Estimating lending impacts using original 800+ households

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18:11

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Contents

Wooldridge (2010)

```
# Only change the trimming conditions to switch between "1 or 4" to "NoFlood"
ThisIsNoFlood ← F
if (ThisIsNoFlood)
  pathsaveHere ← pathsaveNoFlood else
  pathsaveHere ← pathsaveOriginal1600Memo3
# Below reads from folder pathsaveReadFilesMergeAdminRoster and
# saves as XXXTrimmed.rds in folder pathsaveOriginal1600Memo3
```

Read: c:/data/GUK/analysis/save/ReadFilesMergeAdminRoster/AllMeetingsRosterAdminData.rds.

Further data preparations (trimming, adding shocks, round numbering, creating dummy vectors, interaction terms) for estimation. Produces files: SchoolingAdminDataUsedForEstimation.prn, AllMeetingsRepaymentAdminDataUsedForEstimation.prn, RepaymentAdminDataUsedForEstimation.prn, AssetAdminDataUsedForEstimation.prn, LivestockAdminDataUsedForEstimation.prn, LivestockProductsAdminDataUsedForEstimation.prn, LabourIncomeAdminDataUsedForEstimation.prn, FarmIncomeAdminDataUsedForEstimation.prn, ConsumptionAdminDataUsedForEstimation.prn.

```
# Name it as sch1, sch2 rather than s1, s2 (as in other files) to display "s1" in Trimming
# Following files are created in ImpactEstimatin_body1.rnw using paste0(path1234, "data_re
# This includes each file + xid (admin) info
s1 ← readRDS(paste0(pathsaveHere2, "RosterAdminSchoolingData.rds"))
ar ← readRDS(paste0(pathsaveHere2, "RosterAdminData.rds"))
arA ← readRDS(paste0(pathsaveHere2, "AllMeetingsRosterAdminData.rds"))
ass ← readRDS(paste0(pathsaveHere2, "AssetAdminData.rds"))
lvo ← readRDS(paste0(pathsaveHere2, "LivestockAdminData.rds"))
lvp ← readRDS(paste0(pathsaveHere2, "LivestockProductsAdminData.rds"))
lab ← readRDS(paste0(pathsaveHere2, "LabourIncomeAdminData.rds"))
far ← readRDS(paste0(pathsaveHere2, "FarmRevenueAdminData.rds"))
con ← readRDS(paste0(pathsaveHere2, "ConsumptionAdminData.rds"))
shk ← readRDS(paste0(pathsaveHere2, "Shocks.rds"))
interterms ← c("Time.2", "Time.3", "Time.4")
Arms ← c("Traditional", "Large", "LargeGrace", "Cow")
arms ← c("traditional", "large", "large grace", "cow")
povertystatus ← c("UltraPoor", "ModeratelyPoor")
s1[, tee := survey]
Obs ← NULL
shk ← shk[survey == 1, ]
shk[, grepout("gid|Dat|Ye|Mo|surv|code", colnames(shk)) := NULL]
setkey(shk, groupid, hhid)
# shk[, Month := factor(Month, levels =
#   c("January", "February", "March", "April",
#   #"May", "June", "July",
#   "August", "September", "November", "October",   "December"))]
dimchange ← dimchangeRd1 ← NULL
for (j in 1:length(datafiles)) {
#  if (j == 1) print0(paste("old|iRej|^g in Mstatus", "==>", "con|^dro|^rep in Mgroup", "=
  dd ← get(datafiles[j])
  if (!any(grepl("^tee$", colnames(dd)))) dd[, tee := 1:.N, by = hhid]
  # show trimming results
  dimchange ← rbind(dimchange, paste(datafiles[j], ":", nrow(dd),
    "==>",
    nrow(dd[grepl("old|iRej|^g", Mstatus), ]),
#     "==>",
#     nrow(dd[grepl("old|iRej|^g", Mstatus), ][grepl("con|dro", Mgroup), ]),
    "==>",
    nrow(dd[grepl("old|iRej|^g", Mstatus), ][!grepl("tw|dou", TradGroup), ])
```

```
    ))
  dimchangeRd1 ← rbind(dimchangeRd1, paste(datafiles[j], ":", nrow(dd[tee == 1, ]),
    "==>",
    nrow(dd[tee == 1 & grepl("old|iRej|^g", Mstatus), ]),
#     "==>",
#     nrow(dd[grepl("old|iRej|^g", Mstatus), ][grepl("con|dro", Mgroup), ]),
    "==>",
    nrow(dd[tee == 1 & grepl("old|iRej|^g", Mstatus), ][!grepl("tw|dou", TradGroup), ])
    ))
}
dmch ← gsub("==>", " & $\\\\Rightarrow$ &", dimchange)
dmch ← gsub(":", " & ", dmch)
#dmch ← rbind("file & & old$|$iRej$|$\\^{}g in \\textsf{Mstatus} && con$|$dro in \\textsf
dmch ← rbind("file & & old$|$iRej$|$\\^{}g in \\textsf{Mstatus} && No tw$|$dou in \\texts
  "\\makebox[1.5cm]{\\footnotesize all rounds}&&&&&",
  dmch)
dmch ← gsub("$", " \\\\\\\\ ", dmch)
dmchRd1 ← gsub("==>", " & $\\\\Rightarrow$ &", dimchangeRd1)
dmchRd1 ← gsub(":", " & ", dmchRd1)
dmchRd1 ← rbind("\\makebox[1.5cm]{\\footnotesize round 1 only}&&&&&",
  dmchRd1)
#dmchRd1 ← rbind("file & & old$|$iRej$|$\\^{}g in \\textsf{Mstatus} && No tw$|$dou in \\t
dmchRd1 ← gsub("$", " \\\\\\\\ ", dmchRd1)
hleft = c("\\sf", c(rbind(rep("\\hfill", 2), rep("\\hfil", 2)), "\\hfill"))
hcenter = c(1.5, c(rbind(rep(1, 2), rep(1.5, 2)), 1))
write.tablev(
  rbind(paste("\\begin{tabular}{",
    paste(paste0(">{\\footnotesize ", hleft, "}", "p{", hcenter, "cm}", "<{}"), collapse =
  dmch,
  dmchRd1,
  "\\end{tabular}"),
  paste0(pathsaveHere, "TrimmingNumObsTable.tex"), colnamestrue = F)
#print0(rbind(paste("(old|iRej|^g in Mstatus)", "==>", "(con|^dro|^rep in Mgroup)", "==>",
```

```
for (j in 1:length(datafiles)) {
  dd ← get(datafiles[j])
  setkey(dd, hhid, Year, Month)
  if (!any(grepl("^tee$", colnames(dd)))) dd[, tee := 1:.N, by = hhid]
  dd[, Arm := droplevels(Arm)]
  if (any(grepl("IntDate", colnames(dd))))
    dd[, Year := as.integer(strftime(IntDate, format = "%Y"))] else
  if (any(grepl("^Date$", colnames(dd))))
    dd[, Year := as.integer(strftime(Date, format = "%Y"))]
  # 1. Keep only membership = 1 or 4, which corresponds to
  # Mstatus old, iRej, gR, gE
  dd ← dd[grepl("old|iRej|^g", Mstatus), ]
  # 2. Keep only continuing, dropouts members in Mgroup.
  #dd ← dd[grepl("con|dro", Mgroup), ]
  # Rejecters do not receive loans. So I need to relax creditstatus = yes condition.
  # Remark out the following:
  # dd ← dd[grepl("Yes", creditstatus), ]
  #  dd ← dd[as.Date(DisDate1) < as.Date("2015-01-01"), ]
  dd ← dd[!grepl("tw|dou", TradGroup), ]
#grepl("es", creditstatus) & as.Date(DisDate1) ≤ as.Date("2015-01-01") & !grepl("tw|dou",
  setkey(dd, groupid, hhid)
  dd[, MonthGap := min(DisDate1, na.rm = T), by = groupid]
```

```
dd[MonthGap == Inf, MonthGap := NA]
dd[, MonthGap := round(
  as.numeric(DisDate1 - MonthGap)/(60*60*24*30.4375), 2)]
dd[, BStatus := BorrowerStatus]
dd[grepl("gRe", Mstatus), BStatus := "group rejection"]
dd[grepl("iRej", Mstatus), BStatus := "individual rejection"]
dd[grepl("gEr", Mstatus), BStatus := "rejection by flood"]
dd[, BStatus := factor(BStatus, levels = c("borrower", "pure saver",
  "individual rejection", "group rejection", "rejection by flood"))]
# merge shock module
setkey(dd, hhid, Year, Month)
setkey(dd, groupid, hhid)
dd <- shk[dd]
dd[, c("en") := NULL]
dd[, teeyr := 1]
dd[Year == 2014, teeyr := 2]
dd[Year == 2015, teeyr := 3]
dd[Year == 2016, teeyr := 3]
dd[Year == 2017, teeyr := 4]
dd[, Time := teeyr]
setkey(dd, hhid, Year, teeyr)
# Replace Arm with RArm
dd[, ArmUsedPreviously := Arm]; dd[, Arm := RArm]
dd <- data.table(dd,
  makeDummyFromFactor(dd[, Arm], reference = NULL))
if (any(grepl("dummyLarge grace", colnames(dd))))
  setnames(dd, grepout("dummyLarge grace", colnames(dd)),
    gsub("dummyLarge g", "dummyLargeG",
      grepout("dummyLarge grace", colnames(dd))))
if (any(grepl("dummyNANA", colnames(dd))))
  dd[, dummyNANA := NULL]
#dd[, dummyDropOuts := NULL]
dd[, povertystatus := factor(povertystatus,
  labels = c("Ultra Poor", "Moderately Poor"))]
dd <- data.table(dd,
  makeDummyFromFactor(dd[, povertystatus], reference = NULL))
setnames(dd, c("dummyUltra Poor", "dummyModerately Poor"),
  c("dummyUltraPoor", "dummyModeratelyPoor"))
dd[, c("Size", "Grace", "Item") := .("SmallSize", "WithoutGrace", "Cash")]
dd[!grepl("tra", Arm), Size := "LargeSize"]
dd[grepl("gr|cow", Arm), Grace := "WithGrace"]
dd[grepl("cow", Arm), Item := "InKind"]
dd[, c("Grace", "Size", "Item") :=
  .(factor(Grace), factor(Size, levels = c("LargeSize", "SmallSize")),
    factor(Item))]
dd <- data.table(dd,
  makeDummyFromFactor(dd[, Size], reference = NULL),
  makeDummyFromFactor(dd[, Grace], reference = NULL),
  makeDummyFromFactor(dd[, Item], reference = NULL))
# create demeaned dummies
tobe.interacted <- c(Arms, povertystatus,
  c("SmallSize", "LargeSize", "WithoutGrace", "WithGrace", "Cash", "InKind"))
for (k in tobe.interacted)
  dd[, paste0("DemeanedDummy", k) :=
    eval(parse(text =
```

```
			paste0("dummy", k)
		)) -
		mean(
			eval(parse(text =
				paste0("dummy", k)
			))
			, na.rm = T)
	]
	for (i in interterms) {
		i1 <- unlist(strsplit(i, "\\."))
		i2 <- i1[2]; i1 <- i1[1]
		i0 <- gsub("\\.", "", i)
		dd[, (i) := as.numeric(eval(parse(text=i1)) == i2)]
		dd[, paste0("Demeaned", i0) :=
			eval(parse(text=i)) - mean(eval(parse(text=i)), na.rm = T)]
		for (k in tobe.interacted)
			dd[, paste0("dummy", k, ".", i0) :=
				eval(parse(text=paste0("Demeaned", i0))) *
				eval(parse(text=paste0("DemeanedDummy", k)))]
		# undemeand (UD) interactions
		for (k in tobe.interacted)
			dd[, paste0("UDdummy", k, ".", i0) :=
				eval(parse(text=i)) *
				eval(parse(text = paste0("dummy", k)))]
	}
	# Only for livestock to create demeand HadCows*Arm, HadCows*Arm*Time interactions
	if (grepl("lvo", datafiles[j])) {
		# demean HadCows
		dd[, "demeanedHadCows" := dummyHadCows - mean(dummyHadCows)]
		dd[, paste0("dummyHadCows.", "dummy", levels(dd[, .Arm])) := 0L]
		dd[, paste0(rep(paste0("dummyHadCows.", "dummy", levels(dd[, .Arm])), 2),
			rep(paste0(".Time", 3:4), each = 4)) := 0L]
		# HadCows * Arm, HadCows * Arm * Time
		for (a in c(levels(dd[, .Arm]), levels(dd[, Size]),
			levels(dd[, Grace]), levels(dd[, Item]))) {
			dd[, paste0("dummyHadCows.dummy", a) :=
				eval(parse(text=paste0("DemeanedDummy", a))) * demeanedHadCows]
			dd[, paste0("dummyHadCows.dummy", a, ".Time", 3:4) :=
				.(eval(parse(text = paste0("dummyHadCows.dummy", a))) * DemeanedTime3,
					eval(parse(text = paste0("dummyHadCows.dummy", a))) * DemeanedTime4)]
		}
	}
	dd[, grepout("Demea|demeanedHad|i.group|group.id", colnames(dd)) := NULL]
	Obs <- rbind(Obs, cbind(datafiles[j], dd[, .(obs = .N), by = .(Arm, tee)]))
	assign(datafiles[j], dd)
	saveRDS(dd, paste0(pathsaveHere, DataFileNames[j], "Trimmed.rds"))
	fwrite(dd, paste0(pathsaveHere, DataFileNames[j], "Trimmed.prn"),
		sep = "\t", quote = F)
}
```

Save: c:/data/GUK/analysis/save/Original1600Memo3/AllMeetingsRepaymentTrimmed.rds.

```
ar <- readRDS(paste0(pathsaveHere, DataFileNames[3], "Trimmed.rds"))
ar[, MonthGap := min(DisDate1, na.rm = T), by = groupid]
ar[MonthGap == Inf, MonthGap := NA]
ar[, MonthGap := round(
	as.numeric(DisDate1 - MonthGap)/(60*60*24*30.4375), 2)]
```

```
ar[, BStatus := BorrowerStatus]
ar[grepl("gRe", Mstatus), BStatus := "group rejection"]
ar[grepl("iRej", Mstatus), BStatus := "individual rejection"]
ar[grepl("gEr", Mstatus), BStatus := "rejection by flood"]
ar[, BStatus := factor(BStatus, levels = c("borrower", "pure saver",
  "individual rejection", "group rejection", "rejection by flood"))]
saveRDS(ar, paste0(pathsaveHere, DataFileNames[3], "InitialSample.rds"))
```

```
for (i in 1:length(DataFileNames))
  assign(datafiles[i], readRDS(paste0(pathsaveHere, DataFileNames[i], "Trimmed.rds")))
#ar ← readRDS(paste0(pathsaveHere, DataFileNames[3], "InitialSample.rds"))
ObsIS ← tabIniSamp ← NULL
for (d in 1:length(datafiles)) {
  #if (d == 3) next
  x ← get(datafiles[d])
  td ← data.table(t(as.matrix(table(x[tee == 1L, o800]))))
  td[, FileName := DataFileNames[d]]
  tabIniSamp ← rbindlist(list(tabIniSamp, td), use.names = T, fill = T)
  ObsIS ← rbind(ObsIS, cbind(datafiles[j], x[o800 == 1L,
    .(obs = .N), by = .(Arm, tee)]))
}
setcolorder(tabIniSamp, c("FileName", "1", "0"))
```

TABLE 1: DATA TRIMMING RESULTS

file		old|iRej|^g in Mstatus		No tw|dou in TradGroup	
all rounds					
s1	9007	⇒	6013	⇒	5781
arA	91344	⇒	66240	⇒	61200
ar	33223	⇒	24806	⇒	23612
ass	7989	⇒	5958	⇒	5649
lvo	7989	⇒	5953	⇒	5645
lvp	15964	⇒	11914	⇒	11296
lab	16004	⇒	12102	⇒	11723
far	589	⇒	411	⇒	393
con	5888	⇒	4360	⇒	4051
round 1 only					
s1	2582	⇒	1931	⇒	1931
arA	1903	⇒	1380	⇒	1275
ar	2123	⇒	1600	⇒	1600
ass	2121	⇒	1596	⇒	1596
lvo	2121	⇒	1574	⇒	1574
lvp	2119	⇒	1598	⇒	1598
lab	2121	⇒	1596	⇒	1596
far	336	⇒	236	⇒	226
con	2022	⇒	1505	⇒	1401

Source: GUK survey data.

Notes: 1. Top panel is observations for all rounds. Bottom panel is observations for round 1 only. We aim for ITT estimates and need to retain original sampled individuals. old|iRej|^g in Mstatus are strings for old members, individual rejecters, group rejecters, group erosion. con|^dro|^rep in Mgroup indicates continuing, dropouts, replacing members. tw|dou in TradGroup are members who received loans twice and double amount in the 2nd loans. They are omitted from analysis because they are under a different treatment arm.

2.

```
setnames(Obs, "V1", "file")
Obs[, Arm := factor(Arm, levels = arms)]
# from long to wide: Arm1, Arm2, ... with rows in fileX * teeY
Obs ← reshape(Obs, direction = "wide", idvar = c("file", "tee"),
  timevar = "Arm", v.names = "obs")
setnames(Obs, grepout("obs", colnames(Obs)),
  gsub("obs.", "", grepout("obs", colnames(Obs))))
setcolorder(Obs, c("file", "tee", "traditional", "large", "large grace", "cow"))
setkey(Obs, file, tee)
```

```
s1 ← readRDS(paste0(pathsaveHere2, "RosterAdminSchoolingData.rds"))
ass ← readRDS(paste0(pathsaveHere2, "AssetAdminData.rds"))
lvo ← readRDS(paste0(pathsaveHere2, "LivestockAdminData.rds"))
lvp ← readRDS(paste0(pathsaveHere2, "LivestockProductsAdminData.rds"))
lab ← readRDS(paste0(pathsaveHere2, "LabourIncomeAdminData.rds"))
far ← readRDS(paste0(pathsaveHere2, "FarmRevenueAdminData.rds"))
con ← readRDS(paste0(pathsaveHere2, "ConsumptionAdminData.rds"))
shk ← readRDS(paste0(pathsaveHere2, "Shocks.rds"))
ar ← readRDS(paste0(pathsaveHere2, "RosterAdminData.rds"))
arA ← readRDS(paste0(pathsaveHere2, "AllMeetingsRosterAdminData.rds"))
ar[, teenum := 1:.N, by = .(hhid, survey)]
lab[, teenum := 1:.N, by = .(hhid, survey)]
con[, tee := (1:.N)+1, by = hhid]
s1[, tee := survey]
armtabs ← armtabs.o1600 ← NULL
for (i in 1:length(datafiles[-2])) {
  dx ← get(datafiles[-2][i])
  setorder(dx, hhid, survey, Year, Month)
  if (!any(grepl("^tee$", colnames(dx)))) dx[, tee := 1:.N, by = hhid]
  dx ← dx[tee < AttritIn, ]
  if (i != grep("con", datafiles[-2])) {
    for (j in 1:4) {
      armtabs ← rbind(armtabs,
         table0(dx[tee == j, RArm]))
      armtabs.o1600 ← rbind(armtabs.o1600,
         table0(dx[tee == j & o1600 == 1L, RArm]))
     }
  } else
    for (j in 2:4) {
      armtabs ← rbind(armtabs,
         table0(dx[tee == j & AttritIn != 2, RArm]))
      armtabs.o1600 ← rbind(armtabs.o1600,
         table0(dx[tee == j & AttritIn != 2 & o1600 == 1L, RArm]))
    }
}
armtabs ← data.table(armtabs)
armtabs[, total := rowSums(armtabs)]
armtabs ← data.table(
  files =
    paste0("\\makebox[1cm]{\\scriptsize ",
      c(rep(datafiles[-c(2, grep("con", datafiles))], each = 4),
        rep("con", each = 3)),
      "}")
  ,
  rounds =
    c(rep(1:4, length(datafiles)-2), 2:4)
  , armtabs)
armtabs[-seq(1, nrow(armtabs), 4), files := ""]
armtabs.o1600 ← data.table(armtabs.o1600)
armtabs.o1600[, total := rowSums(armtabs.o1600)]
armtabs.o1600 ← data.table(
  files =
    paste0("\\makebox[1cm]{\\scriptsize ",
      c(rep(datafiles[-c(2, grep("con", datafiles))], each = 4),
        rep("con", each = 3)),
```

```
      "}")
  ,
  rounds =
    c(rep(1:4, length(datafiles)-2), 2:4)
  , armtabs.o1600)
armtabs.o1600[-seq(1, nrow(armtabs.o1600), 4), files := ""]
amt <- latextab(as.matrix(armtabs),
  hleft = "\\scriptsize\\hfil$", hcenter = c(1, rep(1.5, ncol(armtabs)-1)), hright = "$",
  headercolor = "gray80", adjustlineskip = "-.4ex", delimiterline= NULL,
  alternatecolor = "gray90")
amt.o1600 <- latextab(as.matrix(armtabs.o1600),
  hleft = "\\scriptsize\\hfil$", hcenter = c(1, rep(1.5, ncol(armtabs.o1600)-1)), hright =
  headercolor = "gray80", adjustlineskip = "-.4ex", delimiterline= NULL,
  alternatecolor = "gray90")
write.tablev(amt,  paste0(pathsaveHere, "NumObsOriginalHHs_all.tex"),
  colnamestrue = F)
write.tablev(amt.o1600,  paste0(pathsaveHere, "NumObsOriginalHHs_o1600.tex"),
  colnamestrue = F)
```

```
for (i in 1:length(DataFileNames))
  assign(datafiles[i], readRDS(
    paste0(pathsaveHere, DataFileNames[i], "InitialSample.rds")
    ))
ar[, teenum := 1:.N, by = .(hhid, survey)]
lab[, teenum := 1:.N, by = .(hhid, survey)]
con[, tee := tee + 1L]
s1[, tee := survey]
armtabs.o800 <- NULL
for (i in 1:length(datafiles[-2])) {
  dx <- get(datafiles[-2][i])
  setorder(dx, hhid, survey, Year, Month)
  if (!any(grepl("^tee$", colnames(dx)))) dx[, tee := 1:.N, by = hhid]
  dx <- dx[tee < AttritIn, ]
  if (i != grep("con", datafiles[-2])) {
    for (j in 1:4) {
      armtabs.o800 <- rbind(armtabs.o800,
         table0(dx[tee == j & o800 == 1L, RArm]))
     }
  } else
    for (j in 2:4) {
      armtabs.o800 <- rbind(armtabs.o800,
         table0(dx[tee == j & AttritIn != 2 & o800 == 1L, RArm]))
    }
}
armtabs.o800 <- data.table(armtabs.o800)
armtabs.o800[, total := rowSums(armtabs.o800)]
armtabs.o800 <- data.table(
  files =
    paste0("\\makebox[1cm]{\\scriptsize ",
      c(rep(datafiles[-c(2, grep("con", datafiles))], each = 4),
        rep("con", each = 3)),
      "}")
  ,
  rounds =
    c(rep(1:4, length(datafiles)-2), 2:4)
  , armtabs.o800)
```

```
armtabs.o800[-seq(1, nrow(armtabs.o800), 4), files := ""]
amt.o800 ← latextab(as.matrix(armtabs.o800),
  hleft = "\\scriptsize\\hfil$", hcenter = c(1, rep(1.5, ncol(armtabs.o800)-1)), hright =
headercolor = "gray80", adjustlineskip = "-.4ex", delimiterline= NULL,
  alternatecolor = "gray90")
write.tablev(amt.o800,  paste0(pathsaveHere, "NumObsOriginalHHs_o800.tex"),
  colnamestrue = F)
```

Table 2: Number of observations in each file at round 1 from HHs with single treatment

files	rounds	traditional	large	large grace	cow	total
s1	1	728	622	618	614	2582
	2	610	501	452	496	2059
	3	555	474	433	449	1911
	4	488	427	393	388	1696
ar	1	605	504	507	507	2123
	2	590	491	457	485	2023
	3	583	487	453	473	1996
	4	539	482	447	442	1910
ass	1	603	504	507	507	2121
	2	590	491	457	484	2022
	3	581	485	453	467	1986
	4	528	478	431	418	1855
lvo	1	603	504	507	507	2121
	2	590	491	457	484	2022
	3	581	485	452	466	1984
	4	528	477	412	416	1833
lvp	1	601	504	507	507	2119
	2	588	491	457	485	2021
	3	581	487	453	472	1993
	4	538	483	447	444	1912
lab	1	601	504	507	507	2119
	2	588	491	457	485	2021
	3	581	487	453	472	1993
	4	534	481	443	433	1891
far	1	78	123	70	64	335
	2	35	68	39	30	172
	3	13	27	25	12	77
	4	2	1	2	1	6
con	2	590	490	457	484	2021
	3	581	484	453	470	1988
	4	536	477	435	428	1876

Source: Estimated with GUK administrative and survey data.

