.

[10] SUR estimator uses the asymptotically efficient, feasible, generalized least-squares algorithm to jointly estimate the equations. A detailed treatment of the SUR estimator can be found in Zellner (1962, and 1963).

[11] These findings are based on random-effects (RE) estimates using panel data of 1998/99 and 2010/11. We also attempted fixed-effects (FE) implementation of the SUR estimator. The findings of FE model does not vary much from that of the RE model except for that the magnitude of the FE estimates is higher. We decided to report the findings of RE model to avoid upward biases, if any, in the findings of FE.

Overall, the evidence suggests that changes in seasonal borrowing track seasonal income independently of agricultural seasonality and provision of credit agencies, indicating that households are unable to smooth consumption or income through borrowing across seasons if they need to borrow to cope with seasonality. This finding contradicts the null hypothesis of perfect consumption smoothing via borrowing, indicating absence of a perfect credit market. Thus, lack of income or consumption smoothing with borrowing in a lean season is caused more by idiosyncratic factors than an aggregate shock due to agricultural seasonality. Microfinance agencies, despite their outreach (more than 65 percent of rural households are members of MFIs in Bangladesh, as noted in Khandker, Khalily and Samad 2016) and innovative program design, have failed to reduce seasonality of borrowing to the extent that seasonality of income is still a factor in household borrowing. Of course, this does not mean households find it difficult to smooth income and consumption during lean seasons in case they fail to borrow.[12]

6. Test of seasonality of financial intermediation

Like households, MFIs operating in rural areas are found vulnerable to agricultural seasonality. But seasonality of microfinance intermediation does not necessarily mean that seasonality affects MFI performance. It is worth examining whether seasonality of MFI investment, proxied by lending, influences MFI's income portfolio (e.g., loan outstanding, loan recovery and savings mobilized) beyond and above what is normally affected by agricultural seasonality. Typically, borrowers would borrow more, repay less and save less in a lean season. On the other hand, borrowers would repay more, borrow less but save more during a season after the harvest. But as a profit-making (or at least loss-averting) institutions, MFIs would like to maintain a regular flow of funds available for disbursement and other purposes

[12] Seasonality of income is not a major issue in recent years in Bangladesh as households find alternatives to borrowing (such as operating income-earning activities outside local areas through seasonal migration) that help them smooth consumption and income, and thus avoiding starvation (see Khandker and Mahmud 2012). A recent study has documented that microfinance has in fact helped seasonal out-migration which in turn helps smooth shortfalls in seasonal income and employment (Shonchoy 2015).

through regular and reliable deposit mobilization or loan repayment by borrowers so that they do not feel cash crunched.

There are two possible ways an MFI can avert the negative consequences of covariate risk: (a) Diversify its portfolio across sectors and (b) draw resources from markets and other sources such as donors to handle the cash crunch in the lean season when borrowers do not repay loans. Bangladeshi MFIs are mostly rural-based and hardly able to diversify their portfolios between urban and rural areas. However, MFIs diversify their portfolios between agricultural and non-agricultural activities, seasonal and non-seasonal activities, and lending to women and men. Also MFIs are able to borrow from PKSF and market sources. More importantly, MFIs in Bangladesh practice group-based lending to ensure loan repayments through group pressure on a timely fashion, which is a major reason for low loan default costs for MFIs in Bangladesh. It is also worth noting that group pressure may not work much in a rural setting when group members are subject to the same covariate risk.[13] It is yet to be determined if the seasonality of agriculture affects MFI portfolio management behavior beyond and above what is caused normally by agriculture seasonality.

Consider the following monthly portfolio management behavior of a typical MFI:

$$\ln Y_{jt} = \alpha D_{kt} + \beta_1 \ln L_t + \beta_2 \ln l_{jt} + \gamma M_{jt} + \delta T + \varepsilon_{jt} \qquad (2)$$

Here Y_{jt} refers to a vector of MFI level portfolio management indicators such as monthly loan outstanding, loan recovery, and savings mobilized in a month j of a year t;[14] L measures the monthly average loan disbursement, l_{jt} measures the ratio of monthly loan disbursement to average monthly loan disbursement in a particular year, meaning that average of l would be close to 1.

[13] This covariate risk has perhaps induced Grameen Bank to introduce an emergency savings scheme which allows the members to borrow during such an emergency situation and avert defaulting on loans (Hossain 1988; Khandker 1998).
[14] Y can also measure the share of MFIs who default to PKSF loans in a particular month. This is a good indicator for overall MFI performance.

M_{jt} is a vector of aggregate monthly MFI characteristics such as the number of male and female members, D measures seasonal dummies, and T represents dummy variables for year. ε is unobserved characteristics with zero mean and constant variance, while α, β, γ. δ, and δ are parameters to be estimated. Two seasonal dummies are included to capture the role of two lean seasons, *lean 1* is the dummy for the lean seasons of February-March, and *lean 2* is the *Monga* season of September-November.[15]

Given logarithmic specification of equation (2), β_1 refers to the percentage change in MFI performance indicator such as loan outstanding due to a one percent increase in the average loan disbursement, while β_2 measures the percentage change in loan outstanding due to a one percentage point increase in the ratio of actual seasonal loan disbursement to average seasonal disbursement for the season. As lending is an instrument of an MFI to support its income generation in any month with a given interest rate, a higher disbursement would imply a higher loan outstanding and vice versa, given the loan repayment schedule. Also, given forced savings and weekly repayment practices of MFIs in Bangladesh, a higher volume of lending would mean higher volumes of savings and loan repayments.[16] We expect β_1 to be always positive for loans outstanding, repayment, and savings against lending.

In contrast, β_2 can be zero, positive or negative. Thus, if $\beta_2 = 0$, seasonality of loan disbursement is not an issue, and seasonal portfolio management behavior is determined by the average volume of loan disbursement. However, if $\beta_2 \neq 0$, there is a seasonality, meaning seasonality tracks MFI portfolio management behavior. More specifically, if there is the presence of seasonality, we can have either (i) $\beta_1 > \beta_2$ or (ii) $\beta_1 < \beta_2$. If $\beta_1 > \beta_2$, then MFI portfolio is more sensitive to average disbursement and less to seasonality of lending. That is, some degree of portfolio adjustment takes place to overcome the weak seasonality of the portfolio due to agriculture cycle. Conversely, if $\beta_1 < \beta_2$, the MFI portfolio is

[15] Unlike the way we have treated lean and non-lean seasons in household level analysis, we merge the two non-lean seasons (*Aus* and *Aman*) into one season for MFI-level analysis. So the excluded category is one non-lean season covering six months.
[16] As part of MFI practices, borrowers are to save a certain percentage of a loan at the time of borrowing.

more sensitive to seasonality; in this case, the MFI may be forced to manage the portfolio in such a manner that is not profitable. That is, the test of seasonality of financial intermediation for the MFIs ultimately rests on whether β_2 is statistically different from zero.

Estimation of equation (2) involves empirical issues such as the joint distribution of lending and other indicators of MFI portfolio investment. That is, measurement errors in loan disbursement, for example, are likely to be correlated with measurement errors in loan outstanding, inducing an attenuation factor that biases the coefficients toward zero. We are using a lagged dependent variable (LDV) method to reduce such bias. We also use some exogenous agroclimate data such as monthly rainfall and temperature as additional controls to reduce attenuation bias (Table 3). As this is an aggregate-level (MFI-level) data analysis, it is difficult to control such bias fully. Yet, as the estimates are subject to downward bias, we would observe some seasonality in financial intermediation if we find that β_2 is statistically significant even at the 10 percent level.

Table 5 presents the summary statistics of all essential variables for our econometric analysis across the projects. The average monthly disbursement is the highest for microenterprise loans followed by seasonal loans. This means that the monthly volumes of loans outstanding, loans recovered and savings mobilized are the highest for microenterprise than other activities. The loan recovery rate is about 99 percent for all categories of lending except for rural loans (98 percent). It seems that the MFI performance is slightly better in the urban areas than in rural areas. It is no wonder that in urban areas loan volume is higher, so is recovery, outstanding, and savings mobilized compared to those in rural loans. Women members in MFIs are six times as numerous as male members. Note that not all members are necessarily borrowers at a given time.

Tables 6-9 present the regression results of equation (2) showing the impacts of seasonality of disbursement on loans outstanding, loans recovered, savings mobilized, and the percentage of MFIs that default. The Breusch-Godfrey p value for all individual regressions is greater than 0.01, indicating that

there is a no significant serial autocorrelation in the model estimations for all categories of loans. After controlling for the two lean seasons and other variables, we measure the net effect of average monthly loan disbursement and its monthly share on the outcomes. Overall, average loan disbursement increases loan outstanding and loan recovery, but not savings mobilized. Thus, in the overall portfolio a 10 percent increase in loan disbursement increases loan outstanding by 1.26 percent and loan recovery by 6.1 percent. However, it does not necessarily increase overall savings.[17]

Tables 6-9 also show that lean seasons have a negative effect on MFI portfolios. While lean season 1 affects negatively the overall loan disbursement, lean season 2 (which is *Monga*) affects negatively the overall loan recovery, and savings mobilized.

Of particular interest is whether seasonality of the MFI investment portfolio, measured by loan disbursement, affects MFI income portfolio such as loan outstanding, savings, and loan recovered beyond and above the effects of seasonality of agriculture captured by the two lean season dummies. In fact, as reported in these tables, seasonality of lending does influence seasonal distribution of MFI income portfolio for most of the outcomes considered. For example, for the overall PKSF portfolio, a 10 percent increase in the average monthly loan disbursement increases monthly loan outstanding by almost 1.13 percent, while a 10 percentage points increase in the seasonal monthly share of lending increases overall monthly loan outstanding by almost 0.7 percent. For a few categories, the effects of seasonal lending are higher than that of average lending. For example, for the rural category of PKSF loan, while average lending has no bearing on loan outstanding for rural loans, the seasonal share of lending has a statistically significant positive effect (with a coefficient of 0.035) on loan outstanding. Understandably, seasonality of lending has no bearing on urban loans. This means seasonality is more profound for rural loans than urban loans.

[17] That is not the case with urban and seasonal loans, which in fact increase the savings mobilized due to higher volume of lending.

As far as other categories of PKSF loans, seasonality of lending has no profound effect for microenterprise loans on loan outstanding, but it has a pronounced effect on the loan outstanding for ultra-poor and seasonal loan outstanding.

As for the loan recovery, the effect of seasonality is higher for rural loans than for urban loans, and for microenterprise loans than seasonal loan itself. Seasonality also affects savings mobilized more for rural loans than for urban loans, and for microenterprise loans than for seasonal loans. However, seasonality of lending does not seem to affect the loan recovery and savings mobilized for ultra-poor loans. As MFI income portfolios seem more sensitive to seasonality of lending than to average lending for a few loans types, we can conclude that MFIs are forced to manage their portfolio in a way that may not necessarily be profitable. That seasonality tracks MFI portfolio is a reality in Bangladesh.

Microfinance institutions (MFIs) in Bangladesh in essence share clients' seasonal experience as we have noticed in the case of household borrowing. Indeed, as Figure 9 shows, there is a noticeable seasonality as measured by the default rates of MFIs loans from PKSF. Does seasonal pattern in loan default rates of MFIs mean that seasonality also affects the overall performance of MFIs as measured by their defaults to PKSF? We utilized model (2) to estimate the impact of monthly loan disbursement and its share on the likelihood of a MFI default to PKSF in a given month. Results are shown in Table 9.

Interestingly, average lending does not matter for the overall performance of MFIs but seasonality of lending has a statistically significant negative effect on the loan default rates of MFIs, via loans extended for rural activities. In other words, rural financial intermediation is influenced by seasonality of microfinance portfolio managed by PKSF beyond and above those affected by seasonality of agriculture. This does not necessarily mean that agricultural seasonality has affected negatively the overall profitability or sustainability of microfinance institutions in Bangladesh perhaps for a variety of features introduced by MFIs.

Indeed, the microfinance sector in Bangladesh has undergone major changes in recent years to address the seasonality of agriculture with active support from PKSF and its donors, including the Government of Bangladesh and the World Bank. For example, as shown in Figure 10, the microfinance sector has clearly undergone sectoral diversification from rural lending to other types of lending in recent years. For example, while rural credit was some 80 percent of total disbursement of 5 major categories of loan in 2005, it declined slowly over time to less than 50 percent in 2011. During this period, seasonal loans have been introduced to accommodate demand for credit during lean seasons and accounted for some 20 percent of total disbursement in 2011. On the other hand, microenterprise loan for supporting medium-sized enterprises has increased from 4 percent in 2004 to 20 percent in 2011. The MFIs have also managed to support about 6 percent of lending in urban areas. Such a sector-diversification strategy is perhaps essential for MFIs to deal with agricultural seasonality.[18]

7. Conclusions

Seasonality of agriculture is a common phenomenon in many agrarian economies. In many places households, for different reasons, have difficulty coping with income and consumption seasonality, leading to inefficiency in resource allocation. One possible reason for the inability to cope with seasonality is the absence of an active and well-functioning rural credit market and its inability to serve many of the rural households. In fact, in many societies credit rationing is the norm where rural credit markets are characterized by asymmetric information, covariate risk and problems of lack of enforcement of loan contracts.

Seasonality and the synchronic timing of agriculture means that if depositors and borrowers are both engaged in cultivation, depositors would want to withdraw money exactly when borrowers would want to borrow—at the beginning of the production season. On the other hand, depositors would want to make deposits exactly when borrowers would want to make repayments—after the harvest. If rural

[18] Moreover, support through subsidized funds was helpful to absorb shock due to seasonal loan default by MFIs. The interest rate charged by PKSF for on-lending funds to its POs was 7 percent, compared with 12.5 percent charged by POs to the microcredit borrowers during the study periods.

financial intermediation does not operate efficiently due to such covariate risks in production, rural households cannot borrow from local credit markets or handle efficiently seasonality of income and consumption.[19]

Over time, group lending and other innovative mechanisms have been developed in many places to deal with the moral hazard of rural lending. These measures have helped reduce loan default costs for lenders and handle covariate risks caused by agricultural seasonality. Also, where agriculture is highly seasonal, institutions such as MFIs have sought to diversify income by supporting rural nonfarm activities. To help reduce negative effects of covariate risks on income and consumption, they have introduced seasonal loans. Weekly loan repayment schedules and peer monitoring are enforced to avoid non-payment, especially during lean seasons.

The question is whether these measures are adequate to reduce the role of covariate risks in financial intermediation and to help households cope with the seasonality of income and consumption. No study has yet been done, to the best of our knowledge, to demonstrate whether financial inclusion and innovations have sufficiently reduced the negative consequences of covariate risks in financial intermediation in a rural setting.

The paper analyzes both household and institutional data from Bangladesh to examine both issues, namely, (i) whether seasonality still matters in household borrowing in a rural setting with extensive coverage of microfinance, and (ii) whether seasonality still matters in the portfolio management of the MFIs with innovative means to deal with the moral hazard of rural lending. Descriptive analysis of seasonal patterns of household borrowing data exhibits pronounced seasonality in that borrowing is the lowest during the lean season when households need to borrow most. On the other hand, monthly

[19] Predictable seasonality does not pose a risk if the means to avert its negative consequences does not involve a great degree of uncertainty.

microfinance operational data analysis shows that MFI lending, loan outstanding, loan recovery, and savings mobilized are lower in lean seasons than in non-lean seasons.

Seasonal patterns of financial intermediation of the MFIs or seasonality of household borrowing in response to agricultural seasonality does not necessarily mean inefficiency in the resource allocation of either MFIs or households in a rural setting. Inefficiency in resource allocation for the MFIs may occur if MFI lending is affected by seasonality, which in turn influences the MFI income portfolio such as loan outstanding and loan recovery. That means, we need to test if the seasonality of lending affects MFI loan outstanding beyond and above what is affected by agricultural seasonality. Similarly, inefficiency in resource allocation for rural households emerges if seasonality of income induced by agricultural seasonality affects borrowing in support of household consumption or investment. That is, we need to test if income seasonality affects borrowing beyond and above what is normally affected by agricultural seasonality.

Econometric analysis using panel household data involves model estimation where seasonal borrowing is regressed on income seasonality after controlling for agricultural seasonality plus a host of household and community factors affecting household demand for and supply of credit. Results show that despite the outreach of MFIs and their innovative measures to deal with agricultural seasonality, seasonal income induced by agricultural seasonality affects seasonal borrowing of rural households. This means borrowing is sensitive to seasonality of income, meaning supply of credit is not forthcoming when the demand for credit is high, possibly causing inefficiency in the production and consumption of rural households.

Monthly operational data on lending, loan outstanding, loan recovery, and savings mobilized by MFIs are used to test if seasonality affects MFI investment decision beyond and above what is affected normally by agricultural seasonality. We estimated the lagged dependent variable (LDV) method to control for joint dependence of MFI portfolio management behavior. Results confirm that despite innovative measures to deal with seasonality, asymmetric information and lack of enforcement of loan contracts

of rural credit markets, MFI investment induced by seasonality does in fact affect negatively MFI income generating activities. This affects MFI investment decisions, causing inefficiency in resource allocation beyond and above what is caused by agricultural seasonality.

What do the results imply for rural financial intermediation in a rural setting? Households do need to access institutional credit and other means in order to avert the negative consequences of seasonality of agriculture. Rural households must find ways to diversify income that can help them avert risks in agricultural production. They must be able to adopt agricultural technology to enhance productivity, which in turn helps them cope with agricultural seasonality. Rural households must be able to access credit markets to save and borrow as needed. Interfamily transfers and remittances can also help mitigate seasonality of income and credit. In fact, using various means and financial inclusions of MFIs, rural households have increasingly been able to cope with agricultural seasonality and avert the negative consequences of covariate risk such as seasonal hunger in Bangladesh (e.g., Khandker and Mahmud 2012; Khandker and Samad 2016). Public investments in infrastructure such as roads and electrification also helped increase household income, productivity, and investment to reduce the negative effects of seasonality.

MFIs have helped rural households achieve such gains against the negative consequences of seasonality of agriculture. Further innovations in financial innovation would nonetheless be helpful. For example, PKSF may help develop insurance products and make them available to borrowers as well as lenders at affordable prices to safeguard investments against agricultural risk. It would also be helpful if MFIs were able to diversify their own portfolio between rural and urban sectors, modern and traditional sectors, and across income groups without compromising their core objectives. Sectoral diversification is indeed essential to mitigating the risks inherent in rural intermediation.

MFIs may revisit their strict weekly repayment schedule, which often keeps very poor households from accessing microcredit when they badly need it—during the lean season. MFIs may introduce

flexible loan repayment as well as seasonal loans during lean seasons as a way to help increase borrowers' income and ability to cope with seasonality (e.g., Hashemi 1997, Rahman and Hossain 199), Shonchoy 2014; Shonchoy and Kurosaki 2014). Borrowing without savings may also be allowed; similarly, more convenient, available and voluntary saving services may be promoted to deal with income seasonality (Nteziyaremye et al. 2001). Non-financial interventions such as seasonal public works, crop insurance, and food price stabilization may be supported to help promote the coping capacity of lenders and borrowers in a rural setting (McCulloch and Baulch 2002). Training and technical aid to undertake non-agricultural income generating activities may be provided by MFIs focusing on lean seasons. MFIs should also be offered flexibility in the repayments of their loans from PKSF during lean seasons.