Notes: 1. Sample is all households: Original 1600 and added households through new groups and individuals replacing opt-out members. All households in traditional arm who received more than one loan are excluded.

2.

Table 3: Number of observations in each file at round 1 from original 1600 HHs

files	rounds	traditional	large	large grace	cow	total
s1	1	460	479	505	487	1931
	2	293	379	350	381	1403
	3	263	358	337	349	1307
	4	214	321	304	301	1140
ar	1	400	400	400	400	1600
	2	385	389	352	379	1505
	3	363	386	349	367	1465
	4	299	382	343	341	1365
ass	1	398	400	400	400	1598
	2	283	389	352	378	1402
	3	276	384	349	365	1374
	4	238	378	330	329	1275
lvo	1	398	400	400	400	1598
	2	283	389	352	378	1402
	3	276	384	348	365	1373
	4	238	377	330	327	1272
lvp	1	398	400	400	400	1598
	2	387	389	352	379	1507
	3	277	386	349	366	1378
	4	240	382	343	342	1307
lab	1	398	400	400	400	1598
	2	385	389	352	379	1505
	3	364	386	349	367	1466
	4	303	381	342	340	1366
far	1	21	96	52	57	226
	2	5	51	28	27	111
	3	2	22	17	12	53
	4	2	1	2	1	6
con	2	283	388	352	378	1401
	3	276	383	349	365	1373
	4	238	377	331	331	1277

Source: Estimated with GUK administrative and survey data.

Notes:
1. Sample is original 1600 households who agree to join the group. This includes households who later dropped out due to flood, group rejections, and individual rejections. All original 1600 households are tracked but some attrit from the sample.
2.

TABLE 4: NUMBER OF OBSERVATIONS IN EACH FILE AT ROUND 1 FROM ORIGINAL 800 HHS

files	rounds	traditional	large	large grace	cow	total
s1	1	232	246	251	235	964
	2	161	197	177	191	726
	3	148	185	165	173	671
	4	118	171	147	143	579
ar	1	200	200	200	200	800
	2	191	195	177	195	758
	3	185	193	174	190	742
	4	159	192	171	176	698
ass	1	199	200	200	200	799
	2	168	195	177	195	735
	3	163	192	174	190	719
	4	143	188	164	171	666
lvo	1	199	200	189	200	788
	2	168	195	177	195	735
	3	163	192	173	190	718
	4	143	188	164	170	665
lvp	1	199	200	200	200	799
	2	192	195	177	195	759
	3	164	193	174	190	721
	4	144	192	171	177	684
lab	1	199	200	200	200	799
	2	191	195	177	195	758
	3	185	193	174	190	742
	4	159	191	170	175	695
far	1	12	46	24	25	107
	2	4	26	13	10	53
	3	2	9	8	4	23
	4	1	1	1	1	4
con	2	168	194	177	195	734
	3	163	191	174	190	718
	4	143	188	165	172	668

Source: Estimated with GUK administrative and survey data.

Notes: 1. Sample is original 800 households who agree to join the group. This includes households who later dropped out due to flood, group rejections, and individual rejections. All original 800 households are tracked but some attrit from the sample.

2.

This file reads data from a list data_read_in_a_list_with_baseline_patched.rds, merge all non-roster files with admin-roster, and saves in c:/data/GUK/analysis/save/Original1600Memo3/.

```
setwd(path1234)
foldername <- list.dirs(path = ".", recursive = T, full.names = T)
fn <- list.files(path = foldername, pattern = ".dta$",
          recursive = T, full.names = T)
fn <- fn[!grepl("orking|Live.*p.dta", fn)]
fn <- unique(fn)
fnd <- tolower(gsub(" ", "\\_", gsub("^.*\\/(.*).dta", "\\1", fn)))
```

I Summary

I.1 Definitions

(125*45*3) or, CumRepaid/(190*45*2)

Traditional A cash loan of Tk. 5600 with one year maturity. Repay Tk 125 * 45 weeks = 5625 each year for 3 years.

Large A cash loan of Tk. 16800 with three year maturity. Repay Tk 125 * 45 weeks * 3 years = 16875

Large Grace A cash loan of Tk. 16800 with a one year grace period and three year maturity. Repay Tk 190 * 45 weeks * 2 years = 17100.

Cow An in-kind loan of a cow worth Tk. 16800 with a one year grace period and three year maturity. Repay Tk 190 * 45 weeks * 2 years = 17100.

LargeSize An indicator variable takes the value of 1 if the arm is Large, Large Grace, or Cow.

WithGrace An indicator variable takes the value of 1 if the arm is Large Grace or Cow.

InKind Same as Cow.

When one uses covariates Large, Large Grace, Cow in estimation, their estimates represent each arm's characteristics relative to Traditional. When one uses covariates LargeSize, WithGrace, InKind, their estimates represent their labeled names.

I.2 Inference

- First-difference estimators are used. This can be seen as an extension of DID to multi-periods (although historically the latter precedes the former). FD is used also for a binary indicator such as schooling.
- All the standard errors are clustered at the group (char) level.
- To aid the understanding if the data is more suited to the assumption of first-difference rather than fixed-effects, I used a check suggested by Wooldridge (2010, 10.71). It is an AR(1) regression of FD residuals. Most of results show low autocorrelations which is consistent with the assumption of FD estimator. The use of cluster-robust standard errors gives consistent estimates of SEs, so it boils down to efficiency.
- I rely more on the formulation using LargeSize, WithGrace, InKind than Large, LargeGrace, Cow due to an ease in interpretation. Numerically, both are equivalent.
- A caution on reading the estimates: All are estimates on increments. If LargeSize has an estimate of 10, then it is a 10 unit larger change than the baseline (traditional). If the interaction of LargeSize with rd 2-3 is 10, then it is a 10 unit larger change than rd 2-3 change of baseline. If the estimated value of intercept is 10 and rd 2-3 is 10, then rd 2-3 change is 20 for baseline, 30 for LargeSize.

I.3 Findings

Overall, the intervention reveals that larger sized loans accerelate the timing of becoming an owner of large livestock without adversely affecting the repayments. This applies to both the ultra poor and the moderately poor. A loan amount seems to have convex returns at a low level of assets. Higher growths come at a cost of slower school progression of older girls and smaller increases in consumption for the arm of in-kind, so the welfare implication is mixed. In addition, given that the number of cows per owner remains the similar after 2 years, it does not provide evidence for accelerated growth of livestock after becoming an owner in this short window. Another note is that the loan repayment was poor for unknown reasons so, in the hindsight, the risks required a higher margin for this type of lending to the target population, which could have reduced participation.

Net saving and repayments Sample uses administrative records of all borrowers in the original 800 households. Smaller net saving for traditional arm. Period of rds 2, 3 saw a positive net saving, then became negative in rd 4 for LargeGrace, Cow. Repayment is greater for Large, LargeGrace, Cow in rds 2, 3. In rd 4, repayment of Large becomes statistically the same with Traditional while LargeGrace, Cow are greater (TABLE 8). TABLE 9 (1) reveals LargeSize have larger net saving while (2) shows WithGrace has a faster decline in rds 2, 3, 4. Repayment is larger with LargeSize but smaller with WithGrace in (3). (4) shows rd 2-3 have larger repayment for WithGrace, which is by design. Repayment is positively autocorrelated and is negatively correlated with previous net saving. The ultra poor repaid just as much as the moderately poor, (TABLE 10). This is evidence against the popular belief that the ultra poor are riskier.

Schooling Enrollment changes are larger for primary school girls in Large and Cow arms for primary but smaller for junior in rd 1 vs rd 4 comparisons (TABLE 11). When seen by attributes in TABLE 12, LargeSize shows smaller changes especially for primary school boys. Primary school girls in LargeSize and InKind show larger changes, while junior and high school girls in LargeSize show smaller changes than boys. This indicates that large sized arms have detrimetal impacts on older girls' schooling but promotional impacts on primary school aged girls. No decline in enrollment changes when repaying for the arms of WithGrace, despite the larger installments.

Assets Household assets increased in all arms. Asset values initially increased then decreased, but do not fully cancel out and remain increased. There might have been liquidation of assets to repay the loans. Productive assets declined consecutively. Flood in rd 1 makes the increase in household assets smaller. Productive assets see a major decline among Large during rd 3-4 period (TABLE 13). Comparison by attributes (TABLE 14) or of rd 2 and rd 4 gives the same picture (TABLE 15). Comparison against the loan non-recipients shows that they also experience a similar, increase-increase-decrease pattern. This indicates that the pattern observed among the loan recipients may be a systemic pattern of the area, not necessarily reflecting the repayment burdern (TABLE 16). Comparison of productive asset holding of loan recipients (FIGURE 3) and loan nonrecipients (FIGURE 4) reveals that productive asset holding declined at the top end of loan nonrecipients in all arms (they only save or left the program). This indicates that the decline in productive asset holding among the loan recipients are not due to the repayment burden but a general pattern of the area.

Livestock Larger increases in holding values in rd 1-2, smaller increases in rd 2-3, no change in rd 3-4. Previous cow owners show a smaller increase in rd 1-2 while not rd 3-4 or rd 2-3 in the Cow arm (TABLE 17). Figures show that cow ownership increased for all arms but the traditional arm (see FIGURE **??**). TABLE 18 shows baseline trend is a large increse in rd 1-2, a small increase in rd 2-3, a small decline in rd 3-4, while LargeSize sees an even larger increase in rd 1-2 and similar trend as baseline afterwards. This shows that member who received a larger sized disbursement could hold on to its level of livestock accumulation. TABLE 19 shows, albeit at p values around 10%, the ultra poor has a larger increase relative to the moderately poor, which is another manifestation against the popular notion that the ultra poor are riskier.

Total asset values Similar resulsts as assets.

Labour incomes Small sample. Increased during rd 2-3 in all arms (TABLE 27).

Consumption Increased during rd 2-3 in all arms, a decrese in rd 3-4 (TABLE 29). Another notable result is that InKind reduced the consumption in rd 3-4 even further than the baseline loan (TABLE 30).

IGAs Multiple IGAs for Tradtional arm. Everyone else chose to invest in cows, suggesting entrepreneurship does not seem to matter in the uptake of loans. It is consistent with the presence of a poverty trap induced by a liquidity constraint and convexity in livestock production technology.

Project choice Traditional arm has a smaller rate of second investments, and second investment amounts are generally smaller (Figure 25). This confirms that most of Traditional arm members do not use own fund to increase the size of investments even after a few years into the program.

One sees changes in investment choices when one compares traditional and all other arms. However, consumption does not seem to differ. Repayments and asset holding are greater in all other arms. These are consistent with households are enforcing the repayment disciplines and reinvesting the proceeds rather than increasing consumption.

```
for (i in 1:length(DataFileNames))
  assign(datafiles[i], readRDS(
    paste0(pathsaveHere, DataFileNames[i], ”Trimmed.rds”)
    ))
# Following files are created in ImpactEstimatin_body1.rnw using paste0(path1234, ”data_re
#for (i in 1:length(DataFileNamesX))
#  assign(datafiles[i], readRDS(paste0(pathsaveHere, DataFileNamesX[i], ”.rds”)))
# what to do with errors like below?
#ass[hhid == 7043715, .(hhid, survey, tee)]
# Table footnote first part that is common across tables.
TabFNTop ← ”First−difference estimates using administrative and survey data. First−differ
TabFNAttributes ← ”\\textsf{LargeSize} is an indicator function if the arm is of large si
TabFNar ← ”Saving and repayment information is taken from administrative data. Time inva
TabFNUP ← ”\\textsf{UltraPoor} is an indicator function if the household is classified as

table0(s1[tee == 1, Mstatus])
s1[, teenum := 1:.N, by = .(hhid, tee)]

ar[, tee := survey]
arA[, tee := survey]
s1[, tee := survey]
armtabs ← NULL
for (i in 1:length(datafiles[−2])) {
  dx ← get(datafiles[−2][i])
  dx ← dx[tee < AttritIn, ]
  # consumption is not asked in rd 1
  if (i != grep(”con”, datafiles[−2])) {
    for (j in 1:4)
      armtabs ←
      #data.table(
      rbind(armtabs,
        table0(dx[tee == j, Arm]))
      #  )
  } else
    for (j in 2:4)
      armtabs ←
      #data.table(
      rbind(armtabs,
        table0(dx[tee == j−1 & AttritIn != 2, Arm])
        )
      #  )
}
armtabs ← data.table(armtabs)
armtabs[, total := rowSums(armtabs)]
armtabs ← data.table(
  files =
    paste0(”\\makebox[1cm]{\\scriptsize ”,
      c(rep(datafiles[−c(2, grep(”con”, datafiles))], each = 4),
        rep(”con”, each = 3)),
      ”}”)
  ,
  rounds =
    c(rep(1:4, length(datafiles)−2), 2:4)
  , armtabs)
armtabs[−seq(1, nrow(armtabs), 4), files := ””]
amt ← latextab(as.matrix(armtabs),
```

```
  hleft = "\\scriptsize\\hfil$", hcenter = c(1, rep(1.5, ncol(armtabs)-1)), hright = "$",
  headercolor = "gray80", adjustlineskip = "-.2ex", delimiterline= NULL,
  alternatecolor = "gray90")
write.tablev(amt, paste0(pathsaveHere, "NumObsOriginalHHs.tex"),
  colnamestrue = F)
```

II Define initial sample

```
nrowsforthis ← function(i)
  nrow(ar[o1600 == 1L & tee == 1 &
  (MonthGap ≤ InitialSampleMonthUpperBound+i | grepl("sav", BorrowerStatus)), ])
nrowsInAr ← data.table(t(as.numeric(lapply(-6:6, nrowsforthis))))
nrowsInAr ← cbind("\\makebox[2.5cm]{\\scriptsize number of observations}", nrowsInAr)
setnames(nrowsInAr, c("Months after first loan", -6:6+6))
UpAndN ← latextab(as.matrix(nrowsInAr),
  hleft = "\\scriptsize\\hfil$", hcenter = c(2.5, rep(.5, ncol(nrowsInAr)-1)),
  hright = "$",
  headercolor = "gray80", adjustlineskip = "-.2ex", delimiterline= NULL,
  alternatecolor = "gray90")
write.tablev(UpAndN, paste0(pathsaveHere, "MonthsGapUBAndSampleSize.tex"),
  colnamestrue = F)
```

The study follows the stepped wedge design within each group due to administrative and budgetary constraints. Our identification strategy is comaprison between arms and we do not use the stepped wedge design to estimate impacts because of possible spillovers within a group and a relatively short period for outcomes to change before the control gets treated [We can estimate within-group, we may just have underestimated impacts]. A half of members in a group, approximately 800 in total, are assigned initially as the treated and then the rest was treated in the following months. So the number of the treated increases as time passes.

For concreteness, we first restrict ourselves to impact estimation on the initially-treated members. (We will later include the members who were treated on a later date.)

We will add a binary indicator function o800 to indicate the initial sample. In below, we first use the roster-administrative data to choose the households of o800, because it has the most complete record. Then, I look for these households in other files and create o800 variable in them.

```
ass[, BStatus := BorrowerStatus]
ass[grepl("gRe", Mstatus), BStatus := "group rejection"]
ass[grepl("gEr", Mstatus), BStatus := "rejection by flood"]
ass[, BStatus := factor(BStatus, levels = c("borrower", "pure saver",
  "group rejection", "rejection by flood"))]
tb ← table0(ass[o1600 == 1L & survey == 1 &
  (MonthGap ≤ InitialSampleMonthUpperBound | grepl("sav", BorrowerStatus)),
  .(BStatus, Arm)])
tb1 ← cbind(tb, total = apply(tb, 1, sum))
tb ← table0(ass[o1600 == 1L & survey == 1 &
  (MonthGap ≤ InitialSampleMonthUpperBound | grepl("sav|qui", BorrowerStatus)),
  .(BStatus, Arm)])
tb2 ← cbind(tb, total = apply(tb, 1, sum))
tb ← cbind(tb1, tb2)
tb ← rbind(tb, total = apply(tb, 2, sum))
tb ← as.matrix(cbind(paste0("\\makebox[2.5cm]{\\scriptsize\\hfill ", rownames(tb), "}"),
IniSampByArm ← latextab(tb,
  hleft = "\\scriptsize\\hfil$", hcenter = c(2.5, rep(.95, ncol(tb)-1)),
  hright = "$",
```

```
  headercolor = "gray80", adjustlineskip = "-.2ex", delimiterline= NULL,
  alternatecolor = "gray90",
  addseparatingcols = 5, separatingcolwidth = .2,
  separatingcoltitle = c("initial sample", "all sample"),
  addsubcoltitlehere = T)
write.tablev(IniSampByArm,
  paste0(pathsaveHere, "InitialSampleSizeByArm.tex")
  , colnamestrue = F)

ar[, tee := NULL]
ar[, tee := as.integer(1:.N), by = hhid]
tb ← table0(ar[o800 == 1L & tee == 1L, .(BStatus, Arm)])
tb1 ← cbind(tb, total = apply(tb, 1, sum))
tb ← table0(ar[tee == 1L, .(BStatus, Arm)])
tb2 ← cbind(tb, total = apply(tb, 1, sum))
tb ← cbind(tb1, tb2)
tb ← rbind(tb, total = apply(tb, 2, sum))
tb ← as.matrix(cbind(paste0("\\makebox[2.5cm]{\\scriptsize\\hfill ", rownames(tb), "}"),
IniSampByArmar ← latextab(tb,
  hleft = "\\scriptsize\\hfil$", hcenter = c(2.5, rep(.95, ncol(tb)-1)),
  hright = "$",
  headercolor = "gray80", adjustlineskip = "-.2ex", delimiterline= NULL,
  alternatecolor = "gray90",
  addseparatingcols = 5, separatingcolwidth = .2,
  separatingcoltitle = c("initial sample", "all sample"),
  addsubcoltitlehere = T)
write.tablev(IniSampByArmar,
  paste0(pathsaveHere, "InitialSampleSizeByArmInAr.tex")
  , colnamestrue = F)

arA ← readRDS(paste0(pathsaveHere, "AllMeetingsRepaymentTrimmed.rds"))
arA[, tee := NULL]
arA[, tee := as.integer(1:.N), by = hhid]
tb ← table0(arA[o800 == 1L & tee == 1L & !grepl("tw|dou", TradGroup),
  .(BStatus, Arm)])
tb1 ← cbind(tb, total = apply(tb, 1, sum))
tb ← table0(arA[tee == 1L & !grepl("tw|dou", TradGroup), .(BStatus, Arm)])
tb2 ← cbind(tb, total = apply(tb, 1, sum))
tb ← cbind(tb1, tb2)
tb ← rbind(tb, total = apply(tb, 2, sum))
tb ← as.matrix(cbind(paste0("\\makebox[2.5cm]{\\scriptsize\\hfill ", rownames(tb), "}"),
IniSampByArmar ← latextab(tb,
  hleft = "\\scriptsize\\hfil$", hcenter = c(2.5, rep(.95, ncol(tb)-1)),
  hright = "$",
  headercolor = "gray80", adjustlineskip = "-.2ex", delimiterline= NULL,
  alternatecolor = "gray90",
  addseparatingcols = 5, separatingcolwidth = .2,
  separatingcoltitle = c("initial sample", "all sample"),
  addsubcoltitlehere = T)
write.tablev(IniSampByArmar,
  paste0(pathsaveHere, "InitialSampleSizeByArmInArA.tex")
  , colnamestrue = F)

arA ← readRDS(paste0(pathsaveHere, DataFileNames[2], "Trimmed.rds"))
arA[, Arm := factor(Arm, levels = arms)]
```

```
#  HH characteristics from ar
iiH ← c("HeadLiteracy", "HeadAge", "HHsize", "FloodInRd1")
# FloodInRd1 has NAs, all entries are NAs for 5 HHs
summary(arA[hhid %in% hhid[is.na(FloodInRd1)],
  .(hhid = factor(hhid), FloodInRd1)])
```

```
      hhid        FloodInRd1
 7010101:48   Min.   : NA
 7137316:48   1st Qu.: NA
 8148207:48   Median : NA
 8148220:48   Mean   :NaN
 8169810:48   3rd Qu.: NA
              Max.   : NA
              NA's   :240
```

```
arA[tee==1, c("groupid", "hhid", "Mstatus", iiH), with = F]
```

```
      groupid      hhid   Mstatus HeadLiteracy HeadAge HHsize FloodInRd1
   1:   70101   7010101 oldMember            0      40      3         NA
   2:   70101   7010102 oldMember            0      50      5          1
   3:   70101   7010103 oldMember            0      32      4          1
   4:   70101   7010104 oldMember            0      28      3          1
   5:   70101   7010105 oldMember            0      30      4          1
  ---
1271:  817105  81710516 oldMember            0      82      6          0
1272:  817105  81710517 oldMember            1      45      5          0
1273:  817105  81710518 oldMember            0      55      4          0
1274:  817105  81710519 oldMember            0      35      3          0
1275:  817105  81710520 oldMember            1      25      5          0
```

```
desH ← arA[o800 == 1 & tee == 1,
  lapply(.SD, mean, na.rm = T), .SDcols = iiH, by = Arm]
desN ← arA[o800 == 1 & tee == 1, lapply(.SD, function(z) length(z[!is.na(z)])),
  .SDcols = iiH, by = Arm]
cns ← colnames(desH[, −1])
desH ← data.table(t(desH[, −1]))
setnames(desH, arms)
desH[, variables := cns]
setcolorder(desH, c("variables", "traditional", "large", "large grace", "cow"))
```

One sees that later receivers could prepare better by saving before disbursement. Cumulative net saving as a percentage of loan amount at the time of disbursement. All arms but traditional have people whose first disbursement is later than 2013. Late receivers, however, are not original 800 HHs.

```
summary(arA[MonthsElapsed < −24, .(groupid = factor(groupid),
  Arm, hhid, DisDate = factor(DisDate1), Date = factor(Date), tee, BStatus,
  value.repay, value.missw, value.NetSaving)])
arA[, c("DisYear1", "DisYear2", "DisYear3") := 2013]
for (yy in 2014:2017)
  for (i in 1:3)
  arA[format(eval(parse(text=paste0("DisDate", i))), format = "%Y") == yy,
    (paste0("DisYear", i)) := yy]
arA[!grepl("tra", Arm), c("DisYear2",   "DisYear3") := NA]
# Accumulated saving at disbursement
AcmSv ← rbindlist(list(arA[o800 == 1 & MonthsElapsed == 1, .(
    MeanNetSaving = mean(CumNetSaving),
    StdNetSaving = var(CumNetSaving)^(.5),
```

```
    Num = .N
  ), by = .(Arm, DisYear1)][order(Arm, DisYear1), ],
arA[o800 == 1 & !is.na(DisYear2) & MonthsElapsed == 13, .(
  MeanEffNetSaving = mean(CumRepaid-CumPlannedInstallment+CumNetSaving),
  StdEffNetSaving = var(CumRepaid-CumPlannedInstallment+CumNetSaving)^(.5),
  Num = .N), by = .(Arm, DisYear2)][order(Arm, DisYear2), ],
arA[o800 == 1 & !is.na(DisYear3) & MonthsElapsed == 25, .(
  MeanEffNetSaving = mean(CumRepaid-CumPlannedInstallment+CumNetSaving),
  StdEffNetSaving = var(CumRepaid-CumPlannedInstallment+CumNetSaving)^(.5),
  Num = .N), by = .(Arm, DisYear3)][order(Arm, DisYear3), ])
)
```

```
Column 2 ['DisYear2'] of item 2 is missing in item 1. Use fill=TRUE to fill with NA (NULL
backwards compatibility. See news item 5 in v1.12.2 for options to control this message.
```

```
setnames(AcmSv, "DisYear1", "DisYear")
setkey(AcmSv, Arm, DisYear)
AcmSv[, LoanAmount := 16800]
AcmSv[grepl("trad", Arm), LoanAmount := 16800/3]
AcmSv[, NetSavRate := round((MeanNetSaving/LoanAmount)*100, 2)]
AcmSv[, StdNetSavRate := StdNetSaving/LoanAmount]
AcmSv[, NetSavRateUB := NetSavRate + 1.96*StdNetSavRate]
AcmSv[, NetSavRateLB := NetSavRate - 1.96*StdNetSavRate]
# keep only first disbursements
AcmSv <- AcmSv[!(grepl("tra", Arm) & DisYear != 2013), ]
# accumulated savings
AcS <- reshape(AcmSv, direction = "wide", idvar = "Arm",
  timevar = "DisYear", v.names = grepout("Me|N", colnames(AcmSv))
  )
cn <- colnames(AcS)
AcS <- data.table(t(AcS[, -(1:2)]))
AcS <- cbind(variables = cn[-(1:2)], AcS)
setnames(AcS, c("variables", "traditional", "large", "large grace", "cow"))
AcS[grepl("^Net", variables), ][, variables := gsub("\\.", " disbursed in ", variables)][
  , variables := gsub("NetSavRate", "Net saving (\\\\\\% of loan)", variables)][]
```

One also sees that traditional has lower repayment rates in the 2nd and 3rd loan years. This can be due to lower returns on small assets, or, moral hazard that they get new disbursements irrespective of loan delinquency.

```
MeanAndStd <- function(x, NARM = T) {
  nx <- names(x)
  if (is.null(dim(x))) x <- matrix(x)
  ms <- c(apply(x, 2, mean, na.rm = NARM),
    apply(x, 2, function(z) var(z, na.rm = NARM)^.5),
    apply(x, 2, function(z) length(z[!is.na(z)])))
  names(ms) <- paste0(nx, rep(c(".mean", ".std", ".N"), each = ncol(x)))
  return(ms)
}
#for (Tee in seq(12, 48, 12))
#rbind(des.repay,
#     arA[!grepl("drop", Mgroup) & grepl("oldMem", Mstatus) &
#       !grepl("pure saver", BorrowerStatus)
#       & MonthsElapsed == Tee, as.list(unlist(lapply(.SD, MeanAndStd))),
#      .SDcols = c("CumRepaid", "CumMisses"), by = Arm]
arA[, value.EffRepay := value.repay + value.NetSaving]
```

```
des.repay ←
    arA[o800 == 1 & !grepl("drop", Mgroup) & grepl("oldMem", Mstatus) &
      !grepl("pure saver", BStatus),
      as.list(unlist(lapply(.SD, MeanAndStd))),
      .SDcols = c("value.repay", "value.EffRepay", "value.missw"),
      by = .(Arm, LoanYear)]
setkey(des.repay, Arm, LoanYear)
des.rep ← reshape(des.repay, direction = "wide", idvar = "Arm",
  timevar = "LoanYear", v.names = grepout("\\.", colnames(des.repay)))
desrep ← t(des.rep[, -1])
colnames(desrep) ← des.rep[, Arm]
rn ← rownames(desrep)
desrep ← data.table(desrep)
desrep[, variables := gsub("value\\.(.*?)\\..*$", "\\1", rn)]
desrep[, stat := gsub("^.*\\.\\.(.*?)\\..*$", "\\1", rn)]
desrep[, LY := as.numeric(gsub("^.*\\.(-?.)$", "\\1", rn))]
desrep ← desrep[grepl("mean", stat) & LY ≥ -1, ]
setkey(desrep, variables, LY)
desrep[, variables := paste0(variables, " in LoanYear", LY)]
desrep[, LY := NULL]
setcolorder(desrep, c("variables", "traditional", "large", "large grace", "cow"))
desRep ← desrep
# number of repayers (this varies with meeting attendance, not a good indicator of sample
desRepN ← data.table(t(c("N", des.rep[, value.repay..N.1]/12, NA)))
setnames(desRepN, colnames(desrep))
```

One may need to take into account of flood influences. Split sample into flood affected and unaffected. Affected by flood does not seem to change the repayment numbers.

```
des.repay0 ←
    arA[!grepl("drop", Mgroup) & grepl("oldMem", Mstatus) &
      !grepl("pure saver", BStatus) & FloodInRd1 == 0,
      as.list(unlist(lapply(.SD, MeanAndStd))),
      .SDcols = c("value.repay", "value.EffRepay", "value.missw"),
      by = .(Arm, LoanYear)]
des.repay1 ←
    arA[!grepl("drop", Mgroup) & grepl("oldMem", Mstatus) &
      !grepl("pure saver", BStatus) & FloodInRd1 == 1,
      as.list(unlist(lapply(.SD, MeanAndStd))),
      .SDcols = c("value.repay", "value.EffRepay", "value.missw"),
      by = .(Arm, LoanYear)]
for (i in 0:1) {
 des.repay ← get(paste0("des.repay", i))
  setkey(des.repay, Arm, LoanYear)
  des.rep ← reshape(des.repay, direction = "wide", idvar = "Arm",
    timevar = "LoanYear", v.names = grepout("\\.", colnames(des.repay)))
  desrep ← t(des.rep[, -1])
  colnames(desrep) ← des.rep[, Arm]
  rn ← rownames(desrep)
  desrep ← data.table(desrep)
  desrep[, variables := gsub("value\\.(.*?)\\..*$", "\\1", rn)]
  desrep[, stat := gsub("^.*\\.\\.(.*?)\\..*$", "\\1", rn)]
  desrep[, LY := as.numeric(gsub("^.*\\.(-?.)$", "\\1", rn))]
  desrep ← desrep[grepl("mean", stat) & LY ≥ -1, ]
  setkey(desrep, variables, LY)
  desrep[, variables := paste0(variables, " in LoanYear", LY)]
  desrep[, LY := NULL]
```

```
  setcolorder(desrep, c(”variables”, ”traditional”, ”large”, ”large grace”, ”cow”))
  cat(paste0(”Flood dummy = ”, i, ”\n”))
  print(desrep[grepl(”Eff”, variables), ])
}
```

```
Flood dummy = 0
                variables traditional    large large grace     cow stat
1: EffRepay in LoanYear-1     134.914  92.6302     107.427 125.272 mean
2:  EffRepay in LoanYear1     392.775 424.1113     170.267 159.228 mean
3:  EffRepay in LoanYear2     193.262 380.2798     463.111 450.849 mean
4:  EffRepay in LoanYear3     244.323 420.4508     546.128 559.819 mean
5:  EffRepay in LoanYear4     336.761 327.4122     323.886 290.930 mean
Flood dummy = 1
                variables traditional   large large grace     cow stat
1: EffRepay in LoanYear-1     111.570 138.420     133.354 118.024 mean
2:  EffRepay in LoanYear1     377.850 458.171     177.118 170.142 mean
3:  EffRepay in LoanYear2     171.004 367.037     460.485 399.643 mean
4:  EffRepay in LoanYear3     214.992 432.284     521.802 491.766 mean
5:  EffRepay in LoanYear4     420.533 397.204     295.058 482.321 mean
```

```
des ← rbindlist(list(desH,
  AcS[grepl(”^Net”, variables), ][, variables :=
    gsub(”\\.”, ” in ”, variables)][
    , variables := gsub(”NetSavRate”, ”Net saving (\\\\\\% of loan)”, variables)][],
  desRep), use.names = T, fill = T
)
des[, stat := NULL]
des[, (arms) := round(.SD, 2), .SDcol = arms]
des ← des[!grepl(”[LU]B|miss”, variables), ]
desN2 ← c(”Number of loan receiving members”,
  t(matrix(unlist(desN[, 2, with = F][c(4, 1, 3, 2)]))))
des ← rbind(as.matrix(des),
  ”Number of loan receiving members” = desN2
  #,”Number of loan recipients” = as.matrix(desRepN[, -ncol(desRepN), with = F])
  )
des ← data.table(des)
des[, variables := gsub(”EffRepay”, ”Effective repayment”, variables)]
des[, variables := gsub(”repay”, ”Repayment”, variables)]
des[, variables := gsub(”LoanYear”, ”Loan Year ”, variables)]
des[, variables := gsub(”Head”, ”Head ”, variables)]
des[, variables := gsub(”HH”, ”Household ”, variables)]
des[, variables := gsub(”^Fl.*”, ”Flood in round 1”, variables)]
DestatByArm ← latextab(as.matrix(des),
  hleft = c(”\\scriptsize\\hfill ”, rep(”\\scriptsize\\hfil$”, ncol(des)−1)),
  hcenter = c(5, rep(1.05, ncol(des)−1)),
  hright = c(””, rep(”$”, ncol(des)−1)),
  headercolor = ”gray80”, adjustlineskip = ”−.2ex”, delimiterline= NULL,
  alternatecolor = ”gray90”)
write.tablev(DestatByArm,
  paste0(pathsaveHere, ”DestatByArm.tex”)
  , colnamestrue = F)
```

Table 5: Descriptive statistics by arm in administrative data

variables	traditional	large	large grace	cow
Head Literacy	0.11	0.14	0.10	0.13
Head Age	37.96	38.12	38.66	37.86
Household size	4.37	4.08	4.17	4.08
Flood in round 1	0.58	0.50	0.36	0.55
Net saving (% of loan) in 2013	3.45	4.02	5.49	6.70
Effective Repaymentment in Loan Year -1	165.45	517.45	567.27	565.26
Effective Repaymentment in Loan Year 1	403.33	493.44	212.63	211.66
Effective Repaymentment in Loan Year 2	179.06	320.09	499.23	455.44
Effective Repaymentment in Loan Year 3	248.21	382.42	566.32	535.22
Effective Repaymentment in Loan Year 4	345.50	314.41	282.75	350.22
Repayment in Loan Year -1	55.19	38.93	0.00	0.00
Repayment in Loan Year 1	352.96	420.63	42.87	37.67
Repayment in Loan Year 2	139.43	272.92	463.21	420.32
Repayment in Loan Year 3	206.11	338.97	538.29	505.76
Repayment in Loan Year 4	318.00	291.86	270.47	333.69
Number of loan receiving members	116	180	180	190

Source: Estimated with GUK administrative and survey data.

Notes: 1. Information of original 800 households. Net saving as percentage of loan amount is a mean over loan recipients whose first disbursement is in 2013. Effective repayment is a sum of repayment and net saving.

2. Loan year -1 is preparation period for loan disbursement when only saving is allowed.

III Estimation using initial sample HHs

Initial sample is defined as the members receiving loans within 6 months after the first loan was disbursed in a group.

```
for (i in 1:length(DataFileNames))
  saveRDS(readRDS(
    paste0(pathsaveHere, DataFileNames[i], "Trimmed.rds")
    ),
    paste0(pathsaveHere, DataFileNames[i], "InitialSample.rds")
    )
for (i in 1:length(DataFileNames))
  write.tablev(readRDS(
    paste0(pathsaveHere, DataFileNames[i], "Trimmed.rds")
    ),
    paste0(pathsaveHere, DataFileNames[i], "InitialSample.prn")
    , colnamestrue = F)
```

III.1 Repayment and net saving

```
#ar <- readRDS(paste0(pathsaveHere, "RosterRepaymentAdminOriginalHHsDataUsedForEstimation.
#arA <- readRDS(paste0(pathsaveHere, "AllMeetingsRosterAdminDataUsedForEstimation.rds"))
arA <- readRDS(paste0(pathsaveHere, DataFileNames[2], "InitialSample.rds"))
if (Only800) arA <- arA[o800 == 1L & !is.na(LoanYear) &
  !grepl("tw|dou", TradGroup), ]
setkey(arA, hhid, tee)
arA[survey == 2, Time.2 := 1L]
#arA[, Mid := 1:.N, by = .(hhid, survey)]
#arA <- arA[Mid == 1, ]
#arA[, Mid := NULL]
arA[, CumSave := CumNetSaving - CumRepaid]
arA[, CumEffectiveRepayment := CumNetSaving + CumRepaid]
for (rr in grepout("^RM", colnames(arA)))
  arA[, (rr) := eval(parse(text=paste0(rr, "*RMDenomination")))]
arA[, Arm := droplevels(Arm)]
arA[, HeadLiteracy := HeadLiteracy + 0]
```

```
source("c:/dropbox/settings/Rsetting/panel_estimator_functions.R")
setorder(arA, hhid, Date)
arA[, grepout("^Time$|UD|[mM]issw|Small|^Size",
  colnames(arA)) := NULL]
arA[, ExcessRepayment := 0]
arA[grepl("bo", BorrowerStatus),
  ExcessRepayment := value.repay - PlannedInstallment]
arA[, CumExcessRepayment := cumsum(ExcessRepayment), by = hhid]
# use only borrowers
arA2 <- arA[grepl("bo", BorrowerStatus),
  #grepout("groupid|^hhid|tee|RArm|^dummy[A-Z]|^dummy.*[a-z]$|Time|CumRepaid$|CumE.*t$|Cum
  grepout("^groupid|^hhid|survey|tee|LY|^dummy[A-Z]|^dummy.*[a-z]$|Time|CumRepaid$|CumE.*t
  colnames(arA)), with = F]
arA1 = copy(arA2)
arA1[, grepout("RM", colnames(arA1)) := NULL]
#  hhid == 7096302, 3 have round 1 observation which corresponds to pre disbursement date.
# dar1 <- prepFDData(ar1[!((hhid == 7096302 & tee == 1) | (hhid == 7096303 & tee == 1)), ]
#   Group = "^hhid$", TimeVar = "tee", Cluster = "groupid",
#   LevelCovariates = "^dumm.*[a-z]$|RAr|Floo|^Time\\..$|HeadL|HeadA|LoanY",
#   drop.if.NA.in.differencing = T, LevelPeriodToKeep = "last",
#   use.var.name.for.dummy.prefix = F, print.messages = F)
# dar2 <- prepFDData(ar1, Group = "^hhid$", TimeVar = "tee", Cluster = "groupid",
#   LevelCovariates = "^dumm.*[a-z]$|RAr|Floo|^Time\\..$|HeadL|HeadA|LoanY",
#   drop.if.NA.in.differencing = T, LevelPeriodToKeep = "last",
#   use.var.name.for.dummy.prefix = F, print.messages = F)
dl <- FirstDiffPanelData(X = arA1,
  Group = "^hhid$", TimeVar = "^tee$", Cluster = "^groupid$",
  LevelCovariates = "^dummy|Head|surve|^Time\\..$|^LY[2-4]|Female$|Floo|Eldest|^Arm|^cred.
```

```
Dropped 576 obs due to NA.
```

```
dard1 <- dl$diff
ard1 <- arA1[-as.numeric(unlist(dl$droppedRows)), ]
ard1[, c("Repaid", "NetSaving", "ExcessRepayment") :=
  .(c(CumRepaid[1], firstdiff(CumRepaid)),
    c(CumNetSaving[1], firstdiff(CumNetSaving)),
    c(CumExcessRepayment[1], firstdiff(CumExcessRepayment))), by = hhid]
meanar1 <- ard1[, .(
  MeanFDCumRepaid = mean(Repaid),
  MeanFDCumNetSaving = mean(NetSaving),
  MeanFDCumExcessRepayment = mean(ExcessRepayment)),
  by = survey][survey == 1, ]
dl <- FirstDiffPanelData(X = arA2,
  Group = "^hhid$", TimeVar = "tee", Cluster = "groupid",
  LevelCovariates = "^dummy|Head|surve|^Time\\..$|Female$|Floo|Eldest|^Arm|^cred.*s$|xid$|
```

```
Dropped 2789 obs due to NA.
```

```
dard2 <- dl$diff
ard2 <- arA2[-as.numeric(unlist(dl$droppedRows)), ]
ard2[, c("Repaid", "NetSaving", "ExcessRepayment") :=
  .(c(CumRepaid[1], firstdiff(CumRepaid)),
    c(CumNetSaving[1], firstdiff(CumNetSaving)),
    c(CumExcessRepayment[1], firstdiff(CumExcessRepayment))), by = hhid]
meanar2 <- ard2[, .(
```

```
  MeanFDCumRepaid = mean(Repaid),
  MeanFDCumNetSaving = mean(NetSaving),
  MeanFDCumExcessRepayment = mean(ExcessRepayment)),
  , by = survey][survey == 1, ]
meanar ← rbind("dard1" =meanar1, "dard2" =meanar2)
datas ← c("dard1", "dard2")
for (i in 1:length(datas)) {
  dat ← get(datas[i])
  # need to keep Time.?2 because there are many tee/meetings per HH in a given survey rour
  dat[, grepout("^en$", colnames(dat)) := NULL]
  dat[, Tee := .N, by = hhid]
  dat ← dat[Tee > 1, ]
  assign(datas[i], dat)
}
```

Repayment formally started in round 2. So taking a first-difference leaves us with period 2-3 and period 3-4. After first-differencing, arA has 26388 rows with 17, 22, 1, 2, 134, 194, 206 individuals with repeatedly observed for 42, 43, 44, 45, 46, 47, 48 times, respectively. By survey rounds, there are 28, 561, 555, 554, 405 observations per household in rounds 1, 2, 3, 4, respectively. This is smaller than the InitialSample size of 800 because the survey includes and follows up on rejecters and residents whose houses are washed away by flood, while repayment is defined only for the borrowers.

Saving started in rd 1. Repayment and saving are more frequent than survey rounds. In regressions, we opted to use survey rounds as period indicators and do not use meeting rounds to reduce the number of dummy variables.

TABLE 6: INITIAL SAMPLE BY ARM IN ADMINISTRATIVE DATA

	initial sample					all sample				
	traditional	large	large grace	cow	total	traditional	large	large grace	cow	total
borrower	109	171	167	153	600	205	348	338	308	1199
pure saver	0	0	0	0	0	22	0	0	0	22
individual rejection	31	9	13	37	90	53	12	22	72	159
group rejection	40	20	10	0	70	80	40	20	0	140
rejection by flood	20	0	10	10	40	40	0	20	20	80
total	200	200	200	200	800	400	400	400	400	1600

Source: Estimated with GUK administrative and survey data.

Notes: 1. Number of individuals who received a loan/cow. Left panel are initial 800 members who were offered at the first round, including individuals who declined or left the group. Right panel also includes members who were offered on a later date.

TABLE 7: INITIAL SAMPLE BY ARM IN REPAYMENT DATA

	initial sample					all sample				
	traditional	large	large grace	cow	total	traditional	large	large grace	cow	total
borrower	85	171	167	153	576	100	348	338	308	1094
pure saver	0	0	0	0	0	22	0	0	0	22
individual rejection	31	9	13	37	90	53	12	22	72	159
group rejection	0	0	0	0	0	0	0	0	0	0
rejection by flood	0	0	0	0	0	0	0	0	0	0
total	116	180	180	190	666	175	360	360	380	1275

Source: Estimated with GUK administrative and survey data.

Notes: 1. Number of individuals who received a loan/cow. Left panel in TABLE 7 is initial 800 members who were offered at the first round, including individuals who declined or left the group. Right panel also includes members who were offered on a later date.

TABLE 6 shows the tabuation of InitisalSample by arms. Left panel are InitialSample including pure savers and members who left the group. Right panel includes late borrowers who were initially assigned as the control. One can see that traditional arm members have the highest proportion to be pure savers or to exit from the group. This shows the stronger reluctance of traditional arm members to borrow.

Note all binary interaction terms are demeaned and then interacted.

```
#ar <- readRDS(paste0(pathsaveHere, "RosterAdminDataUsedForEstimation.rds"))
#arA <- readRDS(paste0(pathsaveHere, "AllMeetingsRosterAdminDataUsedForEstimation.rds"))
#arA <- readRDS(paste0(pathsaveHere, DataFileNames[2], "Trimmed.rds"))
arA <- readRDS(paste0(pathsaveHere, DataFileNames[2], "InitialSample.rds"))
if (Only800) arA <- arA[o800 == 1L & !grepl("tw|dou", TradGroup) &
  !is.na(LoanYear), ]
arA[, CumSave := CumNetSaving - CumRepaid]
arA[, CumEffectiveRepayment := CumNetSaving + CumRepaid]
arA[, Arm := droplevels(Arm)]
arA[, HeadLiteracy := HeadLiteracy + 0]
source("c:/dropbox/settings/Rsetting/panel_estimator_functions.R")
setorder(arA, hhid, Date)
arA[, grepout("^Time$", colnames(arA)) := NULL]
#arA[, c("dummyForcedDropOuts") := NULL]
table0(arA[LoanMonth == 1, .(LoanYear, RArm)])
table0(arA[, .(survey, RArm)])
```

```
table0(arA[is.na(CumRepaid), .(tee, Arm)])
```

Tabulation at rd 1:

```
tb <- table0(arA[survey == 1, .(Mstatus, RArm)])
tb <- cbind(tb, total = apply(tb, 1, sum))
tb <- rbind(tb, total = apply(tb, 2, sum))
```