In short, with easier credit access, flexible repayment and savings, and non-agricultural income generating activities, borrowers from seasonality-prone areas can smooth income and consumption. Rural financial intermediaries must also be able to avoid default loans due to crop seasonality through sectoral diversification and other means, and thus save themselves from defaulting on their loans. This will, eventually, not only contribute to reducing seasonality of income and poverty, but also make microfinance sector better and viable in a rural setting.

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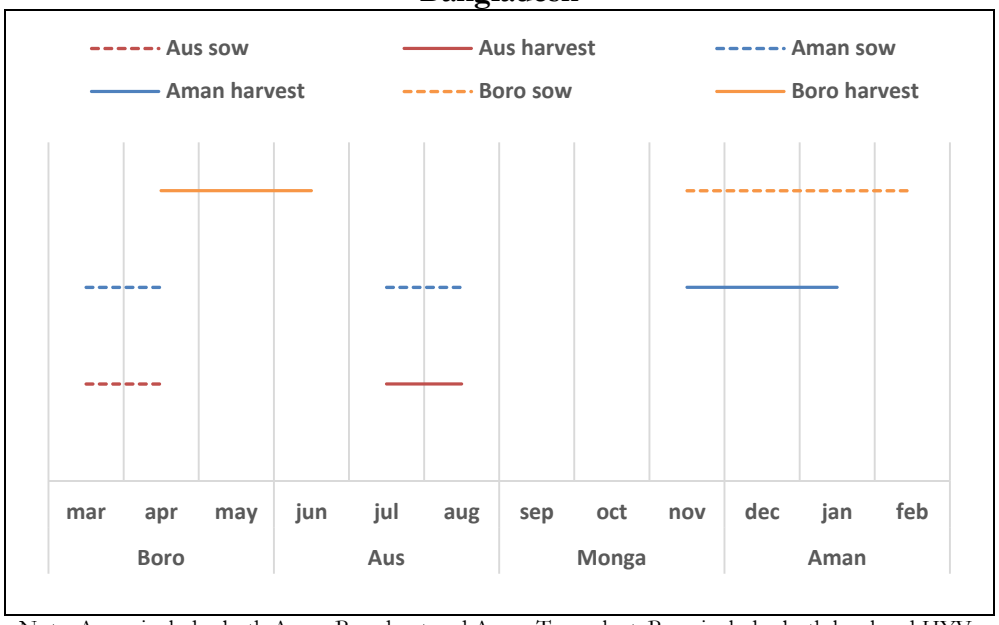
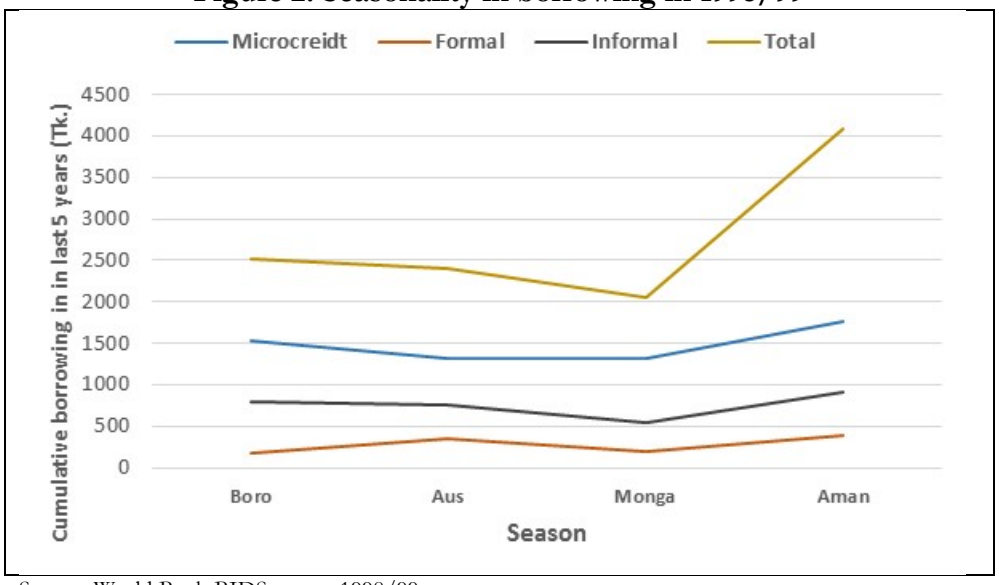
Figure 1: Sowing/transplanting and harvesting periods of paddy in Bangladesh



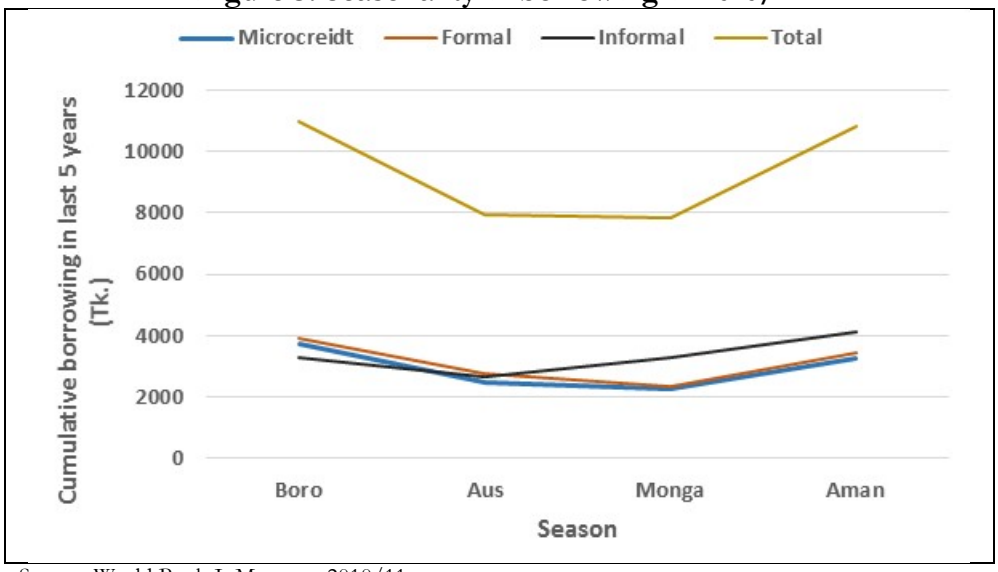
Note: Aman includes both Aman Broadcast and Aman Transplant, Boro includes both local and HYV.
Source: BBS 2004

Figure 2: Seasonality in borrowing in 1998/99



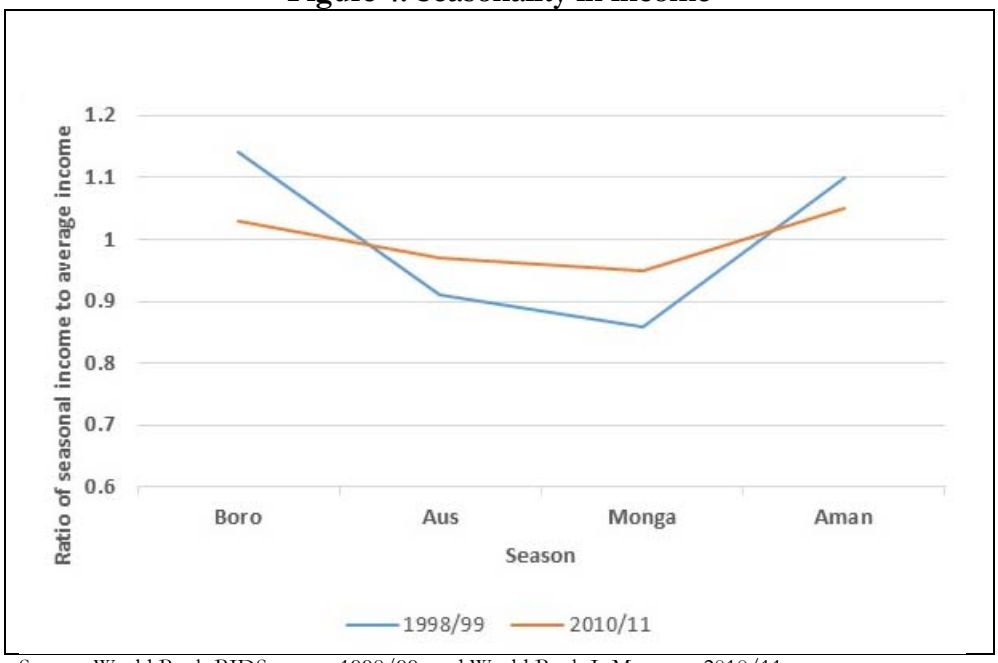
Source: World Bank-BIDS survey 1998/99

Figure 3: Seasonality in borrowing in 2010/11



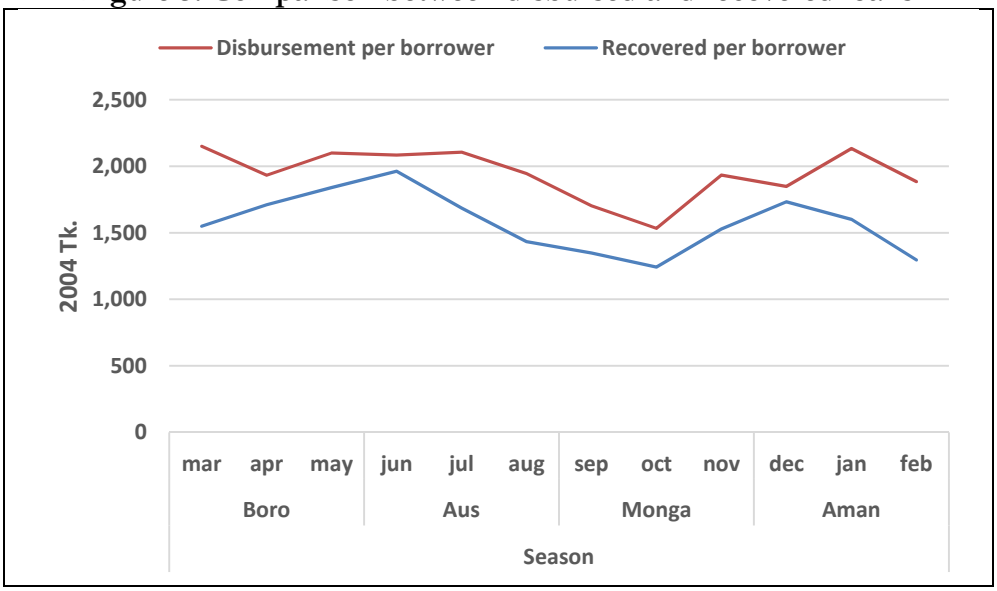
Source: World Bank-InM survey 2010/11

Figure 4: Seasonality in income



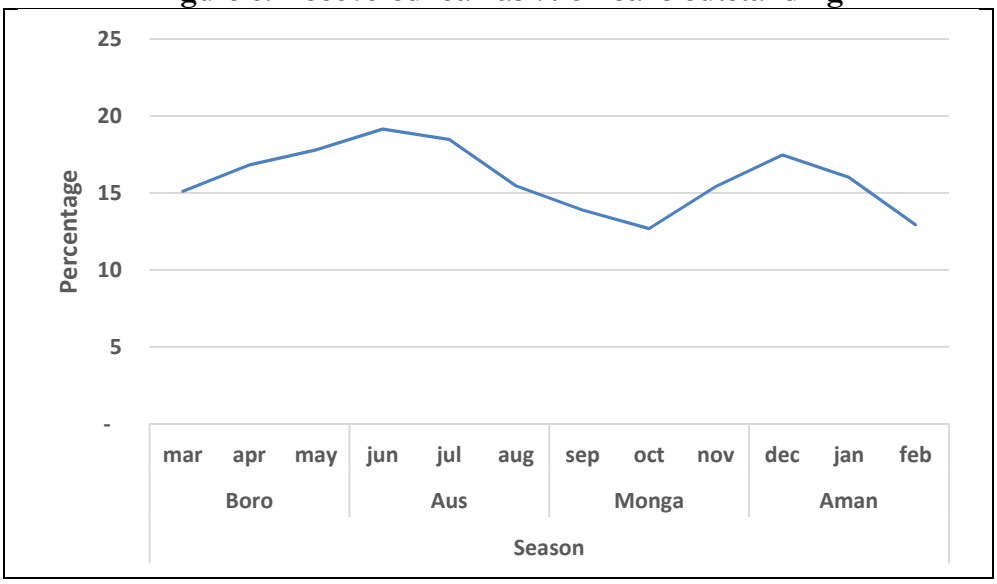
Source: World Bank-BIDS survey 1998/99, and World Bank-InM survey 2010/11

Figure 5: Comparison between disbursed and recovered loans



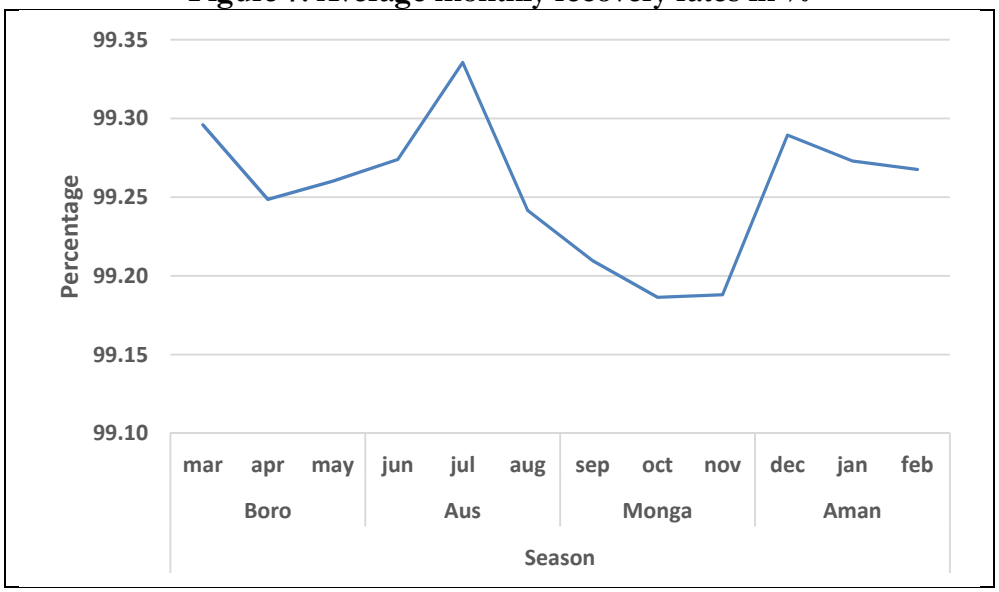
Source: PKSF (2011)

Figure 6: Recovered loan as % of loans outstanding



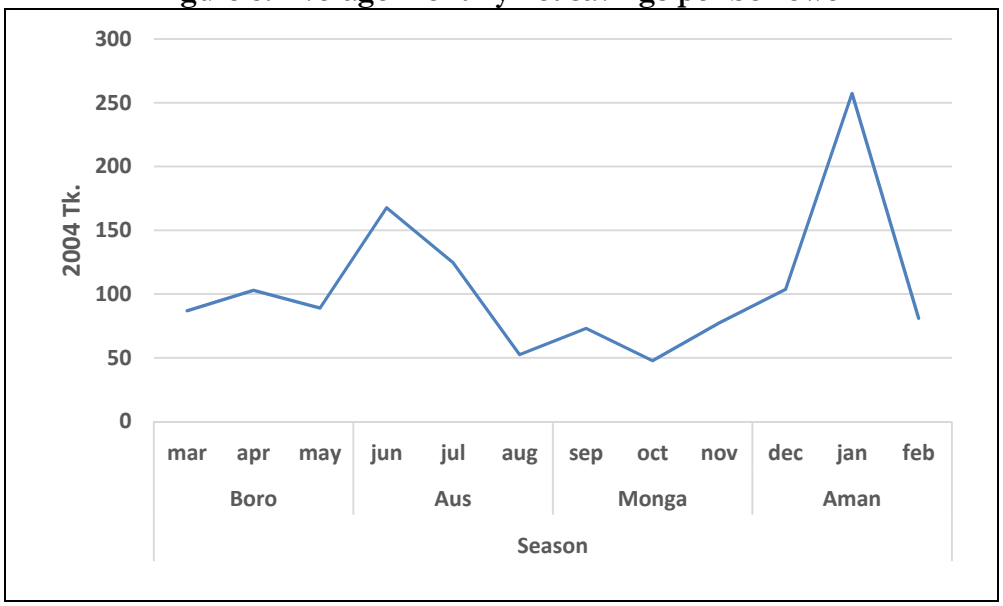
Source: PKSF (2011)

Figure 7: Average monthly recovery rates in %



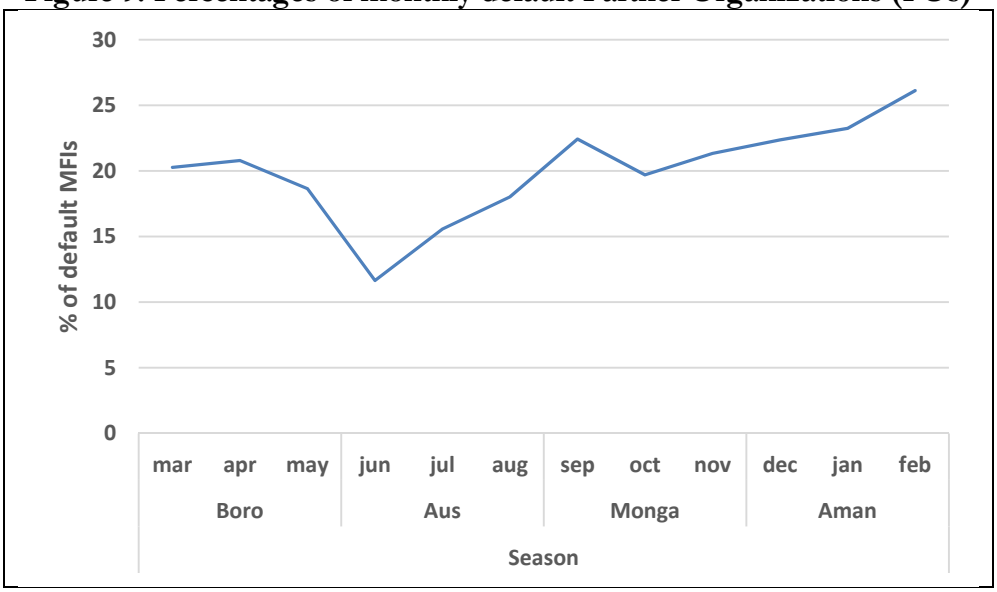
Source: PKSF (2011)