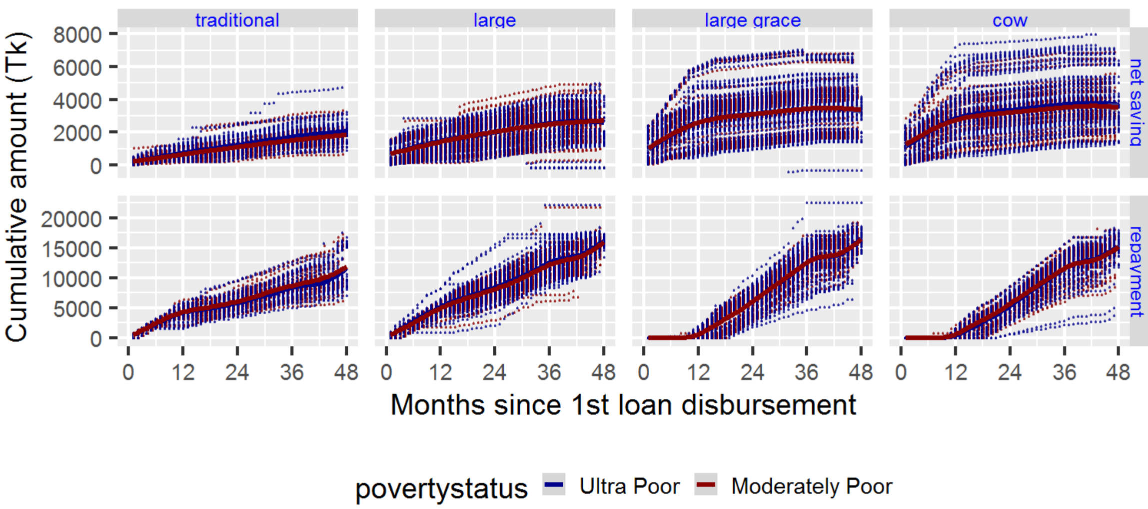
```
library(ggplot2)
ga <- arA[!is.na(Date) & !is.na(DisDate1) & grepl("Yes", creditstatus),
  .(Arm, hhid, povertystatus, MonthsElapsed,
  CumNetSaving, CumRepaid)]
ga1 <- ga[, !grepl("Ne", colnames(ga)), with = F]
ga1[, variable := "repayment"]
ga2 <- ga[, !grepl("Rep", colnames(ga)), with = F]
ga2[, variable := "net saving"]
setnames(ga1, grepout("Re", colnames(ga1)), "amount")
setnames(ga2, grepout("Ne", colnames(ga2)), "amount")
ga <- rbindlist(list(ga1, ga2))
ColourForPoints <- c("darkblue", "darkred")
g <- ggplot(ga,
  aes(x = MonthsElapsed, y = amount,
    colour = povertystatus, group = povertystatus)) +
  geom_point(aes(fill = povertystatus), size = .01,
    position = position_dodge(width = .5), #colour = "transparent",
    alpha = .6) +
  geom_smooth(span = .5, size = .75,
    aes(colour = povertystatus, group = povertystatus)) +
  scale_colour_manual(values = ColourForPoints) +
  scale_fill_manual(values = c("blue", "red")) +
#  scale_shape_manual(values=c(21, 25)) +
  theme(
    legend.position="bottom",
    legend.text = element_text(size = 7),
    legend.title = element_text(size = 9),
    legend.key = element_rect(fill = "white"),
    legend.key.size = unit(.25, "cm"),
    axis.text = element_text(size = 7),
    axis.title = element_text(size = 9),
    strip.text.x = element_text(color = "blue", size = 6,
```

```
      margin = margin(0, .5, 0, .5, "cm")),
    strip.text.y = element_text(color = "blue", size = 6,
      margin = margin(.5, 0, .5, 0, "cm"))
  ) +
  scale_y_continuous() +
  scale_x_continuous(limits = c(0, 48), breaks = seq(0, 48, 12)) +
  xlab("Months since 1st loan disbursement") +
  ylab("Cumulative amount (Tk)") +
  facet_grid(variable ~ Arm, scales = "free_y")
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo2/",
    "CumulativeWeeklyNetSavingAndRepayment.png"),
  g,
  width = 13, height = 6, units = "cm",
  dpi = 300
 )
```

```
library(ggplot2)
ga <- arA[!is.na(Date) & !is.na(DisDate1) & grepl("Yes", creditstatus) &
  grepl("bo", BStatus) & o800 == 1L,
  .(Arm, hhid, povertystatus, MonthsElapsed,
  CumNetSaving, CumRepaid, CumRepaidRate, CumEffectiveRepaidRate)]
# ga1: amount
ga1 <- ga[, !grepl("Ne|Rate", colnames(ga)), with = F]
ga1[, variable := "repayment"]
# ga2: rate
ga20 = copy(ga)
ga20 <- ga20[, grepout("Ne|Repaid$|variab", colnames(ga20)) := NULL]
ga20 <- ga20[!is.na(CumEffectiveRepaidRate) &
  !is.na(CumEffectiveRepaidRate), ]
ga21 <- ga20[, .(Arm, hhid, povertystatus, MonthsElapsed, CumEffectiveRepaidRate)]
ga22 <- ga20[, .(Arm, hhid, povertystatus, MonthsElapsed, CumRepaidRate)]
setnames(ga21, "CumEffectiveRepaidRate", "value")
setnames(ga22, "CumRepaidRate", "value")
ga21[, variable := "Repay+net saving"]
ga22[, variable := "Repayment"]
ga2 <- rbindlist(list(ga21, ga22))
ga2[, variable := factor(variable,
  levels = c("Repayment", "Repay+net saving"))]
setnames(ga1, grepout("Re", colnames(ga1)), "amount")
#setnames(ga2, grepout("Re", colnames(ga2)), "amount")
#ga <- rbindlist(list(ga1, ga2))
ColourForPoints <- c("darkblue", "darkred")
g <- ggplot(ga2,
  aes(x = MonthsElapsed, y = value,
    colour = povertystatus, group = povertystatus)) +
  geom_point(aes(fill = povertystatus), size = .01,
    position = position_dodge(width = .5), #colour = "transparent",
    alpha = .6) +
  geom_smooth(span = .5, size = .5, #colour = "blue",
    aes(colour = povertystatus, group = povertystatus)) +
  scale_colour_manual(values = ColourForPoints) +
  scale_fill_manual(values = c("blue", "red")) +
#  scale_shape_manual(values=c(21, 25)) +
  theme(
```

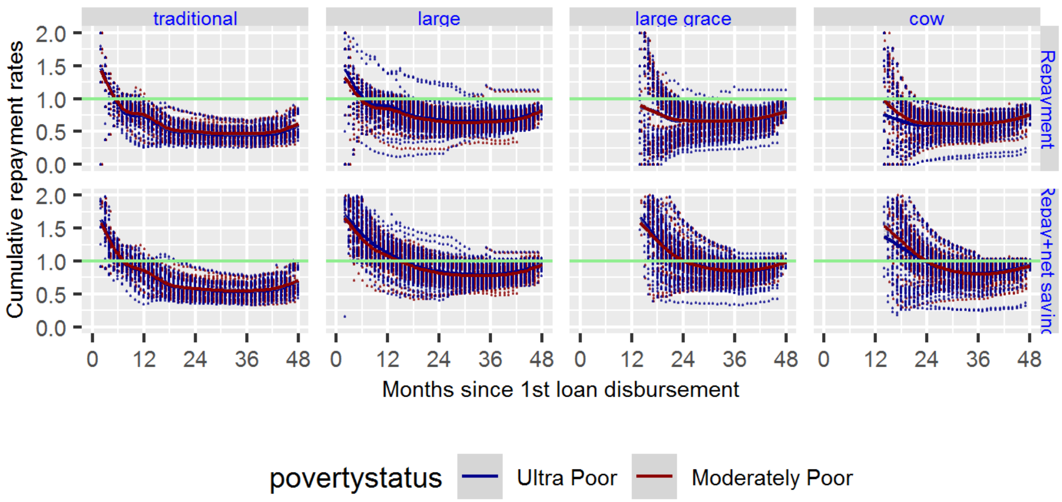
```
    legend.position="bottom",
    legend.text = element_text(size = 7),
    legend.title = element_text(size = 9),
    legend.key = element_rect(fill = "white"),
    legend.key.size = unit(.5, "cm"),
    axis.text = element_text(size = 7),
    axis.title = element_text(size = 7),
    strip.text.x = element_text(color = "blue", size = 6,
      margin = margin(0, .5, 0, .5, "cm")),
    strip.text.y = element_text(color = "blue", size = 6,
      margin = margin(.5, 0, .5, 0, "cm"))
  ) +
  scale_y_continuous(limits = c(0, 2)) +
  scale_x_continuous(limits = c(0, 48), breaks = seq(0, 48, 12)) +
  xlab("Months since 1st loan disbursement") +
  ylab("Cumulative repayment rates") +
  facet_grid(variable ~ Arm, scales = "free_y") +
  geom_hline(aes(yintercept = 1), colour = "lightgreen", data = ga2)
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo2/",
    "CumulativeWeeklyRepaymentRateByPovertystatus.png"),
  g,
  width = 12, height = 6, units = "cm",
  dpi = 300
)
```

FIGURE 1: CUMULATIVE WEEKLY NET SAVING AND REPAYMENT



Note: Each dot represents weekly observations. Only members who received loans are shown. Each panel shows cumulative net saving (saving - withdrawal) or cumulative repayment against weeks after first disbursement. Lines are smoothed lines with a penalized cubic regression spline in ggplot2::geom_smooth function, originally from mgcv::gam with bs='cs'.

FIGURE 2: CUMULATIVE WEEKLY NET REPAYMENT RATES



Note: Each dot represents weekly observations. Only members who received loans are shown. Each panel shows ratios of cumulative repayment against cumulative due amount, sum of cumulative repayment and cumulative net saving (saving - withdrawal) against cumulative due amount, against weeks after first disbursement. Lines are smoothed lines with a penalized cubic regression spline in ggplot2::geom_smooth function, originally from mgcv::gam with bs='cs'.

```
#ar ← readRDS(paste0(pathsaveHere, "RosterRepaymentAdminOriginalHHsDataUsedForEstimation.
#arA ← readRDS(paste0(pathsaveHere, "AllMeetingsRosterAdminDataUsedForEstimation.rds"))
arA ← readRDS(paste0(pathsaveHere, DataFileNames[2], "InitialSample.rds"))
if (Only800) arA ← arA[o800 == 1L & !is.na(LoanYear) &
  !grepl("tw|dou", TradGroup), ]
setkey(arA, hhid, tee)
arA[survey == 2, Time.2 := 1L]
#arA[, Mid := 1:.N, by = .(hhid, survey)]
#arA ← arA[Mid == 1, ]
#arA[, Mid := NULL]
arA[, CumSave := CumNetSaving − CumRepaid]
arA[, CumEffectiveRepayment := CumNetSaving + CumRepaid]
for (rr in grepout("^RM", colnames(arA)))
  arA[, (rr) := eval(parse(text=paste0(rr, "*RMDenomination")))]
arA[, Arm := droplevels(Arm)]
arA[, HeadLiteracy := HeadLiteracy + 0]
source("c:/dropbox/settings/Rsetting/panel_estimator_functions.R")
setorder(arA, hhid, Date)
arA[, grepout("^Time$|UD|[mM]issw|Small|^Size",
  colnames(arA)) := NULL]
arA[, ExcessRepayment := 0]
arA[grepl("bo", BorrowerStatus),
  ExcessRepayment := value.repay − PlannedInstallment]
arA[, CumExcessRepayment := cumsum(ExcessRepayment), by = hhid]
# use only borrowers
arA2 ← arA[grepl("bo", BorrowerStatus),
  #grepout("groupid|^hhid|tee|RArm|^dummy[A-Z]|^dummy.*[a-z]$|Time|CumRepaid$|CumE.*t$|Cum
  grepout("^groupid|^hhid|survey|tee|LY|^dummy[A−Z]|^dummy.*[a−z]$|Time|CumRepaid$|CumE.*t
  colnames(arA)), with = F]
arA1 = copy(arA2)
arA1[, grepout("RM", colnames(arA1)) := NULL]
#  hhid == 7096302, 3 have round 1 observation which corresponds to pre disbursement date.
# dar1 ← prepFDData(ar1[!((hhid == 7096302 & tee == 1) | (hhid == 7096303 & tee == 1)),
#   Group = "^hhid$", TimeVar = "tee", Cluster = "groupid",
#   LevelCovariates = "^dumm.*[a-z]$|RAr|Floo|^Time\\..$|HeadL|HeadA|LoanY",
#   drop.if.NA.in.differencing = T, LevelPeriodToKeep = "last",
#   use.var.name.for.dummy.prefix = F, print.messages = F)
```

```
# dar2 ← prepFDData(ar1, Group = "^hhid$", TimeVar = "tee", Cluster = "groupid",
#   LevelCovariates = "^dumm.*[a-z]$|RAr|Floo|^Time\\..$|HeadL|HeadA|LoanY",
#   drop.if.NA.in.differencing = T, LevelPeriodToKeep = "last",
#   use.var.name.for.dummy.prefix = F, print.messages = F)
dl ← FirstDiffPanelData(X = arA1,
  Group = "^hhid$", TimeVar = "^tee$", Cluster = "^groupid$",
  LevelCovariates = "^dummy|Head|surve|^Time\\..$|^LY[2-4]|Female$|Floo|Eldest|^Arm|^cred.
dard1 ← dl$diff
ard1 ← arA1[-as.numeric(unlist(dl$droppedRows)), ]
ard1[, c("Repaid", "NetSaving", "ExcessRepayment") :=
  .(c(CumRepaid[1], firstdiff(CumRepaid)),
    c(CumNetSaving[1], firstdiff(CumNetSaving)),
    c(CumExcessRepayment[1], firstdiff(CumExcessRepayment))), by = hhid]
meanar1 ← ard1[, .(
  MeanFDCumRepaid = mean(Repaid),
  MeanFDCumNetSaving = mean(NetSaving),
  MeanFDCumExcessRepayment = mean(ExcessRepayment)),
  by = survey][survey == 1, ]
dl ← FirstDiffPanelData(X = arA2,
  Group = "^hhid$", TimeVar = "tee", Cluster = "groupid",
  LevelCovariates = "^dummy|Head|surve|^Time\\..$|Female$|Floo|Eldest|^Arm|^cred.*s$|xid$|
dard2 ← dl$diff
ard2 ← arA2[-as.numeric(unlist(dl$droppedRows)), ]
ard2[, c("Repaid", "NetSaving", "ExcessRepayment") :=
  .(c(CumRepaid[1], firstdiff(CumRepaid)),
    c(CumNetSaving[1], firstdiff(CumNetSaving)),
    c(CumExcessRepayment[1], firstdiff(CumExcessRepayment))), by = hhid]
meanar2 ← ard2[, .(
  MeanFDCumRepaid = mean(Repaid),
  MeanFDCumNetSaving = mean(NetSaving),
  MeanFDCumExcessRepayment = mean(ExcessRepayment)),
  , by = survey][survey == 1, ]
meanar ← rbind("dard1" =meanar1, "dard2" =meanar2)
datas ← c("dard1", "dard2")
for (i in 1:length(datas)) {
  dat ← get(datas[i])
  # need to keep Time.?2 because there are many tee/meetings per HH in a given survey rour
  dat[, grepout("^en$", colnames(dat)) := NULL]
  dat[, Tee := .N, by = hhid]
  dat ← dat[Tee > 1, ]
  assign(datas[i], dat)
}
```

```
FileName ← "Saving"
FileNameHeader ← paste0(c("", "Grace", "PovertyStatus", "Size", "Attributes"),
  "OriginalHHs")
# length(arsuffixes) = Number of est results tables to be produced
arsuffixes ← c("", "g", "p", "s", "a")
listheader ← paste0("sv", arsuffixes)
Regressands ← c(rep("CumNetSaving", 2), rep("CumRepaid", 3),
  rep("CumEffectiveRepayment", 3), rep("CumExcessRepayment", 3))
DataToUse1 ← DataToUse2 ← c("dard1", "dard2",
  rep(c("dard1", rep("dard2", 2)), 3))
Addseparatingcols = c(2, 5, 8); Separatingcolwidth = rep(.1, 3)
Separatingcoltitle = c("Cumulative net saving", "Cumulative repayment",
   "\\mpage{3cm}{\\hfil Cumulative net saving \\\\\\hfil +cumulative repayment}",
```

```
  "Cumulative excess repayment")

source(paste0(pathprogram, "RepaymentCovariateSelection.R"))

exclheader ← paste0("excl", arsuffixes)
source(paste0(pathprogram, "FDEstimationFile.R"))
saveRDS(fdplist, paste0(pathsave, "FD_saving.rds"))

Regressands ←  c(rep("^value.NetSaving$", 2), rep("^value.repay$", 3),
  rep("^EffectiveRepayment$", 3), rep("^ExcessRepayment$", 3))
DataToUse1 ← DataToUse2 ← c("dard1", "dard2",
  rep(c("dard1", rep("dard2", 2)), 3))
FileNameHeader ← paste0("Flow",
  c("", "Grace", "PovertyStatus", "Size", "Attributes"),
  "OriginalHHs")
Addseparatingcols = c(2, 5, 8); Separatingcolwidth = rep(.1, 3)
Separatingcoltitle = c("Net saving", "Repayment",
  "Net saving + Repayment", "Excess repayment")
listheader ← paste0("svf", arsuffixes)

source(paste0(pathprogram, "FlowRepaymentCovariateSelection.R"))

exclheader ← paste0("excl", arsuffixes)
source(paste0(pathprogram, "FDEstimationFile.R"))

# svX ← sv12$data[, .(tee,
#   T2 = dummyTraditional.Time2 > 0, L2 = dummyLarge.Time2 > 0,
#   G2 = dummyLargeGrace.Time2 > 0, C2 = dummyCow.Time2 > 0,
#   T3 = dummyTraditional.Time3 > 0, L3 = dummyLarge.Time3 > 0,
#   G3 = dummyLargeGrace.Time3 > 0, C3 = dummyCow.Time3 > 0,
#   T4 = dummyTraditional.Time4 > 0, L4 = dummyLarge.Time4 > 0,
#   G4 = dummyLargeGrace.Time4 > 0, C4 = dummyCow.Time4 > 0 )]
# svX ← sv12$data[, .(
#   dummyTraditional.Time2 , dummyLarge.Time2 ,
#   dummyLargeGrace.Time2 , dummyCow.Time2 ,
#   dummyTraditional.Time3 , dummyLarge.Time3 ,
#   dummyLargeGrace.Time3 , dummyCow.Time3 ,
#   dummyTraditional.Time4 , dummyLarge.Time4 ,
#   dummyLargeGrace.Time4 , dummyCow.Time4 )]
LinDependent ← function(z, ShowMostDependent = F, ReturnColNames = F)
#  From CrossVal: https://stats.stackexchange.com/questions/16327/testing-for-linear-depen
#  The weakness of this function is that it does not specify which columns are jointly lin
#  ShowMostDependent: if T, returns column that is least linearly independent, if F, retur
{
  if (!is.matrix(z)) z ← as.matrix(z)
  rankofz ← qr(z)$rank
  if (rankofz == ncol(z)) message("Full rank.") else
  {
    rankifremoved ← sapply(1:ncol(z), function (x) qr(z[, −x])$rank)
    if (ReturnColNames) {
      if (ShowMostDependent)
        this ← colnames(z)[rankifremoved == max(rankifremoved)] else
        this ← colnames(z)[rankifremoved == ncol(z) − 1]
    } else {
      if (!ShowMostDependent)
```

```
        this ← which(rankifremoved == max(rankifremoved)) else
        this ← which(rankifremoved == ncol(z) − 1)
    }
    return(this)
  }
}
# svX ← as.matrix(sv12$data[, .(
#   Time.2, dummyLarge.Time2,
#   dummyLargeGrace.Time2, dummyCow.Time2,
#   Time.3 , dummyLarge.Time3 ,
#   dummyLargeGrace.Time3 , dummyCow.Time3 ,
#   Time.4 , dummyLarge.Time4 ,
#   dummyLargeGrace.Time4, dummyCow.Time4 )])
#LinDependent(svX, F, T)
```

```
arsv ← ar[, .(Arm, groupid, hhid, tee = as.factor(tee))]
svDatalist ← list(arsv, arsv, arsv, arsv, arsv, arsv, arsv, arsv)

InTermsSV ← lapply(svDatalist, function(x)
  interactXY(
    makeDummyFromFactor(x[, Arm], NULL),
    makeDummyFromFactor(x[, tee], NULL)
    ))
InTermsSV ← rbindlist(lapply(InTermsSV, function(x) {
  z ← data.table(t(c(nrow(x), unlist(lapply(1:ncol(x), function(i) sum(x[, i, with = F]))
  setnames(z, gsub(" ", "", gsub("dummy", "", c("total", colnames(x)))))
  z
}))
InTermsSV ← InTermsSV[, which(unlist(lapply(InTermsSV, function(x) !all(is.na(x) | x ==
InTermsSV ← t(InTermsSV)
colnames(InTermsSV) ← paste0("(", 1:ncol(InTermsSV), ")")
InTermsSV ← InTermsSV[c(grep("Tra", rownames(InTermsSV)),
  grep("Large[^g]", rownames(InTermsSV)),
  grep("Largeg", rownames(InTermsSV)),
  grep("Cow", rownames(InTermsSV)),
  grep("total", rownames(InTermsSV))
  ), ]
# reorder within a group
rn.j ← rownames(InTermsSV)
newroworder ← NULL
for (j in c("Tra", "Large[^g]", "Largeg", "Cow"))
  newroworder ← c(newroworder,
    c(grep(paste0(j, ".*ale$"), rn.j), grep(paste0(j, ".*P"), rn.j),
      grep(paste0(j, ".*J"), rn.j), grep(paste0(j, ".*H"), rn.j)))
InTermsSV ← InTermsSV[c(newroworder, nrow(InTermsSV)), ]

arA ← readRDS(paste0(pathsaveHere, DataFileNames[2], "InitialSample.rds"))
if (Only800) arA ← arA[o800 == 1L & grepl("bo", BStatus), ]
DesRep ← arA[,
  .(Arm, hhid, povertystatus, BStatus,
    Date, DisDate1, tee, MtgNum,
    CumEffectiveRepayment, CumRepaid, CumPlannedInstallment,
    CumEffectiveRepaidRate, CumRepaidRate, EffectivelyFullyRepaid
  )]
# Note: when CumPlannedInstallment==0, RepaidRate is NA
DesRep[, FullyRepaid := 0L]
```

```r
DesRep[, FullyRepaid := as.integer(any(
  !is.na(CumRepaidRate) & tee > 24 & CumRepaidRate ≥ 1
  )),
  by = hhid]
addmargins(table(DesRep[tee == 1, .(Arm, FullyRepaid)]),
  1:2, sum, T)
```

```
              FullyRepaid
Arm              0   1 sum
  traditional   85   0  85
  large        167   4 171
  large grace  163   4 167
  cow          152   1 153
  sum          567   9 576
```

```r
TabRepay ← addmargins(table(DesRep[tee == 1 & grepl("bo", BStatus),
  .(Arm, EffectivelyFullyRepaid)]), 1:2, sum, T)
dnTR ← dimnames(TabRepay)
TabRepay ← data.table(as.matrix.data.frame(TabRepay))
TabRepay[, Arm := dnTR$Arm]
TabRepay[, FullRepayRate := round(V2/V3*100, 2)]
setcolorder(TabRepay, c(4, 1:3, 5))
setnames(TabRepay, c("Arm", "no", "yes", "sum", "FullRepayRate"))
TabRepay[grepl("sum", Arm), Arm := "overall"]
saveRDS(TabRepay, paste0(pathprogram,
  "table/ImpactEstimationOriginal1600Memo3/RepaymentTable.rds"))
```

```r
#dummy chunk
```

Table 8: FD estimation of cumulative net saving and repayment

	Cumulative net saving		Cumulative repayment			Cumulative net saving +cumulative repayment			Cumulative excess repayment		
covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(Intercept)	39.0***	36.6***	250.3***	231.3***	232.0***	289.3***	267.9***	263.8***	−161.9***	−180.1***	−179.6***
	(2.1)	(2.2)	(15.8)	(17.0)	(15.5)	(16.8)	(17.9)	(16.4)	(15.8)	(16.6)	(14.9)
Large	7.2**	28.4***	79.0***	170.0***	162.1***	86.2***	198.4***	206.5***	76.1***	45.2*	35.5*
	(3.5)	(4.8)	(16.5)	(23.5)	(21.1)	(17.6)	(25.1)	(22.3)	(16.6)	(23.2)	(21.1)
LargeGrace	18.6***	109.1***	87.0***	−158.8***	−205.8***	105.6***	−49.6*	−74.6***	85.2***	252.6***	202.7***
	(4.2)	(19.1)	(18.2)	(23.0)	(12.2)	(18.2)	(29.5)	(24.6)	(18.6)	(22.7)	(12.2)
Cow	20.1***	111.5***	80.9***	−169.8***	−204.7***	101.0***	−58.3**	−66.5***	76.5***	241.5***	203.2***
	(5.0)	(16.7)	(16.9)	(23.4)	(12.3)	(17.5)	(29.0)	(23.8)	(17.1)	(23.2)	(12.2)
LY2		18.7***		47.3*	−59.2***		66.0**	−35.4*		439.9***	328.7***
		(3.4)		(26.0)	(20.2)		(26.5)	(19.7)		(63.2)	(45.2)
Large × LY2		−19.4***		−132.3***	−51.9***		−151.6***	−86.5***		−176.2***	−91.8***
		(4.9)		(15.3)	(15.8)		(19.1)	(16.5)		(16.8)	(17.6)
LargeGrace × LY2		−111.3***		386.8***	292.0***		275.5***	165.2***		−400.1***	−496.6***
		(19.0)		(21.2)	(32.7)		(32.0)	(41.0)		(21.9)	(33.5)
Cow × LY2		−114.6***		355.0***	259.4***		240.4***	124.9***		−433.3***	−529.5***
		(15.9)		(27.2)	(26.3)		(30.1)	(28.4)		(28.0)	(26.6)
LY3		22.6***		40.0	−118.4***		62.7**	−91.0***		411.6***	246.9***
		(4.3)		(28.1)	(21.7)		(29.6)	(21.8)		(71.9)	(54.5)
Large × LY3		−21.9***		−61.7***	−88.6***		−83.5***	−126.1***		−70.1***	−97.2***
		(5.5)		(19.1)	(19.7)		(19.5)	(19.6)		(18.7)	(19.3)
LargeGrace × LY3		−118.1***		466.4***	506.2***		348.3***	364.9***		−361.1***	−318.3***
		(20.2)		(19.3)	(11.5)		(33.2)	(27.4)		(19.1)	(11.5)
Cow × LY3		−119.0***		444.9***	475.4***		326.0***	328.0***		−381.1***	−347.1***
		(16.5)		(28.8)	(21.1)		(34.7)	(30.6)		(28.7)	(20.5)
LY4		32.1***		141.6***	−0.7		173.8***	34.0		579.2***	432.2***
		(5.5)		(40.5)	(23.6)		(43.4)	(25.3)		(79.1)	(53.3)
Large × LY4		−43.3***		−118.8***	−105.0***		−162.1***	−165.9***		411.2***	427.4***
		(7.0)		(42.1)	(29.2)		(44.3)	(31.4)		(41.7)	(28.5)
LargeGrace × LY4		−134.3***		188.6***	330.4***		54.3	174.4***		182.6***	330.5***
		(20.2)		(37.0)	(18.7)		(47.1)	(35.3)		(37.0)	(17.7)
Cow × LY4		−132.5***		262.7***	344.6***		130.2**	186.7***		256.5***	343.1***
		(17.5)		(45.1)	(18.7)		(53.8)	(34.5)		(45.1)	(18.0)
FloodInRd1					−23.7***			−22.1***			−23.2***
					(6.4)			(6.6)			(6.6)
Head literate					7.6			8.7			7.4
					(6.5)			(5.9)			(6.5)
Head age					0.1			0.2			0.1
					(0.2)			(0.2)			(0.3)
6M repayment					4.5***			4.5***			4.6***
					(0.1)			(0.1)			(0.1)
6M net saving					0.3***			2.0***			0.1
					(0.1)			(0.2)			(0.1)
6M other member net saving					−0.5*			−1.7***			−0.2
					(0.3)			(0.3)			(0.4)
6M other member Repaid					− 0.0			− 0.0			0.0
					(0.3)			(0.3)			(0.4)
$\bar{R}^2$	0.006	0.16	0.006	0.112	0.768	0.008	0.081	0.741	0.004	0.279	0.773
$\hat{\rho}$	0.538	0.274	0.629	0.430	0.395	0.577	0.411	0.379	0.568	0.377	0.331
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	26388	24175	26388	24175	24051	26388	24175	24051	26388	24175	24051