Figure 8: Average monthly net savings per borrower



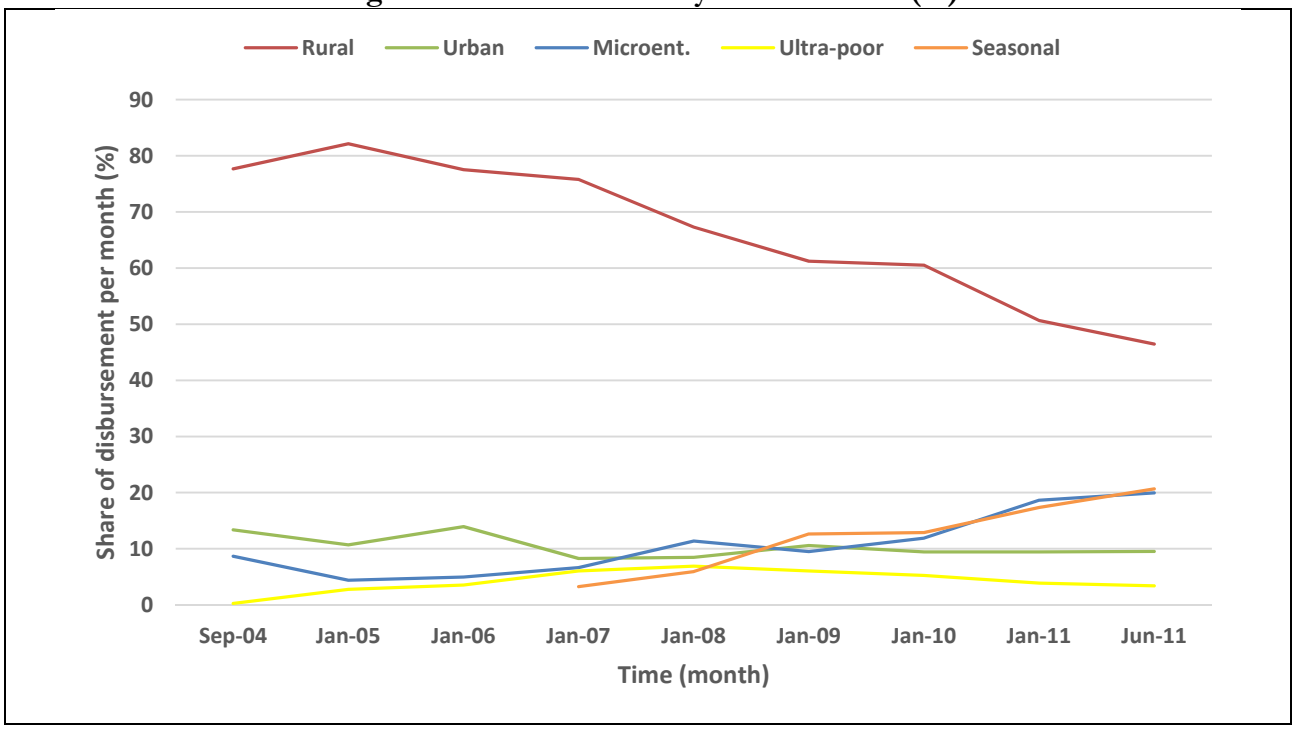
Source: PKSF (2011)

Figure 9: Percentages of monthly default Partner Organizations (POs)



Source: PKSF (2011)

Figure 10: Share of monthly disbursement (%)



Source: PKSF (2011)
Note: Seasonal loan started in February 2007.

Tables

Table 1: Test of significance of seasonality in borrowing and income (N=1,758)

Borrowing amount and seasonal income	Monga season	Non-monga season	t-statistics of the difference
1998/99			
Microcredit borrowing (Tk./month)	152.0	141.4	0.85
Formal borrowing (Tk./month)	27.6	37.8	-0.94
Informal borrowing (Tk./month)	103.0	124.0	-0.83
Total borrowing (Tk./month)	282.5	303.2	-0.66
Ratio of actual seasonal in-come to average seasonal in-come	0.85	1.05	-35.98
2010/11			
Microcredit borrowing (Tk./month)	273.0	337.9	-2.33
Formal borrowing (Tk./month)	41.1	86.9	-1.24
Informal borrowing (Tk./month)	0	445.5	-12.68
Total borrowing (Tk./month)	314.1	870.3	-8.91
Ratio of actual seasonal in-come to average seasonal in-come	0.96	1.01	-17.11
Both years			
Microcredit borrowing (Tk./month)	221.0	253.5	-1.94
Formal borrowing (Tk./month)	35.3	65.8	-1.42
Informal borrowing (Tk./month)	44.2	307.5	-11.50
Total borrowing (Tk./month)	300.6	626.9	-8.55
Ratio of actual seasonal in-come to average seasonal in-come	0.91	1.02	-37.85

Source: World Bank-BIDS survey 1998/99, and World Bank-InM survey 2010/11

Table 2: Test of significance of seasonality in MFI performance indicators (N=401)

MFI performance indicators (mean)	Lean season	Other seasons	t-statistics of the difference
Boro lean season only (Feb-Mar)			
Log of monthly disbursement per borrower	7.202	7.144	-0.507
Log loan outstanding at month's end per borrower	8.879	8.829	-0.488
Log monthly loan recovered per borrower	6.872	6.989	1.045
Log monthly net savings per borrower	3.914	3.896	-0.093
Recovery rate (%)	99.282	99.251	-0.488
Log of monthly default POs	2.488	2.214	-1.584
Monga season only (Sep-Nov)			
Log of monthly disbursement per borrower	7.022	7.197	1.731
Log loan outstanding at month's end per borrower	8.806	8.848	0.446
Log monthly loan recovered per borrower	6.820	7.018	1.986
Log monthly net savings per borrower	3.565	4.002	2.497
Recovery rate (%)	99.195	99.276	1.516
Log of monthly default POs	2.339	2.235	-0.671
Boro and Monga seasons combined			
Log of monthly disbursement per borrower	7.096	7.196	1.129
Log loan outstanding at month's end per borrower	8.836	8.839	0.036
Log monthly loan recovered per borrower	6.841	7.060	2.526
Log monthly net savings per borrower	3.713	4.028	2.162
Recovery rate (%)	99.230	99.274	0.929
Log of monthly default POs	2.400	2.161	-1.771

Source: PKSF (2011)

Table 3a: Estimates of the impacts of income seasonality on borrowing (Household FE estimates)

Selected explanatory variables	Microcredit borrowing during last one year (Tk.)	Formal borrowing during last one year (Tk.)	Informal borrowing during last one year (Tk.)	Total borrowing during last one year (Tk.)	Mean and standard deviations of explanatory variables
Average per capita seasonal income during last one year (Tk.)	0.092**	-0.015	0.053	0.129**	2,764.4
	(2.28)	(-0.86)	(1.28)	(2.13)	(5,844.1)
Ratio of actual seasonal income to average seasonal income	-0.139**	-0.082**	-0.137**	-0.347**	1.0
	(-2.44)	(-1.99)	(-2.38)	(-4.50)	(0.259)
Year (1998/99=0, 2010/11=1)	1.478*	0.434	1.413	2.204*	0.570
	(1.64)	(1.53)	(1.50)	(1.74)	(0.495)
Boro season	0.184**	0.004	0.170**	0.332**	0.25
	(2.57)	(0.19)	(2.11)	(3.01)	(0.433)
Aus season	0.041	0.009	0.166**	0.186*	0.25
	(0.56)	(0.37)	(2.41)	(1.88)	(0.433)
Aman season	0.269**	0.095**	0.370**	0.631**	0.25
	(3.41)	(2.72)	(5.67)	(6.20)	(0.433)
Community has commercial banks	0.218	-0.005	0.362**	0.522**	0.130
	(1.51)	(-0.11)	(2.21)	(2.10)	(0.336)
Number of MFIs operating in the village	0.043*	0.003	-0.021	0.017	5.8
	(1.65)	(0.39)	(-0.69)	(0.40)	(2.86)
R^2	0.158	0.080	0.278	0.322	
N	1,758	1,758	1,758	1,758	
Mean of dependent variables	735.5	174.6	724.4	1,634.4	
	(3,510.4)	(6,162.7)	(5,849.1)	(9,434.3)	

* and ** refer to statistical significance at 10 percent and 5 percent levels or better, respectively.

Note: Figures in parentheses are t-statistics (based on robust standard errors clustered at village-level) except for the last column and last row where they are standard deviations. Regression includes additional control variables such as household head's sex, age and education, household landholding, village infrastructure variables such as presence of primary and secondary schools, electricity, government and NGO food programs, village accessibility and prices of food items.

Source: World Bank-BIDS survey 1998/99, and World Bank-InM survey 2010/11

Table 3b: Estimates of the impacts of income seasonality on borrowing (Random effects estimation using Seemingly Unrelated Regression)

Selected explanatory variables	Microcredit borrowing during last one year (Tk.)	Formal borrowing during last one year (Tk.)	Informal borrowing during last one year (Tk.)	Total borrowing during last one year (Tk.)
Average per capita seasonal income during last one year (Tk.)	0.196** (6.61)	-0.012 (-1.58)	0.137** (6.20)	0.288** (8.65)
Ratio of actual seasonal income to average seasonal income	-0.063* (-1.98)	-0.120** (-4.15)	-0.343** (-4.11)	-0.529** (-4.25)
Year (1998/99=0, 2010/11=1)	2.4344** (2.87)	-0.615** (-2.98)	2.374** (3.89)	3.467** (3.76)
Boro season	-0.011 (-0.15)	0.084** (4.18)	0.430** (7.53)	0.444** (5.23)
Aus season	-0.041 (-0.58)	0.053** (2.73)	0.265** (4.83)	0.279** (3.43)
Aman season	-0.121 (-1.58)	0.161** (8.21)	0.792** (14.17)	0.752** (9.07)
Community has commercial banks	-0.126 (-1.17)	0.134** (5.15)	-0.109 (-1.39)	-0.109 (-0.90)
Number of MFIs operating in the village	0.114** (6.58)	-0.015** (-3.57)	-0.045** (-3.52)	0.058** (2.97)
N	2,342	2,342	2,342	2,342

* and ** refer to statistical significance at 10 percent and 5 percent levels or better, respectively.

Note: Figures in parentheses are t-statistics (based on robust standard errors clustered at village-level). Regression includes additional control variables such as household head's sex, age and education, household landholding, village infrastructure variables such as presence of primary and secondary schools, electricity, government and NGO food programs, village accessibility and prices of food items.

Source: World Bank-BIDS survey 1998/99, and World Bank-InM survey 2010/11

Table 4: Monthly variations in major meteorological variables

Month	Rainfall in millimeter	Temperature in Celsius	Humidity index	Cyclones count (1960-2009)
January	346.8	18.31	77.77	0
February	615.4	21.75	73.29	0
March	1,180.8	25.60	71.40	0
April	2,595.2	28.32	74.81	1
May	9,102	28.90	77.96	10
June	12,820.6	29.00	83.67	0
July	20,049.4	28.25	86.74	0
August	12,862	28.54	85.59	0
September	14,125.2	28.26	85.71	1
October	8,536.4	26.99	83.73	5
November	770.2	23.40	79.68	9
December	58.8	19.93	79.05	3

Source: BMD (2011)

Table 5: Summary statistics of all variables across projects

	Overall	Rural	Urban	Micro-ent.	Ultra-poor	Sea-sonal
Outcome variables						
Loan outstanding at month's end per borrower (Tk.)	9,900	4,392	6,642	26,433	2,795	9,046
	(10,188)	(568)	(1,288)	(11,163)	(564)	(2,140)
Monthly recovered loan per borrower (Tk.)	1,578	665	1,289	3,999	425	1,494
	(1,568)	(194)	(670)	(1,582)	(120)	(904)
Monthly recovery rate (%)	99.26	98.74	99.58	99.22	99.21	99.61
	(0.47)	(0.18)	(0.30)	(0.43)	(0.46)	(0.31)
Net savings at month's end per borrower (Tk)	91.57	14.01	53.04	274.52	26.29	89.53
	(477.45)	(51.07)	(73.25)	(1,013.16)	(27.97)	(151.04)
% of default POs	20.00	66.40	7.17	12.45	6.71	3.57
	(25.77)	(15.50)	(5.85)	(9.21)	(6.23)	(3.09)
Explanatory variables						
Monthly loan disbursement per borrower (Tk.)	1,947	692	1,403	4,983	516	2,196
	(2,019)	(150)	(777)	(2,069)	(128)	(1,331)
Average monthly disbursement per borrower in the fiscal year (Tk.)	1,947	692	1,403	4,983	516	2,196
	(1,887)	(91)	(299)	(1,807)	(28)	(762)
Ratio of actual-to-average monthly disbursement	1.00	1.00	1.00	1.00	1.00	1.00
	(0.33)	(0.17)	(0.42)	(0.25)	(0.23)	(0.50)
Number of male borrowers	127,978	530,407	13,463	32,714	860	43,289
	(209,488)	(41,581)	(8,872)	(28,338)	(314)	(26,860)
Number of female borrowers	1,302,156	4,923,001	479,359	100,267	557,731	201,455
	(1,894,890)	(541,584)	(132,497)	(38,528)	(227,490)	(138,610)
Number of male members	202,253	871,290	17,677	36,313	1,225	50,419
	(354,017)	(167,304)	(12,730)	(30,846)	(550)	(27,453)
Number of female members	1,711,724	6,623,056	576,492	105,631	709,631	202,420
	(2,565,063)	(672,733)	(171,722)	(41,430)	(291,289)	(130,273)
Lean season 1	0.17	0.17	0.17	0.17	0.17	0.18
(February-March)	(0.38)	(0.37)	(0.37)	(0.37)	(0.37)	(0.39)
Lean season 2	0.25	0.25	0.25	0.25	0.25	0.23
(September -November)	(0.43)	(0.44)	(0.44)	(0.44)	(0.44)	(0.42)
Observations	401	84	84	84	84	65

Note: Figures in parentheses are standard deviations.
Source: Palli Karma-Sahayak Foundation (PKSF, 2011)

Table 6: Seasonality in loans outstanding

	Outcome variable: Log monthly loan outstanding per borrower (2004 Tk.)					
Explanatory variables	**Overall**	**Rural**	**Urban**	**Microent.**	**Ultra-poor**	**Seasonal**
First lag of the outcome variable	0.705**	0.945**	0.046	0.245**	0.948**	0.808**
	(25.179)	(25.541)	(0.657)	(2.634)	(21.545)	(12.825)
Log avg. monthly loan disbursement per borrower in a FY (in 2004 Tk.)	0.126**	0.026	0.074**	0.201**	0.061	0.051
	(5.727)	(1.444)	(2.741)	(3.242)	(0.735)	(1.545)
Monthly share of loan disbursement per borrower	0.066**	0.035**	-0.019	-0.038	0.135**	0.069**
	(6.000)	(2.917)	(-0.760)	(-0.792)	(9.000)	(6.900)
Log number of male members	0.031**	-0.017	0.105**	0.375**	0.001	-0.022
	(4.429)	(-1.700)	(3.387)	(6.466)	(0.100)	(-0.957)
Log number of female members	0.023**	0.015	0.235**	-0.339	-0.001	0.084**
	(2.300)	(0.536)	(2.765)	(-6.164)	(-0.063)	(3.111)
Leanseason1 dummy (February-March)	-0.110	0.032	-0.251	-0.009	0.188**	0.103
	(-4.783)	(1.524)	(-6.972)	(-0.079)	(3.032)	(1.561)
Leanseason2 dummy (September-November)	0.033	0.009	-0.030	-0.069	0.051*	0.048*
	(1.435)	(0.429)	(-0.789)	(-0.958)	(1.821)	(1.655)
Leanseason1 multiplied by monthly share of disbursement	0.118**	-0.034	0.234**	-0.002	-0.172	-0.141
	(5.619)	(-1.700)	(8.069)	(-0.017)	(-3.127)	(-1.567)
Leanseason2 multiplied by monthly share of disbursement	-0.022	-0.005	0.036	0.075	-0.047	-0.031
	(-0.917)	(-0.227)	(0.923)	(1.000)	(-1.567)	(-0.939)
Breusch-Godfrey LM p-values		0.292	0.002	0.616	0.076	0.263
Observations	396	83	83	83	83	64
Adjusted R-squared	0.996	0.992	0.957	0.986	0.991	0.982

* and ** refer to statistical significance at 10 percent and 5 percent levels or better, respectively.

Note: Figures in parentheses are t-statistics. Monetary figures such as outstanding, disbursement, savings, recovered loan are realized to June 2004 Tk. Fiscal year dummies, project dummies, intercept terms, interaction of year and month, temperature, humidity, and rainfall variables are included but not reported. Breusch-Godfrey LM p-values indicate no significant autocorrelation if it is greater than 0.01. Since we have five projects, we could not test for panel autocorrelation in the overall regression. Another option of testing autocorrelation in overall regression was to add the figures of all five projects and construct a time series. However, we could then erroneously double-count members and borrowers because borrowers can simultaneously take loans from more than one project.

Source: Palli Karma-Sahayak Foundation (PKSF, 2011)

Table 7: Seasonality in recovered loan

	Outcome variable: Log monthly loan recovered per borrower (2004 Tk.)					
Explanatory variables	**Overall**	**Rural**	**Urban**	**Microent.**	**Ultra-poor**	**Seasonal**
First lag of the outcome variable	0.128**	-0.037	-0.130	0.270**	0.275**	-0.153
	(2.909)	(-0.451)	(-1.413)	(2.842)	(2.183)	(-1.142)
Log avg. monthly loan disbursement per borrower in a FY (in 2004 Tk.)	0.610**	1.109**	0.872**	0.561**	1.043**	0.646**
	(6.630)	(5.716)	(5.450)	(2.408)	(2.647)	(3.230)
Monthly share of loan disbursement per borrower	0.433**	0.872**	0.725**	0.693**	-0.105	0.526**
	(7.098)	(5.484)	(5.254)	(3.667)	(-0.991)	(4.574)
Log number of male members	-0.007	0.006	0.021	0.077	-0.022	0.803**
	(-0.194)	(0.067)	(0.116)	(0.583)	(-0.297)	(2.985)
Log number of female members	0.188**	0.011	0.092	-0.056	0.320**	-0.475
	(3.481)	(0.049)	(0.189)	(-0.381)	(4.051)	(-1.979)
Leanseason1 dummy (February-March)	0.101	-0.200	0.675**	-0.741	-0.290	0.331
	(0.815)	(-0.717)	(3.245)	(-1.665)	(-0.640)	(0.468)
Leanseason2 dummy (September-November)	-0.485	-0.146	-0.293	0.134	-0.156	-1.137
	(-3.880)	(-0.529)	(-1.382)	(0.484)	(-0.754)	(-3.305)
Leanseason1 multiplied by monthly share of disbursement	-0.223	0.221	-0.798	0.709	0.239	-1.041
	(-2.009)	(0.867)	(-4.586)	(1.572)	(0.593)	(-1.097)
Leanseason2 multiplied by monthly share of disbursement	0.386**	0.029	0.163	-0.175	0.159	0.713*
	(2.969)	(0.100)	(0.741)	(-0.618)	(0.723)	(1.881)
Breusch-Godfrey LM p-values		0.796	0.679	0.188	0.000	0.068
Observations	396	83	83	83	83	64
Adjusted R-squared	0.902	0.671	0.580	0.806	0.800	0.650

* and ** refer to statistical significance at 10 percent and 5 percent levels or better, respectively.