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. Saving and repayment information is taken from administrative data. Time invariant household characteristics are taken from household survey data. Administrative data are merged with survey data by the dating the survey rounds in administrative data. Net saving is saving - withdrawal. Excess repayment is repayment - due amount. extsfLY2, LY3, LY4 are dummy variables for second, third, and fourth year into borrowing.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

TABLE 9: FD ESTIMATION OF CUMULATIVE NET SAVING AND REPAYMENT BY ATTRIBUTES

	Cumulative net saving		Cumulative repayment			Cumulative net saving +cumulative repayment			Cumulative excess repayment		
covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(Intercept)	39.0***	36.6***	250.3***	231.3***	232.0***	289.3***	267.9***	263.8***	−161.9***	−180.1***	−179.6***
	(2.1)	(2.2)	(15.8)	(17.0)	(15.5)	(16.8)	(17.9)	(16.4)	(15.8)	(16.6)	(14.9)
Upfront	7.2**	28.4***	79.0***	170.0***	162.1***	86.2***	198.4***	206.5***	76.1***	45.2*	35.5*
	(3.5)	(4.8)	(16.5)	(23.5)	(21.1)	(17.6)	(25.1)	(22.3)	(16.6)	(23.2)	(21.1)
WithGrace	11.4**	80.8***	8.0	−328.7***	−367.8***	19.4**	−248.0***	−281.0***	9.1	207.4***	167.2***
	(4.6)	(19.5)	(10.0)	(22.2)	(18.2)	(8.6)	(29.1)	(27.6)	(11.0)	(22.1)	(18.0)
InKind	1.5	2.4	−6.1	−11.1	1.1	−4.6	−8.7	8.0	−8.6	−11.1	0.4
	(5.8)	(25.2)	(10.8)	(22.0)	(6.4)	(8.5)	(32.5)	(29.1)	(11.8)	(22.0)	(5.6)
LY2		18.7***		47.3*	−59.2***		66.0**	−35.4*		439.9***	328.7***
		(3.4)		(26.0)	(20.2)		(26.5)	(19.7)		(63.2)	(45.2)
Upfront × LY2		−19.4***		−132.3***	−51.9***		−151.6***	−86.5***		−176.2***	−91.8***
		(4.9)		(15.3)	(15.8)		(19.1)	(16.5)		(16.8)	(17.6)
WithGrace × LY2		−91.9***		519.0***	343.9***		427.1***	251.8***		−223.8***	−404.8***
		(19.6)		(26.6)	(36.6)		(37.5)	(44.5)		(27.3)	(37.7)
InKind × LY2		−3.3		−31.8	−32.6		−35.1	−40.3		−33.2	−32.9
		(24.7)		(34.7)	(39.4)		(44.0)	(47.7)		(35.2)	(40.6)
LY3		22.6***		40.0	−118.4***		62.7**	−91.0***		411.6***	246.9***
		(4.3)		(28.1)	(21.7)		(29.6)	(21.8)		(71.9)	(54.5)
Upfront × LY3		−21.9***		−61.7***	−88.6***		−83.5***	−126.1***		−70.1***	−97.2***
		(5.5)		(19.1)	(19.7)		(19.5)	(19.6)		(18.7)	(19.3)
WithGrace × LY3		−96.2***		528.1***	594.8***		431.9***	491.0***		−290.9***	−221.1***
		(20.9)		(27.0)	(22.2)		(38.3)	(33.3)		(26.3)	(21.7)
InKind × LY3		−0.9		−21.5	−30.8		−22.4	−36.9		−20.0	−28.8
		(26.0)		(34.6)	(24.0)		(47.8)	(41.3)		(34.3)	(23.4)
LY4		32.1***		141.6***	−0.7		173.8***	34.0		579.2***	432.2***
		(5.5)		(40.5)	(23.6)		(43.4)	(25.3)		(79.1)	(53.3)
Upfront × LY4		−43.3***		−118.8***	−105.0***		−162.1***	−165.9***		411.2***	427.4***
		(7.0)		(42.1)	(29.2)		(44.3)	(31.4)		(41.7)	(28.5)
WithGrace × LY4		−91.0***		307.4***	435.4***		216.4***	340.4***		−228.6***	−96.9***
		(21.4)		(55.3)	(33.7)		(64.0)	(46.7)		(55.0)	(32.8)
InKind × LY4		1.9		74.1	14.2		75.9	12.3		73.9	12.6
		(26.8)		(57.5)	(24.7)		(71.0)	(49.1)		(57.5)	(23.9)
FloodInRd1					−23.7***			−22.1***			−23.2***
					(6.4)			(6.6)			(6.6)
Head literate					7.6			8.7			7.4
					(6.5)			(5.9)			(6.5)
Head age					0.1			0.2			0.1
					(0.2)			(0.2)			(0.3)
6M repayment					4.5***			4.5***			4.6***
					(0.1)			(0.1)			(0.1)
6M net saving					0.3***			2.0***			0.1
					(0.1)			(0.2)			(0.1)
6M other member net saving					−0.5*			−1.7***			−0.2
					(0.3)			(0.3)			(0.4)
6M other member Repaid					− 0.0			− 0.0			0.0
					(0.3)			(0.3)			(0.4)
$\bar{R}^2$	0.006	0.16	0.006	0.112	0.768	0.008	0.081	0.741	0.004	0.279	0.773
$\hat{\rho}$	0.538	0.274	0.629	0.430	0.395	0.577	0.411	0.379	0.568	0.377	0.331
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	26388	24175	26388	24175	24051	26388	24175	24051	26388	24175	24051

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. LargeSize is an indicator function if the arm is of large size, WithGrace is an indicator function if the arm is with a grace period, InKind is an indicator function if the arm provides a cow. Saving and repayment information is taken from administrative data. Time invariant household characteristics are taken from household survey data. Administrative data are merged with survey data by the dating the survey rounds in administrative data. Net saving is saving - withdrawal. Excess repayment is repayment - due amount. extsfLY2, LY3, LY4 are dummy variables for second, third, and fourth year into borrowing.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

Table 10: FD estimation of net cumulative saving and repayment, ultra poor vs. moderately poor

	Cumulative net saving		Cumulative repayment			Cumulative net saving +cumulative repayment			Cumulative excess repayment		
covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(Intercept)	49.8*** (2.2)	42.2*** (1.6)	325.0*** (5.3)	331.9*** (6.8)	322.7*** (13.4)	374.8*** (5.9)	374.1*** (7.0)	364.1*** (14.2)	−89.9*** (5.3)	−107.1*** (5.1)	−120.4*** (12.7)
UltraPoor	3.0** (1.4)	67.8*** (8.7)	−6.5* (3.6)	−132.2*** (24.5)	−130.6*** (25.3)	−3.5 (3.5)	−64.4*** (21.0)	−49.6** (21.8)	−6.2* (3.6)	72.9*** (17.1)	70.2*** (15.8)
LY2		17.0*** (3.5)		65.5** (26.5)	−55.0*** (19.9)		82.5*** (27.0)	−34.2* (19.9)		407.7*** (57.0)	287.5*** (38.3)
UltraPoor × LY2		−71.5*** (9.9)		142.9*** (35.1)	114.6*** (28.0)		71.4** (30.4)	30.2 (24.0)		−315.9*** (22.3)	−339.9*** (30.6)
LY3		17.6*** (4.3)		87.9*** (29.6)	−83.4*** (19.6)		105.5*** (31.2)	−63.3*** (20.4)		351.3*** (60.9)	179.6*** (43.6)
UltraPoor × LY3		−74.7*** (10.5)		222.1*** (35.1)	222.3*** (38.1)		147.4*** (30.4)	130.2*** (33.0)		−242.2*** (22.0)	−236.4*** (18.6)
LY4		20.7*** (5.4)		171.2*** (40.6)	38.8* (21.7)		191.9*** (43.1)	58.6** (23.8)		569.2*** (77.6)	435.7*** (53.2)
UltraPoor × LY4		−90.8*** (10.7)		84.8*** (29.1)	131.1*** (29.5)		−6.0 (28.8)	24.4 (26.9)		306.2*** (28.8)	357.3*** (16.1)
FloodInRd1					−29.7*** (8.6)			−29.3*** (8.9)			−22.1*** (8.4)
Head literate					7.2 (8.1)			9.3 (8.1)			5.5 (7.3)
Head age					− 0.0 (0.3)			0.1 (0.3)			0.0 (0.3)
6M repayment					4.3*** (0.1)			4.4*** (0.1)			4.3*** (0.1)
6M net saving					0.7*** (0.1)			2.2*** (0.2)			0.1 (0.1)
6M other member net saving					−0.6 (0.4)			−1.7*** (0.4)			0.3 (0.3)
6M other member Repaid					0.1 (0.3)			0.1 (0.3)			− 0.0 (0.4)
$\bar{R}^2$	0	0.084	0	0.029	0.689	0	0.019	0.689	0	0.23	0.682
$\hat{\rho}$	0.522	0.392	0.671	0.602	0.612	0.595	0.554	0.541	0.578	0.413	0.444
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	26388	24175	26388	24175	24051	26388	24175	24051	26388	24175	24051

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. UltraPoor is an indicator function if the household is classified as the ultra poor. Saving and repayment information is taken from administrative data. Time invariant household characteristics are taken from household survey data. Administrative data are merged with survey data by the dating the survey rounds in administrative data. Net saving is saving - withdrawal. Excess repayment is repayment - due amount. extsfLY2, LY3, LY4 are dummy variables for second, third, and fourth year into borrowing.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

Finding III.1 Figure 1 visually presents that repayment is no different between the ultra poor and the moderately poor. The subsequent regression table econometrically confirms this (Table 10).

III.2 Schooling

```
source(paste0(pathprogram, "ReadTrimSchoolingOriginalHHsFDData2.R"))
```

```
Dropped 902 obs due to NA.
Dropped 902 obs due to NA.
Dropped 184 obs due to T<2.
Dropped 616 obs due to NA.
```

Enrollment pattern in original schooling panel. 'n' indicates NA (either attrition or not reported).

```
table0(s.1x[tee == 1, .(ObPattern, SchPattern)])
```

```
         SchPattern
ObPattern 0000 0001 000n 0011 001n 00n0 00n1 00nn 010n 0111 011n 01nn 0n00 0n0n
     0111    0    0    0    0    0    0    0    0    0    0    0    0    0    0
     1000    0    0    0    0    0    0    0    0    0    0    0    0    0    0
     1010    0    0    0    0    0    0    0    0    0    0    0    0    0    1
     1011    0    0    0    0    0    0    0    0    0    0    0    0    0    0
     1100    0    0    0    0    0    0    0    0    0    0    0    3    0    0
     1110    0    0    5    0    2    0    0    1    0    0    3    0    0    0
     1111   21    2   16   12    1    4    1   25    1   83    4    4    1    0
         SchPattern
ObPattern 0n11 0n1n 0nn0 0nn1 0nnn 1000 1001 100n 1011 101n 10n1 10nn 1100 1101
     0111    2    1    0    0    2    0    0    0    0    0    0    0    0    0
     1000    0    0    0    0   32    0    0    0    0    0    0    0    0    0
     1010    0    0    0    0    2    0    0    0    0    0    0    0    0    0
     1011    0    0    0    0    0    0    0    0    0    0    0    0    0    0
     1100    0    0    0    0    1    0    0    0    0    0    0    0    0    0
     1110    0    0    0    0    2    0    0    1    0    1    0    0    0    0
     1111    4    1    3    1   81    5    1    3    6    1    1    8    8    1
         SchPattern
ObPattern 110n 1110 1111 111n 11n1 11nn 1n00 1n01 1n0n 1n11 1n1n 1nn0 1nn1 1nnn
     0111    0    0    0    0    0    0    0    0    0    6    0    0    0    1
     1000    0    0    0    0    0    0    0    0    0    0    0    0    0   22
     1010    0    0    0    0    0    0    0    0    0    0    1    0    0    2
     1011    0    0    0    0    0    0    0    0    0    0    0    0    0    0
     1100    0    0    0    0    0    6    0    0    0    0    0    0    0    0
     1110    0    0    0   25    0    2    0    0    0    0    1    0    0    0
     1111    9    3  397   30    4   26    1    1    1    8    1    1    2   56
```

Left panel is before dropping nnn, right panel is after: Original panel.

```
cbind(table0(s.1x[, .(tee, RArm)]),
  table0(s1x[, .(tee, RArm)]))
```

```
  traditional large large grace cow traditional large large grace cow
1         232   246         251 235         166   208         186 203
2         161   197         177 191         161   197         177 191
3         148   185         165 173         148   185         165 173
4         118   171         147 143         118   171         147 143
```

sch has 2940 rows. Drop 201 observations in sch with nnn in SchPattern.

```
#s.1 ← s.1[!grepl("1001", EnrollPattern), ]
s1x[, Enrolled := as.numeric(Enrolled)]
s1x[, Tee := .N, by = HHMid]
ds1xd[, Tee := .N, by = HHMid]
```

With OLS, 89, 135, 539 individuals are repeatedly observed for 2, 3, 4 times, respectively. With FD, sch is reduced to 1837 rows after first-differencing with 64, 106, 499 individuals with repeatedly observed for 1, 2, 3 times, respectively. Individuals with NAs in Enrolled: 0 obs for sch. Check missingness in schooling level information.

```
table0(apply(s1x[, .(dummyJunior, dummyHigh)], 1, sum))
```

```

   0    1
1575 1164
```

Drop 1575 obs without school level information.

```
s1x ← s1x[apply(s1x[, .(dummyJunior, dummyHigh)], 1, sum) == 1, ]
ds1xd[, grepout("^Tee$", colnames(ds1xd)) := NULL]
```

```
table0(apply(s1x[, .(dummyTraditional, dummyLarge, dummyLargeGrace, dummyCow)], 1, sum))
```

```
table(ds1xd[, tee])
```

```
table(ds1xRd[, tee])
```

```
source(paste0(pathprogram, "ReadTrimSchoolingOriginalHHsFDData2.R"))
```

```
Dropped 902 obs due to NA.
Dropped 902 obs due to NA.
Dropped 184 obs due to T<2.
Dropped 616 obs due to NA.
```

```
FileName ← "Schooling"
Regressands ← rep("Enrolled", 4)
Addseparatingcols = NULL; Separatingcolwidth = NULL
Separatingcoltitle = NULL
```

```
Scsuffixes ← c("", "g", "p", "s", "a", "T", "Tg", "Ts", "D", "Dg", "Da")
exclheader ← paste0("excl", Scsuffixes)
source(paste0(pathprogram, "SchoolingCovariateSelection.R"))
```

```
# Need to place ED14Diff after k > 5.
FileNameHeaderSchooling ← c("", "Grace", "PovertyStatus", "Size", "Attributes",
  "Rd14Diff", "Rd14DiffGrace", "Rd14DiffAttributes")
FileNameHeader ← paste0(FileNameHeaderSchooling, "OriginalHHs")
Scsuffixes ← c("", "g", "p", "s", "a", "D", "Dg", "Da")
listheader ← paste0("sc", Scsuffixes)
exclheader ← paste0("excl", Scsuffixes)
DataToUse1 ← rep("ds1xd", 4)
DataToUse2 ← rep("ds1x34d", 4)
source(paste0(pathprogram, "FDEstimationFile.R"))
```

```
FileNameHeaderSchooling ← c("TInt", "TIntGrace", "TIntSize")
FileNameHeader ← paste0(FileNameHeaderSchooling, "OriginalHHs")
Scsuffixes ← c("T", "Tg", "Ts")
exclheader ← paste0("excl", Scsuffixes)
listheader ← paste0("sc", Scsuffixes)
source(paste0(pathprogram, "FDEstimationFileSchooling.R"))
saveRDS(fdplist, paste0(pathsave, "FD_schooling.rds"))
```

```
#dummy chunk
```

Table 11: FD estimation of school enrollment, round 1 vs. round 4 differences

covariates	(1)	(2)	(3)	(4)
(Intercept)	0.60***	0.75***	0.75***	0.75***
	(0.13)	(0.10)	(0.10)	(0.10)
Secondary	−0.44***	−0.46***	−0.46***	−0.46***
	(0.12)	(0.10)	(0.10)	(0.10)
College	−0.50***	−0.50***	−0.50***	−0.50***
	(0.13)	(0.12)	(0.12)	(0.12)
Large	−0.14	−0.15*	−0.15*	−0.15*
	(0.09)	(0.08)	(0.08)	(0.08)
LargeGrace	−0.11	−0.12	−0.13	−0.13
	(0.10)	(0.09)	(0.09)	(0.09)
Cow	−0.14	−0.15*	−0.16*	−0.16*
	(0.10)	(0.09)	(0.09)	(0.09)
Large × Secondary	−0.03	−0.02	−0.02	−0.02
	(0.15)	(0.13)	(0.13)	(0.13)
LargeGrace × Secondary	−0.06	−0.06	−0.06	−0.06
	(0.14)	(0.13)	(0.13)	(0.13)
Cow × Secondary	0.05	0.07	0.07	0.07
	(0.15)	(0.14)	(0.14)	(0.14)
Large × College	0.01	−0.01	− 0.00	− 0.00
	(0.17)	(0.16)	(0.16)	(0.16)
LargeGrace × College	0.01	−0.01	−0.01	−0.01
	(0.16)	(0.16)	(0.16)	(0.16)
Cow × College	−0.01	0.01	0.01	0.01
	(0.19)	(0.17)	(0.17)	(0.17)
Female		−0.30***	−0.30***	−0.30***
		(0.08)	(0.08)	(0.08)
Secondary × Female		0.61***	0.62***	0.62***
		(0.15)	(0.16)	(0.16)
College × Female		0.51***	0.51***	0.51***
		(0.14)	(0.14)	(0.14)
Large × Female		0.27**	0.27**	0.27**
		(0.12)	(0.12)	(0.12)
LargeGrace × Female		0.20*	0.20*	0.20*
		(0.11)	(0.11)	(0.11)
Cow × Female		0.37***	0.37***	0.37***
		(0.11)	(0.11)	(0.11)
Large × Secondary × Female		−0.51**	−0.51**	−0.51**
		(0.21)	(0.21)	(0.21)
LargeGrace × Secondary × Femal		−0.41**	−0.41**	−0.41**
		(0.20)	(0.20)	(0.20)
Cow × Secondary × Female		−0.58***	−0.58***	−0.58***
		(0.22)	(0.22)	(0.22)
Large × College × Female		−0.36*	−0.36*	−0.36*
		(0.19)	(0.19)	(0.19)
LargeGrace × College × Female		−0.07	−0.06	−0.06
		(0.20)	(0.21)	(0.21)
Cow × College × Female		−0.43*	−0.43*	−0.43*
		(0.24)	(0.23)	(0.23)
FloodInRd1			−0.01	−0.01
			(0.03)	(0.03)
EldestSon			− 0.00	− 0.00
			(0.04)	(0.04)
EldestDaughter			− 0.00	− 0.00
			(0.05)	(0.05)
BStatusindividual rejection	−0.12*	−0.10*	−0.10*	−0.10*
	(0.06)	(0.06)	(0.06)	(0.06)
BStatusgroup rejection	−0.03	−0.06	−0.06	−0.06
	(0.06)	(0.06)	(0.05)	(0.05)
HHsize	0.02	0.05	0.05	0.05
	(0.02)	(0.03)	(0.03)	(0.03)
ChildAgeOrderAtRd1		−0.06	−0.06	−0.06
		(0.04)	(0.04)	(0.04)
$\bar{R}^2$	0.218	0.231	0.226	0.226
N	542	542	542	542

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

Table 12: FD estimation of school enrollment, round 1 vs. round 4 differences by attributes

covariates	(1)	(2)	(3)	(4)
(Intercept)	0.58^{***} (0.06)	0.71^{***} (0.09)	0.71^{***} (0.13)	0.71^{***} (0.13)
Secondary	-0.45^{***} (0.05)	-0.45^{***} (0.10)	-0.45^{***} (0.10)	-0.45^{***} (0.10)
College	-0.50^{***} (0.06)	-0.48^{***} (0.12)	-0.49^{***} (0.13)	-0.49^{***} (0.13)
Upfront	-0.13^{***} (0.05)	-0.12^{*} (0.07)	-0.13^{*} (0.07)	-0.13^{*} (0.07)
WithGrace	0.02 (0.05)	0.03 (0.07)	0.04 (0.07)	0.04 (0.07)
InKind	−0.01 (0.06)	−0.04 (0.08)	−0.05 (0.08)	−0.05 (0.08)
WithGrace × Secondary		−0.03 (0.12)	−0.05 (0.12)	−0.05 (0.12)
WithGrace × College		−0.01 (0.15)	−0.03 (0.15)	−0.03 (0.15)
Upfront × Secondary		−0.03 (0.13)	−0.03 (0.13)	−0.03 (0.13)
Upfront × College		−0.02 (0.16)	−0.02 (0.16)	−0.02 (0.16)
InKind × Secondary		0.13 (0.12)	0.15 (0.12)	0.15 (0.12)
InKind × College		0.01 (0.15)	0.03 (0.15)	0.03 (0.15)
Female		-0.30^{***} (0.08)	-0.30^{***} (0.08)	-0.30^{***} (0.08)
Secondary × Female		0.61^{***} (0.15)	0.61^{***} (0.15)	0.61^{***} (0.15)
College × Female		0.51^{***} (0.14)	0.50^{***} (0.15)	0.50^{***} (0.15)
WithGrace × Female		−0.07 (0.12)	−0.08 (0.12)	−0.08 (0.12)
Upfront × Female		0.28^{**} (0.12)	0.28^{**} (0.12)	0.28^{**} (0.12)
InKind × Female		0.16 (0.11)	0.17 (0.12)	0.17 (0.12)
WithGrace × Secondary × Female		0.10 (0.19)	0.14 (0.20)	0.14 (0.20)
WithGrace × College × Female		0.31 (0.20)	0.35^{*} (0.21)	0.35^{*} (0.21)
Upfront × Secondary × Female		-0.52^{**} (0.21)	-0.51^{**} (0.21)	-0.51^{**} (0.21)
Upfront × College × Female		-0.38^{*} (0.20)	-0.36^{*} (0.19)	-0.36^{*} (0.19)
InKind × Secondary × Female		−0.16 (0.21)	−0.19 (0.21)	−0.19 (0.21)
InKind × College × Female		−0.36 (0.25)	-0.41^{*} (0.25)	-0.41^{*} (0.25)
FloodInRd1			−0.01 (0.03)	−0.01 (0.03)
Head literate			−0.03 (0.08)	−0.03 (0.08)
Head age			0.00 (0.00)	0.00 (0.00)
EldestSon			0.00 (0.05)	0.00 (0.05)
EldestDaughter			− 0.00 (0.05)	− 0.00 (0.05)
HHsize	0.02 (0.02)	0.06^{*} (0.03)	0.06^{*} (0.03)	0.06^{*} (0.03)
ChildAgeOrderAtRd1		−0.07 (0.04)	−0.07 (0.05)	−0.07 (0.05)
$\bar{R}^2$	0.221	0.229	0.225	0.225
N	542	542	539	539