Note: Figures in parentheses are t-statistics. Monetary figures such as outstanding, disbursement, savings, recovered loan are realized to June 2004 Tk. Fiscal year dummies, project dummies, intercept terms, interaction of year and month, temperature, humidity, and rainfall variables are included but not reported. Breusch-Godfrey LM p-values indicate no significant autocorrelation if it is greater than 0.01. Since we have five projects, we could not test for panel autocorrelation in the overall regression. Another option of testing autocorrelation in overall regression was to add the figures of all five projects and construct a time series. However, we could then erroneously double-count members and borrowers because borrowers can simultaneously take loans from more than one project.

Source: Palli Karma-Sahayak Foundation (PKSF, 2011)

Table 8: Seasonality in monthly savings

	Outcome variable: Log net savings at the end of the month per borrower (2004 Tk.)					
Explanatory variables	**Overall**	**Rural**	**Urban**	**Microent.**	**Ultra-poor**	**Seasonal**
First lag of the outcome variable	0.169**	0.316**	0.123	0.121	0.338**	-0.006
	(2.864)	(2.164)	(0.932)	(0.858)	(2.939)	(-0.042)
Log avg. monthly loan disbursement per borrower in a FY (in 2004 Tk.)	0.239	-0.503	1.477*	-0.715	0.807	0.648*
	(0.956)	(-0.350)	(1.918)	(-0.813)	(0.443)	(1.952)
Monthly share of loan disbursement per borrower	0.578**	3.982**	0.881	1.157*	0.731*	0.383**
	(3.568)	(4.010)	(1.617)	(1.717)	(1.669)	(1.964)
Log number of male members	0.164	0.045	0.153	0.595	0.612*	0.059
	(1.519)	(0.070)	(0.227)	(1.217)	(1.883)	(0.141)
Log number of female members	-0.750	4.441**	-0.090	-0.625	-0.813	-0.924
	(-4.808)	(2.374)	(-0.048)	(-1.268)	(-3.213)	(-2.322)
Leanseason1 dummy (February-March)	-0.171	4.400**	0.579	1.438	0.857	-0.415
	(-0.499)	(2.398)	(0.738)	(0.540)	(0.360)	(-0.357)
Leanseason2 dummy (September-November)	-0.787	0.978	-0.854	-0.308	-1.219	-0.345
	(-2.294)	(0.391)	(-1.040)	(-0.306)	(-1.322)	(-0.658)
Leanseason1 multiplied by monthly share of disbursement	0.120	-3.869	-0.129	-1.599	-0.852	0.603
	(0.401)	(-2.315)	(-0.207)	(-0.604)	(-0.412)	(0.384)
Leanseason2 multiplied by monthly share of disbursement	0.415	-2.341	0.297	-0.074	0.807	0.628
	(1.172)	(-0.906)	(0.352)	(-0.074)	(0.830)	(1.028)
Breusch-Godfrey LM p-values		0.055	0.892	0.234	0.518	0.617
Observations	311	45	59	73	70	64
Adjusted R-squared	0.701	0.426	0.202	0.192	0.476	0.645

* and ** refer to statistical significance at 10 percent and 5 percent levels or better, respectively.

Note: Figures in parentheses are t-statistics. Monetary figures such as outstanding, disbursement, savings, recovered loan are realized to June 2004 Tk. Fiscal year dummies, project dummies, intercept terms, interaction of year and month, temperature, humidity, and rainfall variables are included but not reported. Breusch-Godfrey LM p-values indicate no significant autocorrelation if it is greater than 0.01. Since we have five projects, we could not test for panel autocorrelation in the overall regression. Another option of testing autocorrelation in overall regression was to add the figures of all five projects and construct a time series. However, we could then erroneously double-count members and borrowers because borrowers can simultaneously take loans from more than one project.

Source: Palli Karma-Sahayak Foundation (PKSF, 2011)

Table 9: Seasonality in institutional default rates

	Outcome variable: Log of monthly default organizations					
Explanatory variables	**Overall**	**Rural**	**Urban**	**Microent.**	**Ultra-poor**	**Seasonal**
First lag of the outcome variable	0.329**	0.102	0.370**	0.327**	0.328**	0.356**
	(6.580)	(0.773)	(3.058)	(2.477)	(2.877)	(2.657)
Log avg. monthly loan disbursement per borrower in a FY (in 2004 Tk.)	-0.085	0.308	-0.292	-0.334	1.468	0.070
	(-0.567)	(1.426)	(-0.970)	(-0.568)	(0.997)	(0.241)
Monthly share of loan disbursement per borrower	-0.067	-0.380	0.014	0.034	-0.258	-0.134
	(-0.663)	(-1.959)	(0.048)	(0.077)	(-0.637)	(-0.793)
Log number of male members	0.210**	-0.079	0.224	0.681*	-0.127	0.343
	(3.387)	(-0.718)	(0.615)	(1.841)	(-0.429)	(0.903)
Log number of female members	0.160*	0.552*	0.727	-0.032	0.853**	0.159
	(1.798)	(1.846)	(0.723)	(-0.094)	(3.068)	(0.448)
Leanseason1 dummy (February-March)	-0.105	-0.140	-0.120	0.882	0.785	-2.869
	(-0.505)	(-0.411)	(-0.295)	(0.851)	(0.441)	(-2.719)
Leanseason2 dummy (September-November)	-0.150	-0.467	0.104	-0.162	0.317	-0.318
	(-0.714)	(-1.362)	(0.240)	(-0.247)	(0.372)	(-0.656)
Leanseason1 multiplied by monthly share of disbursement	0.147	0.139	0.088	-0.767	-0.524	3.869**
	(0.795)	(0.448)	(0.260)	(-0.732)	(-0.331)	(2.730)
Leanseason2 multiplied by monthly share of disbursement	0.423*	0.620*	0.295	0.393	0.039	0.523
	(1.949)	(1.742)	(0.654)	(0.587)	(0.044)	(0.910)
Breusch-Godfrey LM p-values		0.561	0.118	0.678	0.043	0.021
Observations	396	83	83	83	83	64
Adjusted R-squared	0.885	0.353	0.696	0.744	0.666	0.589

* and ** refer to statistical significance at 10 percent and 5 percent levels or better, respectively.

Note: Figures in parentheses are t-statistics. Monetary figures such as outstanding, disbursement, savings, recovered loan are realized to June 2004 Tk. Fiscal year dummies, project dummies, intercept terms, interaction of year and month, temperature, humidity, and rainfall variables are included but not reported. Breusch-Godfrey LM p-values indicate no significant autocorrelation if it is greater than 0.01. Since we have five projects, we could not test for panel autocorrelation in the overall regression. Another option of testing autocorrelation in overall regression was to add the figures of all five projects and construct a time series. However, we could then erroneously double-count members and borrowers because borrowers can simultaneously take loans from more than one project.

Source: Palli Karma-Sahayak Foundation (PKSF, 2011)

Appendix A

Program level monthly data of PKSF MFIs in Bangladesh (PKSF, 2011)

The program-level data came from Palli Karma-Sahayak Foundation (PKSF), an apex organization for Bangladeshi microfinance institutions. PKSF finances and supports various programs in 262 MFIs—called Partner Organizations (POs) of PKSF (PKSF 2011). In 2010, Bangladesh Microfinance Statistics reported around 750 MFIs (InM and CDF 2011), which makes our sample representing the microcredit sector of Bangladesh. PKSF lends to POs at a subsidized rate of interest. POs then lend to individual micro-borrowers and repays PKSF from the revenue generated. These POs are scattered all over the country, where PKSF has implemented more than 30 different types of microcredit programs. Many programs are project-based and run for a fixed time, such as an affordable microcredit program in a cyclone-affected area, whereas many other programs like rural microcredit are continuous. We broadly categorized nine large and continuous programs by five credit products: rural microcredit (RMC), urban microcredit (UMC), microenterprise (ME), ultra-poor (UP), and agricultural or seasonal loan (ASL). Among these five categories, ME includes two PKSF projects: Microenterprise Lending (MEL), and Micro Enterprise (GOB); UP contains three PKSF projects: Ultra-Poor Program (UPP), Credit for Hard-Core Poor (HCP), and Financial Services for the Poorest (FSP); and, ASL consists of three PKSF projects: Microfinance for Marginal and Small Farmers (MFMSF), Seasonal Loan (SL), and Agriculture Sector Microcredit (ASM). These programs account for about 90 percent of PKSF's total loan disbursement to POs in FY2009-10, among which RMC alone contributed up to 40 percent. Table A1 provides an overview of the program categories.

Of the total RMC members, 77% got loan, and the average size of RMC loan to beneficiaries is Tk. 12,085. The UMC program is for the vulnerable people who live in the metropolitan areas of Bangladesh. They are landless and live on day-labor and petty trade. They mainly live in the slums or roadside

sheds with very limited resources to generate income. In FY 2009-10, the average loan size of UMC beneficiaries was Tk. 14,509. About 78 percent of the members under the UMC program got a loan.

The ME program facilitates employment generation at micro-enterprise level. The beneficiaries from RMC or UMC who graduate to a certain level of business ownership that employs other people become eligible for ME loan ranging from Tk. 30,000 to Tk. 300,000. This program mainly came into operation in November 2004. The MEL is another microenterprise program that was continued. At present, MEL has only limited operation. The UPP is a specialized program for extreme poor with features like flexible savings and non-financial supports for operating income generating activities. In FY 2009-10, the average loan size under this program was Tk. 6,474. About 76 percent of UPP members are borrowers. This program was also initiated in November 2004. The two other two programs for the extreme poor, HCP and FSP, were until February 2005 and July 2009, respectively.

MFMSF started its operation in June 2005 to deliver sustainable demand-driven microcredit services to poor farming communities to increase agricultural production through access to credit and to provide information about adoption of new technologies and linkages to markets. The Project was continued until June 2011. The SL program has been specifically shaped for small and marginal farmers who are involved in crop and non-crop farming activities. Income generating activities under this program include crop cultivation and processing, livestock, fisheries, agro-forestry, agro-processing etc. PKSF launched ASM in FY 2008-09 to implement the experience and lessons learned from MFMSF.