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and Pr[$\rho = 0$] is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. LargeSize is an indicator function if the arm is of large size, WithGrace is an indicator function if the arm is with a grace period, InKind is an indicator function if the arm provides a cow. Saving and repayment information is taken from administrative data. Time invariant household characteristics are taken from household survey data. Administrative data are merged with survey data by the dating the survey rounds in administrative data. Net saving is saving - withdrawal. Excess repayment is repayment - due amount. extsfLY2, LY3, LY4 are dummy variables for second, third, and fourth year into borrowing.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

III.3 Assets

Assets reportd in rd 1 is too small, indicating possible errors or different way of reporting only in rd 1. So we also examine rd 2 vs. rd 4 differences (as3, as4).

```
source(paste0(pathprogram, "ReadTrimAssetOriginalHHsFDData.R"))
```

```
Dropped 64 obs due to T<2.
Dropped 735 obs due to NA.
Dropped 64 obs due to T<2.
Dropped 1604 obs due to NA.
Dropped 64 obs due to T<2.
Dropped 735 obs due to NA.
Dropped 64 obs due to T<2.
Dropped 1604 obs due to NA.
Dropped 69 obs due to T<2.
Dropped 666 obs due to NA.
Dropped 69 obs due to T<2.
Dropped 721 obs due to NA.
Dropped 69 obs due to T<2.
Dropped 666 obs due to NA.
Dropped 69 obs due to T<2.
Dropped 721 obs due to NA.
```

Main assets are household assets (HAssetAmount) and production assets (PAssetAmount) both with 2919 observations. After first-differencing, they become 2120 observations, with 16, 106, 1998 households observed for 2, 3, 4 times. We also examine rd 2 vs. rd 4 differences, which has 1401 observations. After first-differencing, they become 666 observations.

```
FileName <- "Asset"
FileNameHeader <- paste0(c("", "Grace", "PovertyStatus", "Size", "Attributes",
  "Rd24Diff", "Rd24Grace", "Rd24DiffAttributes"), "OriginalHHs")
Assuffixes <- c("", "G", "P", "S", "a", "D", "DG", "Da")
listheader <- paste0("as", Assuffixes)
DataToUse1 <- c(rep("das1d", 3), "das1Rd", rep("das2d", 3), "das2Rd")
DataToUse2 <- c(rep("das3d", 3), "das3Rd", rep("das4d", 3), "das4Rd")
Regressands <- c(rep("HAssetAmount", 4), rep("PAssetAmount", 4))
Addseparatingcols = 4; Separatingcolwidth = .2
Separatingcoltitle = c("Household asset amount (Tk)", "Productive asset amount (Tk)")

source(paste0(pathprogram, "AssetCovariateSelection.R"))

exclheader <- paste0("excl", Assuffixes)
source(paste0(pathprogram, "FDEstimationFile.R"))
saveRDS(fdplist, paste0(pathsave, "FD_assets.rds"))

#dummy chunk
```

Table 13: FD estimation of assets

	Household asset amount (Tk)				Productive asset amount (Tk)			
covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	6395.1***	8078.7***	8843.5***	8764.5***	−191.0***	128.1	168.6	−508.7*
	(999.1)	(1397.3)	(1491.6)	(2638.5)	(53.1)	(241.5)	(261.3)	(303.8)
Large	2141.7	2205.9	2501.5	3303.5	143.2	591.4*	599.1*	−572.7
	(2043.1)	(1843.8)	(1842.1)	(3156.8)	(150.2)	(335.7)	(342.1)	(671.9)
LargeGrace	956.9	1288.1	1119.6	4296.5	−88.7	160.8	153.5	−122.6
	(1437.5)	(1561.3)	(1495.7)	(3293.7)	(114.8)	(278.5)	(277.8)	(377.9)
Cow	214.6	1654.0	1721.9	−258.6	158.0*	238.2*	246.1*	79.9
	(1565.5)	(2306.5)	(2275.6)	(3357.2)	(85.4)	(140.7)	(140.2)	(276.9)
rd 2 - 3		1078.7	1071.5			−688.4	−689.8	
		(2284.8)	(2315.3)			(511.4)	(512.7)	
Large × rd 2 - 3		3514.7	3577.1			−2328.1	−2330.6	
		(4634.4)	(4635.5)			(1546.7)	(1550.5)	
LargeGrace × rd 2 - 3		3867.8	3936.2			−804.4	−804.9	
		(5534.5)	(5535.5)			(1110.2)	(1113.0)	
Cow × rd 2 - 3		−5856.3	−6009.4			−382.8	−385.7	
		(7504.3)	(7641.7)			(609.7)	(610.4)	
rd 3 - 4		−7762.4***	−7707.7***	−9211.1***		−881.3**	−884.1**	−41.3
		(1887.0)	(1864.8)	(2206.2)		(417.9)	(419.7)	(255.5)
Large × rd 3 - 4		−2824.9	−2838.2	−9134.0		−2367.3**	−2373.5**	181.8
		(3374.9)	(3387.8)	(5923.4)		(1091.7)	(1094.3)	(912.1)
LargeGrace × rd 3 - 4		−6008.2**	−6073.0**	−16468.4***		−1808.6	−1819.9	−962.6
		(3013.1)	(3010.1)	(5502.5)		(1143.5)	(1153.2)	(672.6)
Cow × rd 3 - 4		−9417.1	−9289.9	−8991.9*		−540.9	−547.8	−53.9
		(5890.6)	(5794.3)	(5344.1)		(370.8)	(371.0)	(384.1)
FloodInRd1			−1811.4**	−996.7			−53.8	556.3*
			(867.5)	(1178.3)			(120.7)	(314.5)
Head literate			507.1	−1385.2			−140.1**	182.6
			(1326.7)	(3409.1)			(70.7)	(254.7)
6M repayment				−6842.9*				398.1
				(4033.2)				(638.5)
6M net saving				28300.2				−1351.8
				(21629.7)				(2575.7)
6M other member net saving				−25104.7				−1289.8
				(39253.7)				(2003.0)
6M other member Repaid				2139.0				−253.3
				(3933.7)				(568.4)
$T = 2$	16	16	16	23	16	16	16	23
$T = 3$	53	53	50	611	53	53	50	611
$T = 4$	666	666	666	0	666	666	666	0
$\bar{R}^2$	−0.001	0.018	0.018	0.029	−0.001	0.003	0.002	−0.002
$\hat{\rho}$	0.073	0.086	0.079	−0.030	−0.081	−0.137	−0.132	0.477
$\Pr[\hat{\rho} = 0]$	0.014	0.002	0.004	0.260	0.000	0.000	0.000	0.000
N	2120	2120	2114	1245	2120	2120	2114	1245

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

Table 14: FD estimation of assets by attributes

	Household asset amount (Tk)				Productive asset amount (Tk)			
covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	6395.1***	8078.7***	8843.5***	8764.5***	−191.0***	128.1	168.6	−508.7*
	(999.1)	(1397.3)	(1491.6)	(2638.5)	(53.1)	(241.5)	(261.3)	(303.8)
Upfront	2141.7	2205.9	2501.5	3303.5	143.2	591.4*	599.1*	−572.7
	(2043.1)	(1843.8)	(1842.1)	(3156.8)	(150.2)	(335.7)	(342.1)	(671.9)
WithGrace	−1184.8	−917.8	−1381.8	993.0	−231.9	−430.7	−445.6	450.1
	(2060.1)	(1933.8)	(1903.9)	(3446.0)	(173.5)	(417.1)	(427.8)	(708.7)
InKind	−742.3	365.9	602.3	−4555.1	246.6**	77.5	92.6	202.5
	(1587.7)	(2379.1)	(2352.4)	(2989.0)	(121.8)	(284.7)	(283.7)	(374.6)
rd 2 - 3		1078.7	1071.5			−688.4	−689.8	
		(2284.8)	(2315.3)			(511.4)	(512.7)	
Upfront × rd 2 - 3		3514.7	3577.1			−2328.1	−2330.6	
		(4634.4)	(4635.5)			(1546.7)	(1550.5)	
WithGrace × rd 2 - 3		353.1	359.0			1523.7	1525.7	
		(5021.3)	(5022.4)			(1827.5)	(1832.7)	
InKind × rd 2 - 3		−9724.0	−9945.5			421.5	419.2	
		(7749.2)	(7884.0)			(1148.7)	(1151.6)	
rd 3 - 4		−7762.4***	−7707.7***	−9211.1***		−881.3**	−884.1**	−41.3
		(1887.0)	(1864.8)	(2206.2)		(417.9)	(419.7)	(255.5)
Upfront × rd 3 - 4		−2824.9	−2838.2	−9134.0		−2367.3**	−2373.5**	181.8
		(3374.9)	(3387.8)	(5923.4)		(1091.7)	(1094.3)	(912.1)
WithGrace × rd 3 - 4		−3183.3	−3234.8	−7334.4		558.7	553.6	−1144.3
		(4190.9)	(4203.5)	(6015.8)		(1547.8)	(1555.8)	(1088.8)
InKind × rd 3 - 4		−3409.0	−3216.9	7476.5		1267.7	1272.1	908.6
		(6393.1)	(6301.6)	(5532.6)		(1158.2)	(1167.3)	(643.1)
FloodInRd1			−1811.4**	−996.7			−53.8	556.3*
			(867.5)	(1178.3)			(120.7)	(314.5)
Head literate			507.1	−1385.2			−140.1**	182.6
			(1326.7)	(3409.1)			(70.7)	(254.7)
6M repayment				−6842.9*				398.1
				(4033.2)				(638.5)
6M net saving				28300.2				−1351.8
				(21629.7)				(2575.7)
6M other member net saving				−25104.7				−1289.8
				(39253.7)				(2003.0)
6M other member Repaid				2139.0				−253.3
				(3933.7)				(568.4)
$T = 2$	16	16	16	23	16	16	16	23
$T = 3$	53	53	50	611	53	53	50	611
$T = 4$	666	666	666	0	666	666	666	0
$\bar{R}^2$	−0.001	0.018	0.018	0.029	−0.001	0.003	0.002	−0.002
$\hat{\rho}$	0.073	0.086	0.079	−0.030	−0.081	−0.137	−0.132	0.477
$\Pr[\hat{\rho} = 0]$	0.014	0.002	0.004	0.260	0.000	0.000	0.000	0.000
N	2120	2120	2114	1245	2120	2120	2114	1245

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. LargeSize is an indicator function if the arm is of large size, WithGrace is an indicator function if the arm is with a grace period, InKind is an indicator function if the arm provides a cow.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

TABLE 15: FD ESTIMATION OF ASSETS, ROUND 2 AND 4 COMPARISON

	Household asset amount (Tk)				Productive asset amount (Tk)			
covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	11157.3*** (2520.6)	13142.2*** (2894.9)	13142.2*** (2894.9)	13923.1*** (3558.2)	−180.8 (207.8)	−698.7* (364.6)	−698.7* (364.6)	−1016.2** (482.0)
Large	5165.8 (5262.0)	5545.8 (5274.4)	5545.8 (5274.4)	1987.6 (3770.3)	−1290.1 (794.7)	−1415.3* (800.2)	−1415.3* (800.2)	−872.0 (834.9)
LargeGrace	2247.5 (3836.9)	1846.8 (3814.5)	1846.8 (3814.5)	2826.8 (4303.4)	−1093.1 (703.0)	−975.7 (682.1)	−975.7 (682.1)	−663.3 (633.2)
Cow	−4429.7 (4385.9)	−4327.5 (4274.9)	−4327.5 (4274.9)	−3778.1 (4339.1)	7.3 (349.7)	−21.3 (351.1)	−21.3 (351.1)	214.6 (472.6)
FloodInRd1		−3132.3 (2308.3)	−3132.3 (2308.3)	−1261.7 (2341.5)		980.6* (573.6)	980.6* (573.6)	947.1 (609.3)
Head literate		−4167.5 (6823.4)	−4167.5 (6823.4)	−3034.6 (7032.5)		433.7 (510.6)	433.7 (510.6)	418.7 (524.2)
6M repayment				−6206.3* (3736.8)				1394.5** (664.9)
6M net saving				38975.2 (31351.8)				−1360.8 (4083.2)
6M other member net saving				35164.3 (49992.8)				−5083.2 (8220.3)
6M other member Repaid				228.4 (4210.9)				−448.5 (598.5)
$\bar{R}^2$	0.005	0.005	0.005	0.004	0.002	0.003	0.003	−0.001
N	666	666	666	611	666	666	666	611

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates between round 2 and 4. A first-difference is defined as $\Delta x_{t+k} \equiv x_{t+k} - x_t$ for $k = 1, 2, \ldots$. Saving and repayment misses are taken from administrative data and merged with survey data at Year-Month of survey interviews. Intercept terms are omitted in estimating equations. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Household assets do not include livestock. Regressions (1)-(3), (5)-(6) use only arm and calendar information. (4) and (7) use previous six month repayment and saving information which is lacking in rd 1, hence starts from rd 2.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

```
# Compare asset changes between arms and "pure control" (loan nonreceivers)
FileName ← "Asset"
FileNameHeader ← paste0(c("", "Grace", "PovertyStatus", "Size", "Attributes"),
 "OriginalHHs")
FileNameHeader ← paste0(FileNameHeader, "Robustness")
Assuffixes ← c("", "G", "P", "S", "a")
listheader ← paste0("as", Assuffixes)
exclheader ← paste0("excl", Assuffixes)
source(paste0(pathprogram, "AssetCovariateSelectionRobustness.R"))

DataToUse1 ← DataToUse2 ← c(rep("das1d", 3), rep("das2d", 3))
Regressands ← c(rep("HAssetAmount", 3), rep("PAssetAmount", 3))
Addseparatingcols = 3; Separatingcolwidth = .2
Separatingcoltitle = c("Household asset amount (Tk)", "Productive asset amount (Tk)")
source(paste0(pathprogram, "FDEstimationFile.R"))
```

Robustness: To understand underlying pattern of asset accumulation, we compare the loan recipients and loan rejecters. This distinction is made by households by choice, so the indicator variable is considered to be endogenous to asset level. This is a limitation, however, it has its own merit in giving an idea how loan recipients faired during the study period relative to loan nonrecipients. There are 199 individuals who did not receive loans. TABLE 16 shows that the pure controls also experience similar increase-increase-decrease pattern for household assets. This suggests the pattern observed among the loan recipients may be a systemic pattern of the area, not necessarily reflecting the repayment burdern. This partially relieves a concern that repayment burden was excessive for loan recipients.

Table 16: FD estimation of assets, loan recipients vs. pure control

	Household asset amount (Tk)			Productive asset amount (Tk)		
covariates	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	6656.9***	9287.1***	9988.5***	−174.4***	200.6	239.5
	(1598.0)	(2104.0)	(2158.7)	(66.4)	(339.0)	(354.6)
Large	1961.1	1661.0	1990.1	131.7	564.0*	571.2*
	(2715.9)	(2482.7)	(2493.9)	(142.5)	(329.9)	(337.1)
LargeGrace	728.5	592.2	472.9	−103.2	124.4	117.5
	(1785.7)	(1866.0)	(1809.6)	(115.4)	(284.9)	(284.3)
Cow	61.8	1201.7	1299.2	148.3*	213.3	221.0
	(1654.8)	(2239.4)	(2223.2)	(85.7)	(150.5)	(148.8)
PureControl	−556.6	−3604.1	−3497.9	−35.4	−232.5	−231.6
	(2708.8)	(2669.9)	(2678.9)	(65.0)	(534.9)	(533.9)
rd 2 - 3		82.2	69.2		−821.8	−823.1
		(2822.2)	(2865.1)		(612.7)	(614.2)
Large × rd 2 - 3		5135.4	5204.6		−2112.9	−2116.3
		(4709.1)	(4714.9)		(1473.6)	(1477.2)
LargeGrace × rd 2 - 3		5917.6	5993.5		−535.1	−536.4
		(5728.5)	(5737.3)		(1143.4)	(1146.2)
Cow × rd 2 - 3		−4519.0	−4668.0		−207.0	−210.8
		(6985.9)	(7106.4)		(639.4)	(639.9)
PureControl × rd 2 - 3		4688.1	4711.6		625.3	623.6
		(3306.7)	(3344.5)		(696.0)	(696.8)
rd 3 - 4		−8586.8***	−8530.8***		−877.6*	−879.8*
		(2118.2)	(2086.2)		(459.9)	(461.8)
Large × rd 3 - 4		−1488.3	−1507.4		−2364.3**	−2370.8**
		(4642.9)	(4652.2)		(1185.1)	(1187.4)
LargeGrace × rd 3 - 4		−4305.6	−4377.2		−1806.4	−1818.3
		(3578.2)	(3567.0)		(1169.9)	(1178.4)
Cow × rd 3 - 4		−8300.5	−8175.2		−544.9	−552.1
		(5518.4)	(5430.0)		(454.4)	(454.3)
PureControl × rd 3 - 4		3918.8	3922.9		−46.7	−48.6
		(5531.0)	(5515.2)		(934.6)	(935.5)
FloodInRd1			−1789.0**			−50.5
			(859.1)			(120.6)
Head literate			511.2			−140.9*
			(1260.3)			(71.9)
$T = 2$	16	16	16	16	16	16
$T = 3$	53	53	50	53	53	50
$T = 4$	666	666	666	666	666	666
$\bar{R}^2$	−0.001	0.017	0.017	−0.002	0.002	0.001
$\hat{\rho}$	0.071	0.076	0.075	−0.080	−0.145	−0.141
$\Pr[\hat{\rho} = 0]$	0.016	0.005	0.007	0.000	0.000	0.000
N	2120	2120	2114	2120	2120	2114

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates between round 2 and 4. A first-difference is defined as $\Delta x_{t+k} \equiv x_{t+k} - x_t$ for $k = 1, 2, \ldots$. Saving and repayment misses are taken from administrative data and merged with survey data at Year-Month of survey interviews. Pure control is members not receiving loans while they were put on a wait list. Sample is continuing members and replacing members of early rejecters. Household assets do not include livestock. Regressions (1)-(2), (4)-(5) use only arm and calendar information. (3) and (6) information if the household was exposed to the flood in round 1. Pure controls are households who rejected to receive a loan.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

```
ass ← readRDS(paste0(pathsaveHere, "RosterAssetAdminOriginalHHsDataUsedForEstimation.rds
ass ← ass[!(hhid == 7043715 & HAssetAmount == 0), ]
ass[, grepout("Time|Loan", colnames(ass)) := NULL]

library(ggplot2)
assP ← ass[o1600==1L & PAssetAmount > 0, ]
assP[, quantile(PAssetAmount, probs=seq(0, 1, .1))]
```

```
    0%    10%    20%    30%    40%    50%    60%    70%    80%    90%   100%
    10    170    240    300    380    420    500    650    900   1500 133000
```

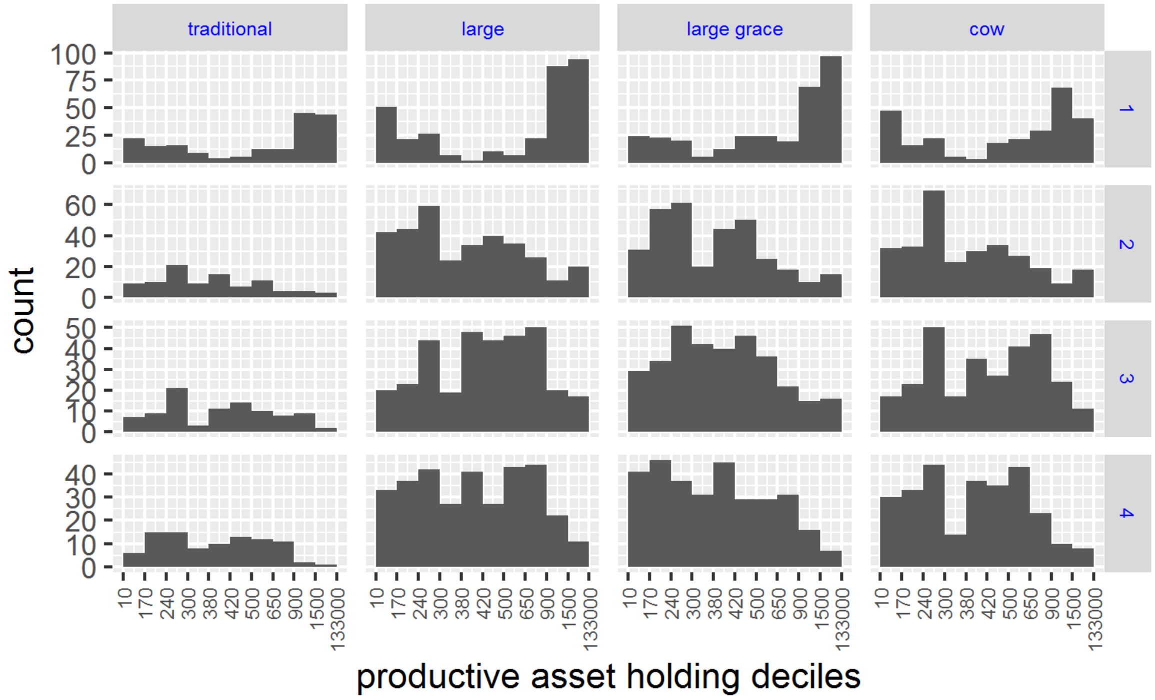
```
assP[, PAssetClass := as.integer(cut(PAssetAmount,
  quantile(PAssetAmount, probs=seq(0, 1, .1)), include.lowest=TRUE))]
g ← ggplot(data = subset(assP, creditstatusFromAss == "Yes"),
  aes(PAssetClass)) +
  geom_histogram(breaks = 0:10) +
```

```
  #scale_x_log10(breaks = c(1, 100, 1000, 10000, 20000, 30000, 50000)) +
  scale_x_continuous(label = assP[, quantile(PAssetAmount, probs=seq(0, 1, .1))],
     breaks = 0:10, name = "productive asset holding deciles") +
  theme(axis.text.x = element_text(size = 6, angle = 90, vjust = .5, hjust = 1),
   strip.text = element_text(size = 6, colour = "blue"))+
  facet_grid(tee ~ Arm, scales = "free_y")
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo2/",
    "ProdAssetClassesByRound.png"),
  g,
  width = 13, height = 8, units = "cm",
  dpi = 300
 )
```

```
library(ggplot2)
g <- ggplot(data = subset(assP, creditstatusFromAss == "No"), aes(PAssetClass)) +
  geom_histogram(breaks = 0:10) +
  #scale_x_log10(breaks = c(1, 100, 1000, 10000, 20000, 30000, 50000)) +
  scale_x_continuous(label = assP[, quantile(PAssetAmount, probs=seq(0, 1, .1))],
     breaks = 0:10, name = "productive asset holding deciles") +
  theme(axis.text.x = element_text(size = 6, angle = 90, vjust = .5, hjust = 1),
   strip.text = element_text(colour = "blue"))+
  facet_grid(tee ~ Arm, scales = "free_y")
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo2/",
    "ProdAssetClassesByRoundLoanNonrecipients.png"),
  g,
  width = 13, height = 8, units = "cm",
  dpi = 300
 )
```

Check what is happening with productive assets.