We have monthly data of all programs for seven years starting from July 2004 to June 2011, except for ASL, which started from February 2006. We calculated monthly loan disbursement, monthly loan recovered, monthly net savings, and monthly number of default POs. Defaulted POs are those that fail to repay PKSF's credit they were supposed to repay in a month. Loan outstanding, as a stock variable, is cumulative as of the last day of the month. Monthly recovery rate is the loan recovered by MFIs as a percentage of recoverable loans. Loan disbursement, recovered, recovery rate, net savings, and loans

outstanding have been calculated for loans extended to individuals by PO, and PO default rates have been calculated for loans given to POs by PKSF.

Figure A.1 shows share of different projects in total monthly disbursement per borrower. Time series of five programs ranked by their per capita loan size: microenterprise, seasonal credit, urban credit, rural credit, and ultra-poor credit, respectively. Microenterprise covers about half of the total per capita disbursement for its larger disbursement size and lower number of borrowers. Although rural microcredit occupies about 40 percent of total disbursement, the large number of borrowers in the rural microcredit program makes per capita disbursement as small as ultra-poor microcredit. Figure A.2 shows the growth of monthly disbursement per capita for each program. The time series follow a somewhat cyclical pattern, which is consistent with the credit literature.

Figures A.1 and A.2 show that urban microcredit increases in 2006 in both absolute and relative terms. The reason is twofold. First, the series of floods in 2004 and 2005 inundated almost two-thirds of the country and necessitated refinancing of small businesses. Thus, disbursement of all types of microcredit grew in 2006. Flood victims in rural areas lost their homestead and livelihood and migrated to nearby urban areas in search of earning opportunities. The demand for urban microcredit was likely to increase because urban microcredit mainly serves day laborers and petty traders in urban regions. From the supply side perspective, MFIs might have focused more on urban disbursement in 2006 to hedge their overall investment. Secondly, PKSF initiated urban microcredit in 2001 and rapidly started expanding the program to more MFIs in 2006-07. The number of active POs serving urban microcredit grew more than double during the period. However, all types of disbursement per capita plunged in 2007 because of the political crisis.

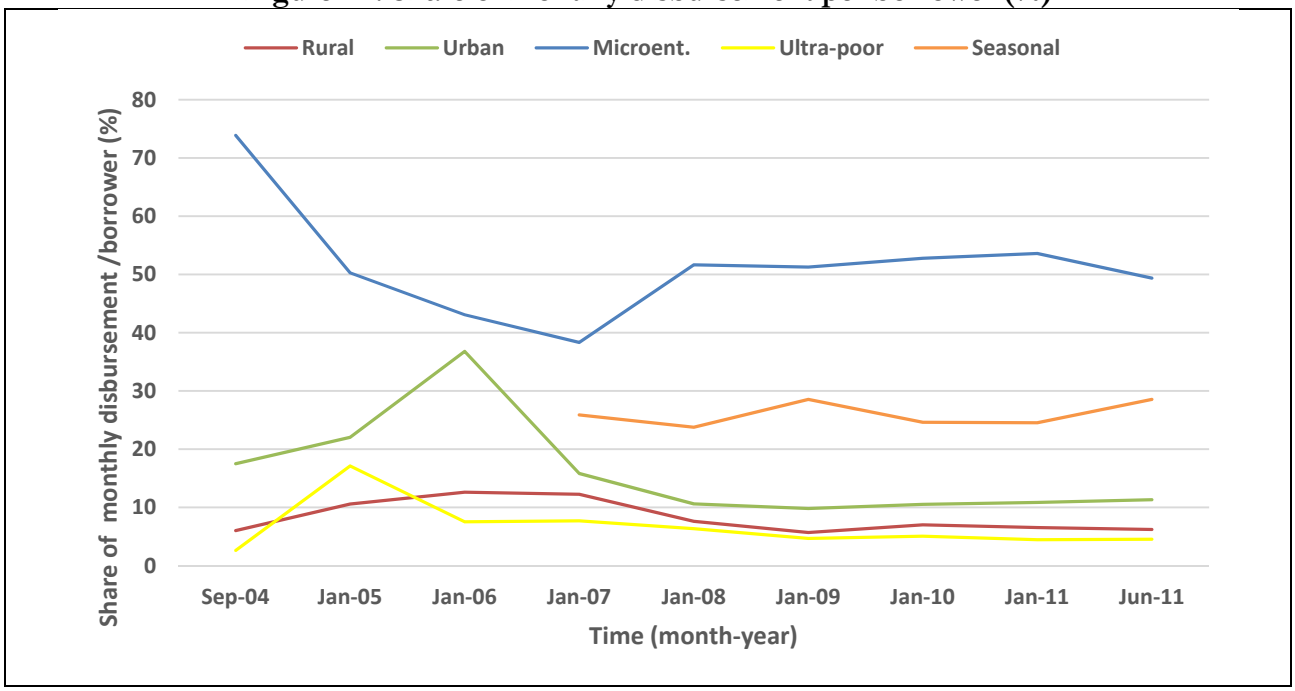
All monetary figures (disbursement, outstanding, savings etc.) are expressed in real terms (June 2004=100). Climate variables, such as average monthly temperature, average countrywide humidity index, and average monthly rainfall came from Bangladesh Meteorological Department (BMD, 2011).

Table A1: The five major credit product categories

Sl. no.	Program type	Description	Average loan size (in 2010)	Lending interest rate (%)	Obs. (months)
1	Rural microcredit (RMC)	For rural crop and non-crop agriculture, small trading, transport and other family-based income generating activities	12,000	12.5	84
2	Urban microcredit (UMC)	For landless day-laborer group living in the metropolitan areas to facilitate petty trade.	15,000	12.5	84
3	Microenterprise loan (ME)	Bigger amount than RMC or UMC for enterprises that employ other people	30,000 to 300,000	12.5	84
4	Credit for ultra poor (UP)	Flexible loan for the extreme poor like beggars in urban areas	6,000	10	84
5	Agricultural or seasonal loan (ASL)	For small and marginal farmers, growers and agro-processors	25,000	12.5	65

Source: PKSF (2011) and authors' calculation

Figure A1: Share of monthly disbursement per borrower (%)

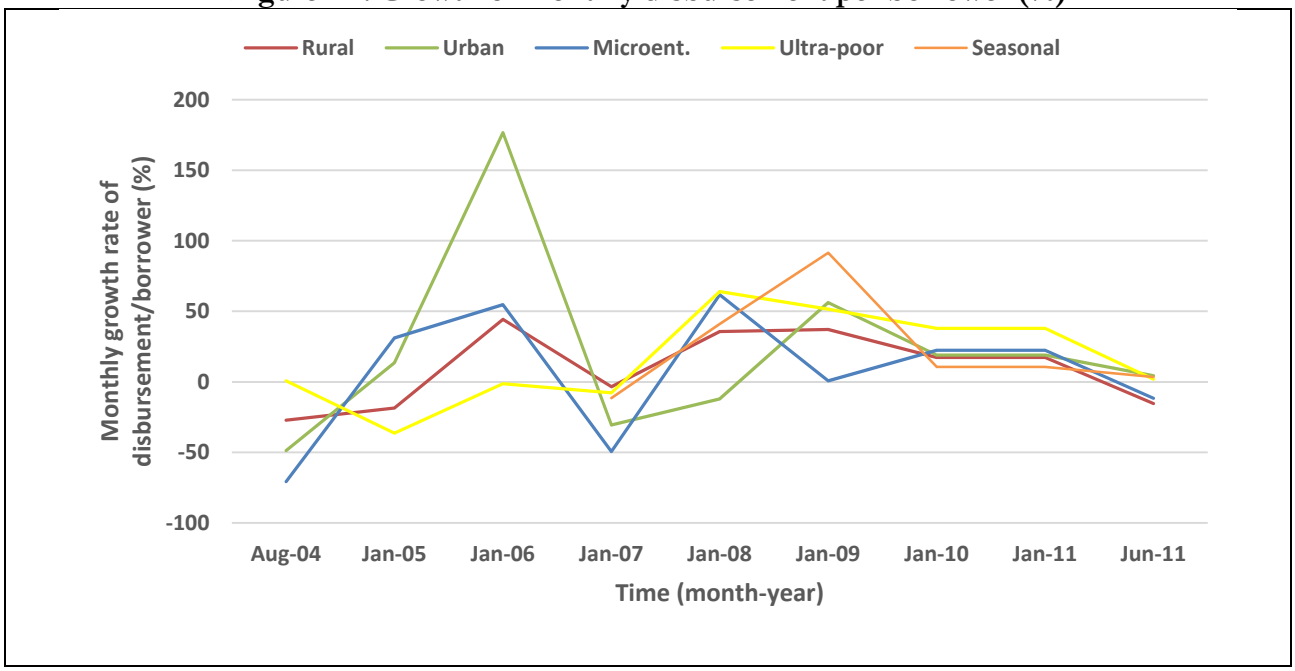


Source: PKSF (2011)

Note:

- Since average microenterprise loan is large, it had higher monthly disbursement per borrower at the beginning when number of borrower was low.
- Seasonal loan started in February 2007.

Figure A2: Growth of monthly disbursement per borrower (%)



Source: PKSF (2011)

Note:

- Seasonal loan started in February 2007.
- High growth of monthly disbursement per borrower for Urban microcredit in 2006 can be attributed to the series of floods in 2004 and 2005. Two thirds of the country inundated and victims migrated to urban areas in 2004-05.
- Political turmoil affected all types of microcredit disbursement in 2007.