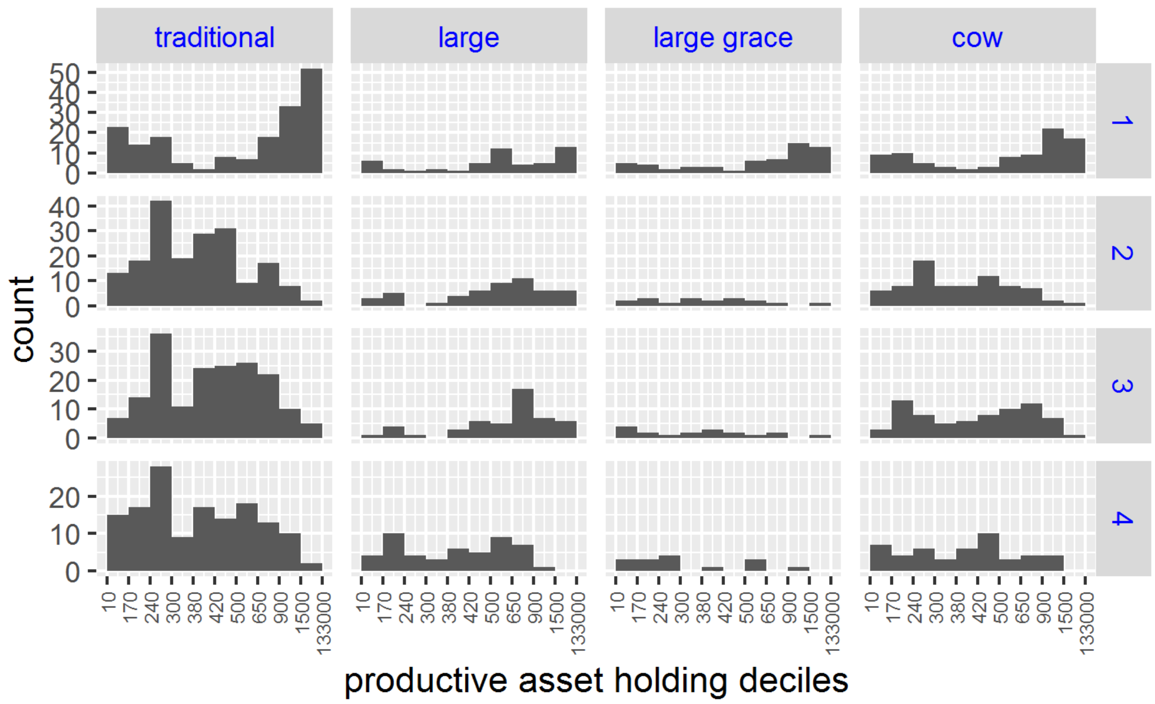
FIGURE 3: PRODUCTIVE ASSET HOLDING OF LOAN RECIPIENTS



Source: Survey data.

Note: Deciles of asset holding are displayed on horizontal axises. Deciles are defined for the productive asset values pooled over all survey rounds. Loan recipients only.

FIGURE 4: PRODUCTIVE ASSET HOLDING OF LOAN NONRECIPIENTS



Source: Survey data.

Note: Deciles of asset holding are displayed on horizontal axises. Deciles are defined for the productive asset values pooled over all survey rounds. Loan nonrecipients only.

III.4 Livestock

```
#lvo ← readRDS(paste0(pathsaveHere, "RosterLivestockAdminOriginalHHsDataUsedForEstimatio
```

```
# added below, this is the sample to use (July 30, 2019)
lvo ← readRDS(paste0(pathsaveHere, DataFileNames[5], "InitialSample.rds"))
lvo[, grepout("Loan|UD|Forced|HadCows.dummyLarge$|HadCows.dummyLarge\\.T|HadCows.dummyLarg
lvostrings ← "^groupid$|hhid|^Arm$|BSta|tee|^dummy[TLCMUWSNI]|^TotalIm|Floo|Time\\.|Head"
if (Only800) lvo ← lvo[o800 == 1, ]
lvoR ← lvo[, grepout(paste0(lvostrings, "|RM"), colnames(lvo)), with = F]
lvo ← lvo[, grepout(lvostrings, colnames(lvo)), with = F]
lvo3 ← lvo[tee == 2 | tee == 4, ]
lvoR3 ← lvoR[tee == 2 | tee == 4, ]
datas ← c("lvo", "lvoR", "lvo3", "lvoR3")
ddatas ← paste0("d", datas)
ddatasd ← paste0(ddatas, "d")
for (i in 1:length(datas)) {
#   dl ← prepFDData(get(datas[i]), Group = "^hhid$", TimeVar = "tee", Cluster = "groupid"
#     LevelCovariates = "^dummy[A-Z].*[a-z]$|^Arm|Floo|^Time\\..$",
#     drop.if.NA.in.differencing = T, LevelPeriodToKeep = "last",
#     use.var.name.for.dummy.prefix = F, print.messages = F)
dl ← FirstDiffPanelData(get(datas[i]),
  Group = "^hhid$", TimeVar = "tee", Cluster = "groupid",
  LevelCovariates = "^dummy|Head|^Time\\..$|Female$|Floo|Eldest|^Arm|BSta|^cred.*s$|xid$|
  dat ← dl$diff
  dat[, grepout("^en$", colnames(dat)) := NULL]
  # Recreate Time.4 which is dropped when kept only 1:(T-1) obs.
  dat[, grepout("Time.?2", colnames(dat)) := NULL]
  assign(ddatas[i], dl)
  assign(ddatasd[i], dat)
}
```

```
Dropped 64 obs due to T<2.
Dropped 735 obs due to NA.
Dropped 64 obs due to T<2.
Dropped 1604 obs due to NA.
Dropped 81 obs due to T<2.
Dropped 665 obs due to NA.
Dropped 81 obs due to T<2.
Dropped 720 obs due to NA.
```

```
dlvoRd ← dlvoRd[tee > 2, ]
addmargins(table0(dlvo$diff[tee==2, .(BStatus, Arm)]), 1:2, sum, T)
```

```
                      Arm
BStatus                traditional large large grace cow sum
  borrower                      84   166         166 152 568
  pure saver                     0     0           0   0   0
  individual rejection          27     9          11  33  80
  group rejection               39    20           0   0  59
  rejection by flood            18     0           0  10  28
  sum                          168   195         177 195 735
```

```
source(paste0(pathprogram, "ReadTrimLivestockFDData.R"))
```

```
Dropped 64 obs due to T<2.
Dropped 735 obs due to NA.
                      Arm
BStatus                traditional large large grace cow sum
  borrower                      84   166         166 152 568
  pure saver                     0     0           0   0   0
```

```
  individual rejection          27     9           11  33  80
  group rejection               39    20            0   0  59
  rejection by flood            18     0            0  10  28
  sum                          168   195          177 195 735
Dropped 64 obs due to T<2.
Dropped 1604 obs due to NA.
Dropped 81 obs due to T<2.
Dropped 665 obs due to NA.
Dropped 81 obs due to T<2.
Dropped 720 obs due to NA.
```

```
FileName ← "Livestock"
FileNameHeader ← paste0(c("", "Grace", "PovertyStatus", "Size", "Attributes",
    "TInt", "TIntGrace", "TIntSize", "Rd14Diff", "Rd14DiffGrace", "Rd14DiffAttributes"),
     "OriginalHHs")
Lvsuffixes ← c("", "G", "P", "S", "a", "T", "TG", "TS", "D", "DG", "Da")
listheader ← paste0("lv", Lvsuffixes)
DataToUse1 ← rep("dlvod", 7)
DataToUse2 ← rep("dlvo3d", 7)
tableboxwidth ← 4.5
Regressands ← rep("TotalImputedValue", 7)
Addseparatingcols ← NULL; Separatingcolwidth ← NULL
Separatingcoltitle ← NULL

source(paste0(pathprogram, "LivestockCovariateSelection.R"))

exclheader ← paste0("excl", Lvsuffixes)
source(paste0(pathprogram, "FDEstimationFile.R"))
saveRDS(fdplist, paste0(pathsave, "FD_livestock.rds"))

source(paste0(pathprogram, "ReadTrimLivestockFDData.R"))
```

```
Dropped 64 obs due to T<2.
Dropped 735 obs due to NA.
                      Arm
BStatus                traditional large large grace cow sum
  borrower                      84   166          166 152 568
  pure saver                     0     0            0   0   0
  individual rejection          27     9           11  33  80
  group rejection               39    20            0   0  59
  rejection by flood            18     0            0  10  28
  sum                          168   195          177 195 735
Dropped 64 obs due to T<2.
Dropped 1604 obs due to NA.
Dropped 81 obs due to T<2.
Dropped 665 obs due to NA.
Dropped 81 obs due to T<2.
Dropped 720 obs due to NA.
```

```
Regressands ← rep("^NumCows$", 7)
DataToUse1 ← rep("dlvodN", 7)
DataToUse2 ← rep("dlvo3dN", 7)
dlvodN = copy(dlvod)
dlvo3dN = copy(dlvo3d)
dlvodN[, TotalImputedValue:= NULL]
dlvo3dN[, TotalImputedValue:= NULL]
FileName ← "NumCows"
```

```
FileNameHeader ← paste0(c("", "Grace", "PovertyStatus", "Size", "Attributes",
    "TInt", "TIntGrace", "TIntSize", "Rd14Diff", "Rd14DiffGrace", "Rd14DiffAttributes"),
     "OriginalHHs")
Lvsuffixes ← c("", "G", "P", "S", "a", "T", "TG", "TS", "D", "DG", "Da")
listheader ← paste0("cow", Lvsuffixes)
exclheader ← paste0("excl", Lvsuffixes)

source(paste0(pathprogram, "NumCowsCovariateSelection.R"))
source(paste0(pathprogram, "FDEstimationFile.R"))
```

Table 17: FD estimation of livestock holding values

covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	5541.6***	12466.3***	12448.9***	13256.0***	14027.1***	14247.5***	13242.8***
	(578.9)	(1127.1)	(1184.2)	(1170.8)	(1176.1)	(1248.0)	(1168.7)
Large	3010.3***	4638.3***	4620.0***	4932.0***	5043.1***	4015.9***	4987.5***
	(1020.0)	(1364.4)	(1380.9)	(1405.3)	(1420.6)	(1327.1)	(1420.8)
LargeGrace	1971.0**	2617.3*	2642.4*	2781.8**	2835.8**	2842.2**	2828.1**
	(996.0)	(1344.9)	(1353.4)	(1293.4)	(1288.6)	(1323.9)	(1262.2)
Cow	2361.9***	3236.3***	3269.8***	3268.4***	3329.6***	3362.3***	3198.5***
	(850.9)	(1235.0)	(1221.2)	(1097.5)	(1065.8)	(1167.9)	(1076.8)
rd 2 - 3		−11013.2***	−10891.0***	−10890.1***	−11682.1***	−11622.2***	−10887.2***
		(1637.7)	(1646.7)	(1649.8)	(1616.1)	(1609.8)	(1648.9)
Large × rd 2 - 3		−9236.3*	−8803.1*	−8881.9*	−9180.6*	−8571.6	−8893.0*
		(5252.9)	(5286.9)	(5300.7)	(5333.3)	(5381.8)	(5297.1)
LargeGrace × rd 2 - 3		−3544.8	−3550.1	−3576.8	−3712.0	−1770.9	−3602.5
		(3901.2)	(3903.5)	(3907.6)	(3882.0)	(3519.9)	(3906.1)
Cow × rd 2 - 3		−6639.0	−6625.9	−6668.9	−6728.5	−8574.1**	−6684.5
		(4200.7)	(4203.3)	(4204.8)	(4130.6)	(4025.8)	(4204.5)
rd 3 - 4		−12416.6***	−12520.7***	−12531.9***	−14298.5***	−14252.4***	−12548.3***
		(1235.1)	(1228.6)	(1225.9)	(1146.9)	(1141.7)	(1220.5)
Large × rd 3 - 4		−5060.0	−5469.4*	−5583.9*	−6128.0*	−4689.6	−5586.9*
		(3247.0)	(3206.6)	(3227.5)	(3222.3)	(3286.9)	(3225.7)
LargeGrace × rd 3 - 4		−639.5	−629.7	−681.4	−925.5	−388.9	−697.7
		(2726.8)	(2737.4)	(2749.7)	(2589.4)	(2491.1)	(2748.5)
Cow × rd 3 - 4		−908.2	−914.0	−1100.5	−1030.9	−1596.3	−1178.0
		(3117.4)	(3114.5)	(3090.3)	(2914.6)	(3050.9)	(3067.3)
HadCows				−5111.5***	−9600.6***	−11880.0**	
				(1163.1)	(2633.6)	(5395.9)	
Large × HadCows						7373.6	
						(7380.8)	
LargeGrace × HadCows						−3861.6	
						(7035.9)	
Cow × HadCows						−3447.0	
						(6896.6)	
HadCows × rd 2 - 3					4228.0	5057.4	
					(3721.2)	(7298.6)	
Large × HadCows × rd 2 - 3						−2895.0	
						(9623.8)	
LargeGrace × HadCows × rd 2 - 3						−7504.4	
						(9987.2)	
Cow × HadCows × rd 2 - 3						10742.9	
						(10011.1)	
HadCows × rd 3 - 4					9499.0***	11659.0**	
					(3020.9)	(5847.0)	
Large × HadCows × rd 3 - 4						−7017.2	
						(7919.4)	
LargeGrace × HadCows × rd 3 - 4						3794.9	
						(8097.1)	
Cow × HadCows × rd 3 - 4						3099.9	
						(8309.3)	
NumCowsOwnedAtRd1							−3897.2***
							(996.8)
FloodInRd1			227.1	199.7	217.8	204.0	288.2
			(644.1)	(632.2)	(632.6)	(627.8)	(657.1)
Head literate			−867.7	−506.1	−499.0	−396.7	−472.2
			(858.0)	(869.1)	(867.9)	(856.1)	(889.8)
$T = 2$	17	17	16	16	16	16	16
$T = 3$	53	53	51	51	51	51	51
$T = 4$	665	665	665	665	665	665	665
$\bar{R}^2$	0.002	0.083	0.083	0.093	0.098	0.101	0.098
$\hat{\rho}$	−0.205	−0.213	−0.225	−0.246	−0.251	−0.252	−0.251
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	2118	2118	2113	2113	2113	2113	2113

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. Saving and repayment information is taken from administrative data. Time invariant household characteristics are taken from household survey data. Administrative data are merged with survey data by the dating the survey rounds in administrative data. Net saving is saving - withdrawal. Excess repayment is repayment - due amount. extsfLY2, LY3, LY4 are dummy variables for second, third, and fourth year into borrowing. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Regressand is TotalImputedValue, a sum of all livestock holding values evaluated at respective median market prices in the same year.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

Table 18: FD estimation of livestock holding values by attributes

covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	5541.6***	12466.3***	12448.9***	13256.0***	14046.6***	13986.4***	13242.8***
	(578.9)	(1127.1)	(1184.2)	(1170.8)	(1173.5)	(1180.7)	(1168.7)
Upfront	3010.3***	4638.3***	4620.0***	4932.0***	4999.7***	4947.0***	4987.5***
	(1020.0)	(1364.4)	(1380.9)	(1405.3)	(1401.7)	(1341.7)	(1420.8)
WithGrace	−1039.2	−2021.0	−1977.6	−2150.2	−2184.3	−2061.8	−2159.4
	(1167.2)	(1573.1)	(1606.7)	(1630.8)	(1638.0)	(1557.3)	(1635.0)
InKind	390.8	619.0	627.3	486.7	471.0	456.4	370.3
	(1022.8)	(1462.4)	(1448.1)	(1329.9)	(1281.1)	(1276.6)	(1290.0)
rd 2 - 3		−11013.2***	−10891.0***	−10890.1***	−11654.6***	−11622.2***	−10887.2***
		(1637.7)	(1646.7)	(1649.8)	(1605.8)	(1609.8)	(1648.9)
Upfront × rd 2 - 3		−9236.3*	−8803.1*	−8881.9*	−8947.6*	−9106.0*	−8893.0*
		(5252.9)	(5286.9)	(5300.7)	(5331.4)	(5340.8)	(5297.1)
WithGrace × rd 2 - 3		5691.5	5253.0	5305.1	5344.3	5415.6	5290.5
		(4845.6)	(4882.3)	(4896.2)	(4933.0)	(4918.1)	(4892.3)
InKind × rd 2 - 3		−3094.2	−3075.7	−3092.2	−2863.6	−2900.6	−3082.0
		(3678.7)	(3681.9)	(3684.5)	(3427.1)	(3452.7)	(3683.8)
rd 3 - 4		−12416.6***	−12520.7***	−12531.9***	−14285.4***	−14252.4***	−12548.3***
		(1235.1)	(1228.6)	(1225.9)	(1143.1)	(1141.7)	(1220.5)
Upfront × rd 3 - 4		−5060.0	−5469.4*	−5583.9*	−6003.8*	−5984.9*	−5586.9*
		(3247.0)	(3206.6)	(3227.5)	(3206.1)	(3182.7)	(3225.7)
WithGrace × rd 3 - 4		4420.4	4839.7	4902.5	5134.6	5001.2	4889.2
		(3604.1)	(3573.5)	(3585.1)	(3546.5)	(3468.4)	(3580.5)
InKind × rd 3 - 4		−268.7	−284.3	−419.2	−46.1	−40.3	−480.3
		(3487.7)	(3493.9)	(3464.9)	(3182.9)	(3174.5)	(3443.8)
HadCows				−5111.5***	−9706.0***	−9863.3***	
				(1163.1)	(2555.6)	(2463.5)	
HadCows × rd 2 - 3					4455.7	4425.7	
					(3571.7)	(3523.4)	
HadCows × rd 3 - 4					9578.8***	9723.2***	
					(2971.7)	(2904.0)	
NumCowsOwnedAtRd1							−3897.2***
							(996.8)
FloodInRd1			227.1	199.7	208.7	204.0	288.2
			(644.1)	(632.2)	(633.4)	(627.8)	(657.1)
Head literate			−867.7	−506.1	−505.4	−396.7	−472.2
			(858.0)	(869.1)	(869.4)	(856.1)	(889.8)
HadCows × InKind					−2236.1	−345.4	
					(2387.4)	(2706.3)	
HadCows × InKind × rd 2 - 3					15340.1*	21142.2**	
					(8021.1)	(10361.3)	
HadCows × InKind × rd 3 - 4					7003.3	6322.3	
					(6822.0)	(8476.9)	
HadCows × Upfront						5043.7	
						(4107.2)	
HadCows × Upfront × rd 2 - 3						−2895.0	
						(9623.8)	
HadCows × Upfront × rd 3 - 4						−7017.2	
						(7919.4)	
HadCows × WithGrace						−4810.9	
						(3903.0)	
HadCows × WithGrace × rd 2 - 3						−7504.4	
						(9987.2)	
HadCows × WithGrace × rd 3 - 4						3794.9	
						(8097.1)	
$T = 2$	17	17	16	16	16	16	16
$T = 3$	53	53	51	51	51	51	51
$T = 4$	665	665	665	665	665	665	665
$\bar{R}^2$	0.002	0.083	0.083	0.093	0.1	0.101	0.098
$\hat{\rho}$	−0.205	−0.213	−0.225	−0.246	−0.253	−0.252	−0.251
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	2118	2118	2113	2113	2113	2113	2113

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. LargeSize is an indicator function if the arm is of large size, WithGrace is an indicator function if the arm is with a grace period, InKind is an indicator function if the arm provides a cow. Saving and repayment information is taken from administrative data. Time invariant household characteristics are taken from household survey data. Administrative data are merged with survey data by the dating the survey rounds in administrative data. Net saving is saving - withdrawal. Excess repayment is repayment - due amount. extsfLY2, LY3, LY4 are dummy variables for second, third, and fourth year into borrowing. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Regressand is TotalImputedValue, a sum of all livestock holding values evaluated at respective median market prices in the same year.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

Table 19: FD estimation of livestock holding values, ultra vs. moderately poor

covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	7302.9***	15316.5***	15220.6***	16071.8***	16830.7***	16830.7***	16050.6***
	(554.4)	(1421.8)	(1431.1)	(1395.3)	(1345.6)	(1345.6)	(1379.7)
UltraPoor	244.7	−280.6	−312.4	−253.3	−253.6	−253.6	−218.0
	(601.0)	(988.3)	(982.5)	(960.4)	(956.6)	(956.6)	(939.8)
rd 2 - 3		−10909.4***	−10788.3***	−10785.6***	−11483.5***	−11483.5***	−10782.0***
		(1677.0)	(1681.9)	(1685.8)	(1646.5)	(1646.5)	(1685.1)
UltraPoor × rd 2 - 3		1957.8	2134.4	2129.5	2100.3	2100.3	2120.8
		(3759.0)	(3748.0)	(3755.5)	(3760.1)	(3760.1)	(3754.6)
rd 3 - 4		−12372.6***	−12479.4***	−12485.7***	−14132.5***	−14132.5***	−12501.5***
		(1227.3)	(1223.6)	(1222.1)	(1151.9)	(1151.9)	(1216.8)
UltraPoor × rd 3 - 4		4858.6*	4698.7*	4740.7*	4633.3*	4633.3*	4793.3*
		(2629.1)	(2641.4)	(2624.5)	(2606.6)	(2606.6)	(2606.0)
HadCows				−4977.1***	−9104.6***	−9104.6***	
				(1266.8)	(2861.0)	(2861.0)	
HadCows × rd 2 - 3					3748.1	3748.1	
					(3779.4)	(3779.4)	
HadCows × rd 3 - 4					8880.9***	8880.9***	
					(3163.3)	(3163.3)	
NumCowsOwnedAtRd1							−3822.4***
							(1075.1)
FloodInRd1			436.9	432.1	451.2	451.2	519.6
			(607.0)	(585.6)	(586.5)	(586.5)	(592.6)
Head literate			−816.3	−467.6	−461.4	−461.4	−435.0
			(920.6)	(939.4)	(938.6)	(938.6)	(963.1)
$T = 2$	17	17	16	16	16	16	16
$T = 3$	53	53	51	51	51	51	51
$T = 4$	665	665	665	665	665	665	665
$\bar{R}^2$	0	0.078	0.079	0.088	0.092	0.092	0.092
$\hat{\rho}$	−0.139	−0.178	−0.218	−0.234	−0.240	−0.240	−0.238
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	2118	2118	2113	2113	2113	2113	2113

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. UltraPoor is an indicator function if the household is classified as the ultra poor. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Regressand is TotalImputedValue, a sum of all livestock holding values evaluated at respective median market prices in the same year.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

Table 20: FD estimation of cattle holding by attributes

covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	1.0*** (0.1)	0.8*** (0.1)	0.8*** (0.1)	0.7*** (0.1)	0.6*** (0.1)	0.6*** (0.1)	0.7*** (0.1)
Upfront	0.6*** (0.2)	0.5*** (0.2)	0.5*** (0.2)	0.5*** (0.1)	0.5*** (0.1)	0.5*** (0.1)	0.5*** (0.1)
WithGrace	−0.2 (0.2)	−0.2 (0.2)	−0.2 (0.2)	−0.2 (0.2)	−0.2 (0.2)	−0.1 (0.2)	−0.2 (0.2)
InKind	−0.1 (0.1)	−0.1 (0.1)	−0.1 (0.1)	− 0.0 (0.1)	− 0.0 (0.1)	− 0.0 (0.1)	− 0.0 (0.1)
rd 2 - 3		0.2*** (0.0)	0.2*** (0.0)	0.2*** (0.0)	0.2*** (0.0)	0.2*** (0.0)	0.2*** (0.0)
Upfront × rd 2 - 3		−0.1 (0.1)	−0.1 (0.1)	− 0.0 (0.1)	− 0.0 (0.1)	− 0.0 (0.1)	− 0.0 (0.1)
WithGrace × rd 2 - 3		0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)
InKind × rd 2 - 3		−0.1 (0.1)	−0.1 (0.1)	−0.1 (0.1)	−0.1 (0.1)	−0.1 (0.1)	−0.1 (0.1)
rd 3 - 4		0.3*** (0.1)	0.3*** (0.1)	0.3*** (0.1)	0.3*** (0.1)	0.3*** (0.1)	0.3*** (0.1)
Upfront × rd 3 - 4		0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)
WithGrace × rd 3 - 4		0.0 (0.2)	0.1 (0.2)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)
InKind × rd 3 - 4		− 0.0 (0.1)	− 0.0 (0.1)	− 0.0 (0.1)	− 0.0 (0.1)	− 0.0 (0.1)	− 0.0 (0.1)
HadCows				0.7*** (0.1)	0.8*** (0.1)	0.8*** (0.1)	
HadCows × rd 2 - 3					−0.1 (0.1)	−0.2 (0.1)	
HadCows × rd 3 - 4					−0.2* (0.1)	−0.3** (0.1)	
NumCowsOwnedAtRd1							0.4*** (0.1)
FloodInRd1			0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)
Head literate			− 0.0 (0.1)	−0.1 (0.1)	−0.1 (0.1)	−0.1 (0.1)	−0.1 (0.1)
HadCows × InKind					−0.3* (0.2)	−0.2 (0.2)	
HadCows × InKind × rd 2 - 3					0.2 (0.2)	0.4 (0.3)	
HadCows × InKind × rd 3 - 4					0.3 (0.3)	0.7* (0.3)	
HadCows × Upfront						0.6 (0.4)	
HadCows × Upfront × rd 2 - 3						0.3 (0.3)	
HadCows × Upfront × rd 3 - 4						0.4 (0.4)	
HadCows × WithGrace						−0.5 (0.4)	
HadCows × WithGrace × rd 2 - 3						−0.4 (0.3)	
HadCows × WithGrace × rd 3 - 4						−0.7 (0.4)	
$T = 2$	15	15	14	14	14	14	14
$T = 3$	53	53	51	51	51	51	51
$T = 4$	665	665	665	665	665	665	665
$\bar{R}^2$	0.033	0.042	0.041	0.103	0.105	0.112	0.104
$\hat{\rho}$	0.607	0.579	0.582	0.576	0.574	0.571	0.574
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	2049	2049	2044	2044	2044	2044	2044

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. LargeSize is an indicator function if the arm is of large size, WithGrace is an indicator function if the arm is with a grace period, InKind is an indicator function if the arm provides a cow. Saving and repayment information is taken from administrative data. Time invariant household characteristics are taken from household survey data. Administrative data are merged with survey data by the dating the survey rounds in administrative data. Net saving is saving - withdrawal. Excess repayment is repayment - due amount. extsfLY2, LY3, LY4 are dummy variables for second, third, and fourth year into borrowing. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Regressand is NumCows, number of cattle holding.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

TABLE 21: FD ESTIMATION OF CATTLE HOLDING, ULTRA VS. MODERATELY POOR

covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	1.3***	1.1***	1.1***	1.0***	0.9***	0.9***	1.0***
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
UltraPoor	− 0.0	− 0.0	− 0.0	− 0.0	− 0.0	− 0.0	− 0.0
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
rd 2 - 3		0.2***	0.2***	0.2***	0.2***	0.2***	0.2***
		(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
UltraPoor × rd 2 - 3		− 0.0	− 0.0	− 0.0	− 0.0	− 0.0	− 0.0
		(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
rd 3 - 4		0.3***	0.3***	0.3***	0.3***	0.3***	0.3***
		(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
UltraPoor × rd 3 - 4		0.1	0.1	0.1	0.1	0.1	0.1
		(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
HadCows				0.7***	0.8***	0.8***	
				(0.2)	(0.1)	(0.1)	
HadCows × rd 2 - 3					−0.2	−0.2	
					(0.1)	(0.1)	
HadCows × rd 3 - 4					−0.3*	−0.3*	
					(0.1)	(0.1)	
NumCowsOwnedAtRd1							0.5***
							(0.1)
FloodInRd1			0.1	0.1	0.1	0.1	0.1
			(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Head literate			− 0.0	−0.1	−0.1	−0.1	−0.1
			(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
T = 2	15	15	14	14	14	14	14
T = 3	53	53	51	51	51	51	51
T = 4	665	665	665	665	665	665	665
$\bar{R}^2$	0	0.011	0.011	0.077	0.078	0.078	0.079
$\hat{\rho}$	0.588	0.518	0.578	0.571	0.567	0.567	0.590
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	2049	2049	2044	2044	2044	2044	2044

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. LargeSize is an indicator function if the arm is of large size, WithGrace is an indicator function if the arm is with a grace period, InKind is an indicator function if the arm provides a cow. Saving and repayment information is taken from administrative data. Time invariant household characteristics are taken from household survey data. Administrative data are merged with survey data by the dating the survey rounds in administrative data. Net saving is saving - withdrawal. Excess repayment is repayment - due amount. extsfLY2, LY3, LY4 are dummy variables for second, third, and fourth year into borrowing. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Regressand is NumCows, number of cattle holding.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

```
lvo ← readRDS(paste0(pathsaveHere, "LivestockAdminDataUsedForEstimation.rds"))
setkey(lvo, Arm, tee)
lvostat ← lvo[grepl("es", creditstatus),.(MeanIV = mean(TotalImputedValue, na.rm = T),
  StdIV = var(TotalImputedValue, na.rm = T)^(.5),
  N = sum(!is.na(TotalImputedValue))), by = .(Arm, tee)]
lvostat[, c("ciLB", "ciUB") := list(MeanIV − StdIV ∗ qt(.975, N− 1), MeanIV + StdIV ∗ qt(.
setkey(lvo, hhid, survey)
lvo[, HoldingClass := "below 1000"]
lvo[TotalImputedValue ≥ 1000 & TotalImputedValue < 30000,
  HoldingClass := "1000−29999"]
lvo[TotalImputedValue ≥ 30000 & TotalImputedValue < 50000,
  HoldingClass := "30000−49999"]
lvo[TotalImputedValue ≥ 50000,
  HoldingClass := "above 50000"]
lvo[, HoldingClass := factor(HoldingClass,
  levels = c("below 1000", "1000−29999", "30000−49999", "above 50000"))]
setkey(lvo, Arm, HoldingClass, tee)
lvostat2 ← lvo[grepl("es", creditstatus),.(MeanIV = mean(TotalImputedValue, na.rm = T),
  StdIV = var(TotalImputedValue, na.rm = T)^(.5),
  N = sum(!is.na(TotalImputedValue))), by = .(Arm, HoldingClass, tee)]
```

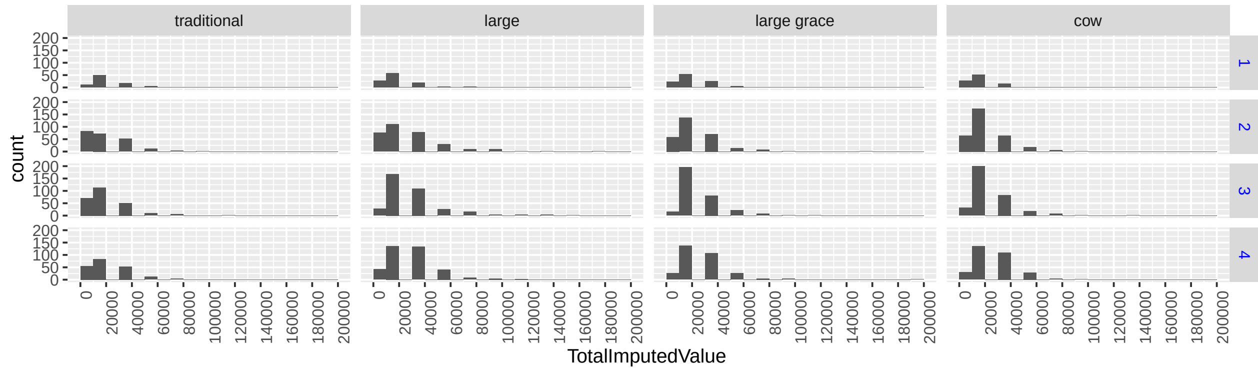


Figure 5: Total imputed value of livestock holding
Livestock holding values are computed by using respective median prices of each year.

```
lvostat2[, c("ciLB", "ciUB") := list(MeanIV − StdIV * qt(.975, N− 1), MeanIV + StdIV * qt(
lvostat3 ← lvo[grepl("es", creditstatus),.(MeanIV = mean(TotalImputedValue, na.rm = T),
  StdIV = var(TotalImputedValue, na.rm = T)^(.5),
  N = sum(!is.na(TotalImputedValue))), by = .(Arm, HoldingClass, Year)]
lvostat3[, c("ciLB", "ciUB") := list(MeanIV − StdIV * qt(.975, N− 1), MeanIV + StdIV * qt(
```

```
library(ggplot2)
ggplot(data = lvo[TotalImputedValue > 0], aes(TotalImputedValue)) +
  geom_histogram(breaks = c(0, seq(10000, 200000, 10000))) +
  #scale_x_log10(breaks = c(1, 100, 1000, 10000, 20000, 30000, 50000)) +
  scale_x_continuous(breaks = seq(0, 200000, 20000)) +
  theme(axis.text.x = element_text(angle = 90, vjust = 1, hjust = 1),
    strip.text.y = element_text(colour = "blue"))+
  facet_grid(tee ~ Arm)
```

```
library(ggplot2)
ggplot(data = lvostat2, aes(HoldingClass, N)) +
  geom_col() +
  xlab("Livestock holding classes") +
  theme(axis.text.x = element_text(angle = 90, vjust = 1, hjust = 1),
      strip.text.y = element_text(colour = "blue"))+
  facet_grid(tee ~ Arm)
```

```
library(ggplot2)
ggplot(data = lvostat3, aes(HoldingClass, N)) +
  geom_col() +
  xlab("Livestock holding classes") +
  theme(axis.text.x = element_text(angle = 90, vjust = 1, hjust = 1),
      strip.text.y = element_text(colour = "blue"))+
  facet_grid(Year ~ Arm)
```

```
lvo ← readRDS(paste0(pathsaveHere, DataFileNames[5], "InitialSample.rds"))
setkey(lvo, Arm, tee)
table0(lvo[o800==1 & tee == 1,.(BStatus, povertystatus)])
```

```
                      povertystatus
BStatus                 Ultra Poor Moderately Poor <NA>
  borrower                     427             172    0
  pure saver                     0               0    0
  individual rejection          56              33    0
  group rejection                0               0   60
```

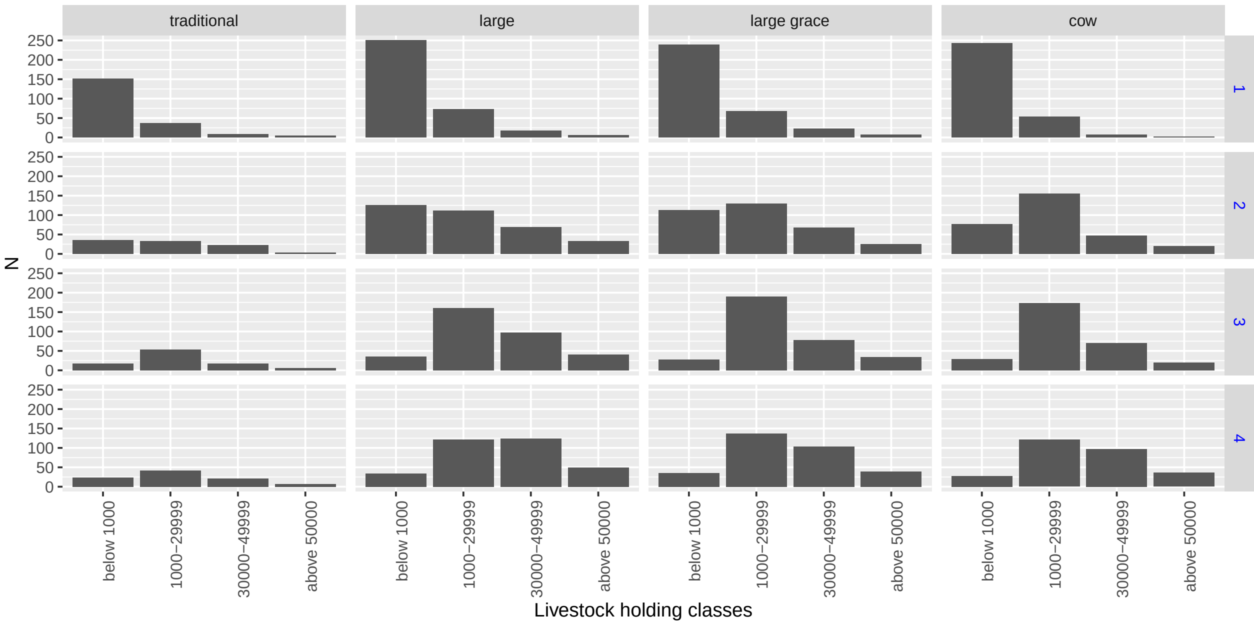


Figure 6: Histogram of livestock holding classes
Livestock holding values are computed by using respective median prices of each year.

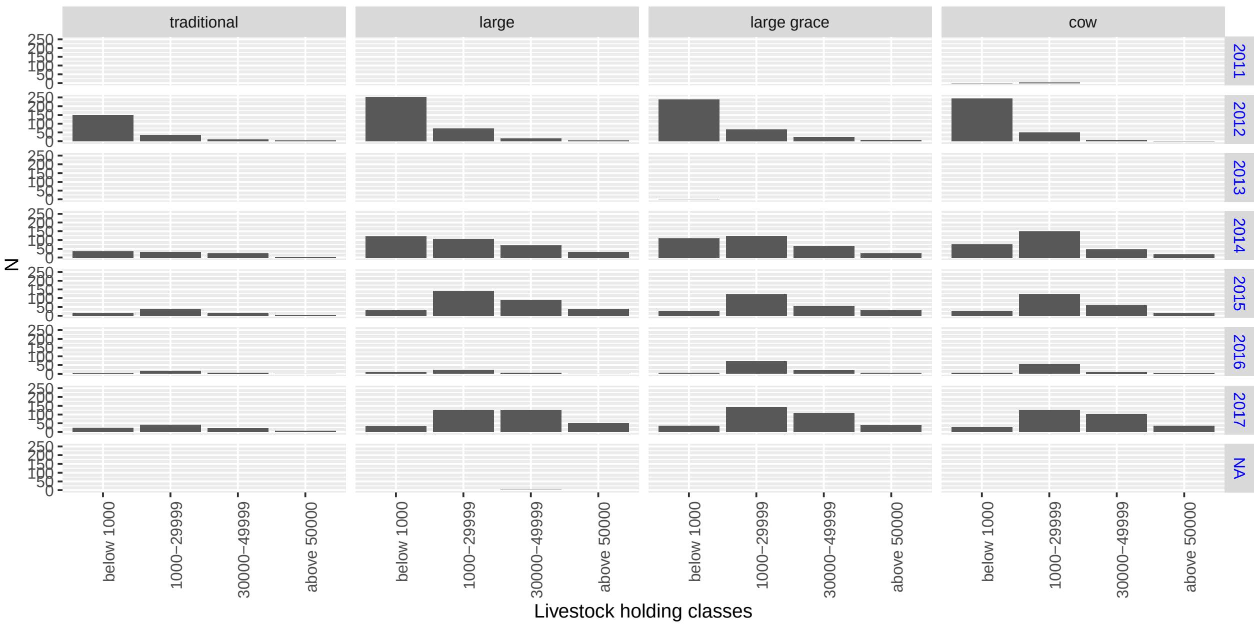


Figure 7: Histogram of livestock holding classes by year
Livestock holding values are computed by using respective median prices of each year.

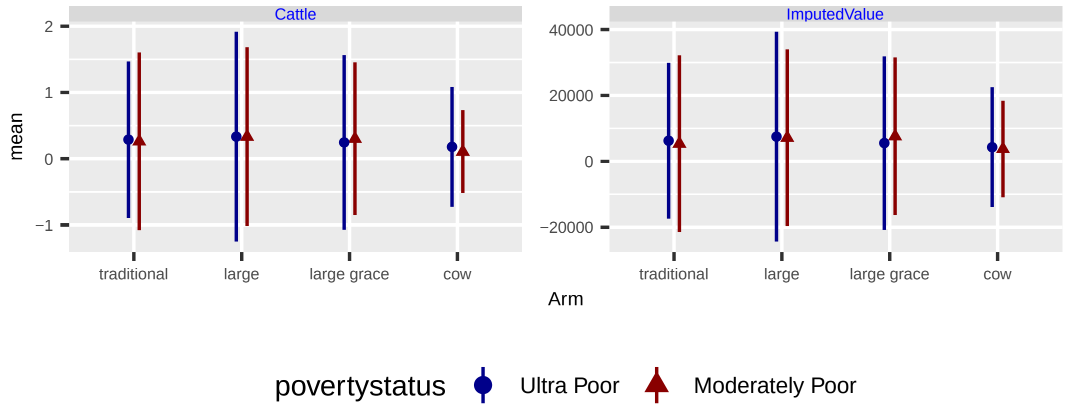
```
  rejection by flood              0                 0    40
```

```
lvostat ← lvo[o800==1 & tee == 1 & !grepl("flo|gr", BStatus),
  .(mean.IV = mean(TotalImputedValue, na.rm = T),
    std.IV = var(TotalImputedValue, na.rm = T)^(.5),
    mean.Cattle = mean(NumCows, na.rm = T),
    std.Cattle = var(NumCows, na.rm = T)^(.5),
    N = sum(!is.na(TotalImputedValue))), by = .(Arm, povertystatus)]
lvostat[, c("lb.ImputedValue", "ub.ImputedValue",
  "lb.Cattle", "ub.Cattle") := list(
    mean.IV − std.IV ∗ qt(.975, N− 1),
```

```
    mean.IV + std.IV * qt(.975, N- 1),
    mean.Cattle - std.Cattle * qt(.975, N- 1),
    mean.Cattle + std.Cattle * qt(.975, N- 1))]
lvostat2 <- reshape(lvostat, direction = "long", idvar = c("Arm", "povertystatus", "N"),
  varying = grepout("^.b", colnames(lvostat)))
lvostat2[, mean := mean.Cattle]
lvostat2[grepl("Im", time), mean := mean.IV]
lvostat2[, std := std.Cattle]
lvostat2[grepl("Im", time), std := std.IV]
lvostat2[, grepout("\\.[CI]", colnames(lvostat2)) := NULL]
library(ggplot2)
g <-
 ggplot(data = lvostat2,
  aes(x=Arm, y=mean)) +
  geom_pointrange(aes(
    colour = povertystatus, shape = povertystatus,
    ymin = lb, ymax = ub),
    stat = "identity", fatten = 1.75,
    position = position_dodge(width = .2)) +
  scale_colour_manual(values = c("darkblue", "darkred")) +
  scale_fill_manual(values = c("blue", "red")) +
  #scale_y_continuous(name = "livestock values (Tk.)")
  theme(
   axis.text.x = element_text(size = 5, vjust = 1, hjust = .5),
   axis.text.y = element_text(size = 5),
   axis.title = element_text(size = 6),
   strip.text.x = element_text(color = "blue", size = 5,
     margin = margin(0, .5, 0, .5, "cm")),
   strip.text.y = element_text(color = "blue", size = 4,
     margin = margin(.5, 0, .5, 0, "cm")),
   legend.text = element_text(size = 7),
   legend.title = element_text(size = 9),
   legend.key = element_rect(fill = "white"),
   legend.key.size = unit(.5, "cm"),
   legend.position = "bottom") +
  facet_wrap( ~ time, scales = "free_y")
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo3/LivestockValuesAtRd1.png"),
  g,
  width = 10, height = 4, units = "cm",
  dpi = 300
 )
setEPS()
postscript(file =
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/LivestockValuesAtRd1.eps")
  , horizontal = F, width = 12/2.54, height = 5/2.54)
print(g)
dev.off()
```

```
pdf
  2
```

FIGURE 8: LIVESTOCK HOLDING AT BASELINE



Source: Survey data.

Note:

- cow reports above 20000 holding in rds 2-4 while traditional does not.

```
lvo[, NumberOfCows := 0L]
lvo[grepl("ow", LivestockCode), NumberOfCows := as.integer(number_owned)]
lvo[,
  .(MeanImputedVal = mean(TotalImputedValue, na.rm = T),
  MeanNumCows = mean(NumberOfCows, na.rm = T),
  N = sum(!is.na(TotalImputedValue))), by = .(Arm, survey)]
```

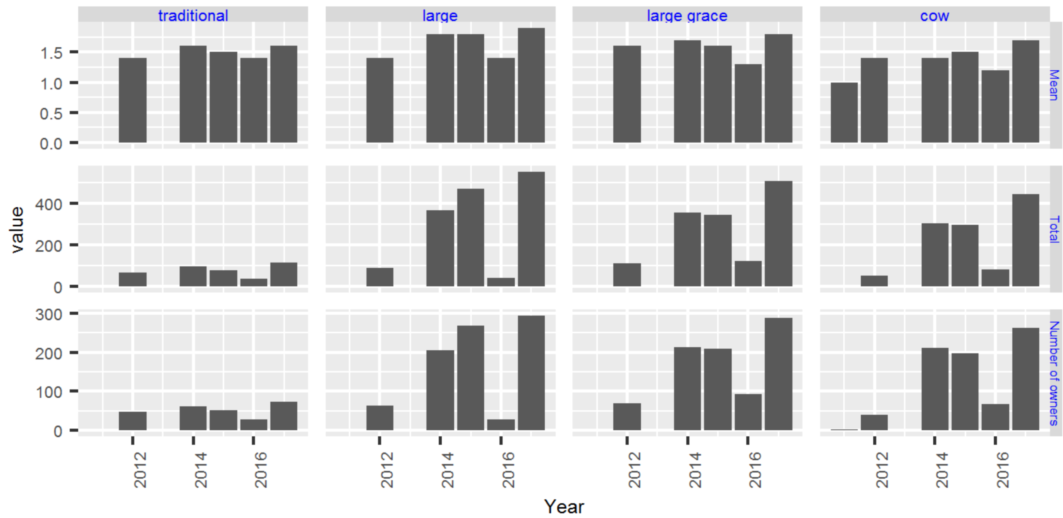
```
           Arm survey MeanImputedVal MeanNumCows   N
 1: traditional      1        5065.33    0.233668 398
 2: traditional      2       15854.00    0.817844 280
 3: traditional      3       20179.62    1.022059 277
 4: traditional      4       21233.75    1.050000 240
 5:       large      2       24992.86    1.278820 383
 6:       large      1        6092.42    0.275689 399
 7:       large      3       31056.41    1.625000 386
 8:       large      4       32686.07    1.630890 382
 9: large grace      1        7392.54    0.333333 399
10: large grace      2       21510.32    1.150943 341
11: large grace      3       27565.65    1.422619 347
12: large grace      4       30276.97    1.528024 343
13:         cow      1        4997.68    0.218045 399
14:         cow      2       20550.29    1.078035 364
15:         cow      3       25399.62    1.300562 365
16:         cow      4       28700.23    1.436950 342
```

```
#lvo[,.(N = sum(!is.na(TotalImputedValue))), by = .(Arm, survey)]
```

```
library(ggplot2)
lvo[, LivestockType := LivestockCode]
lvo[grepl("Ox|Cow", LivestockCode), LivestockType := "Cow/Ox"]
lvo[grepl("Goat|She", LivestockCode), LivestockType := "Goat/Sheep"]
lvo[grepl("Duc|Hen", LivestockCode), LivestockType := "Poultry"]
lvo[, LivestockType := factor(LivestockType)]
lvotype <- lvo[grepl("es", creditstatus),
  .(Std = var(number_owned, na.rm = T)^(.5),
    Total = sum(number_owned, na.rm = T),
    N = sum(!is.na(number_owned)),
    by = .(Arm, LivestockType, Year)]
```

```
lvotype ← lvotype[!is.na(Arm), ]
lvotype[, Mean := round(Total/N, 1)]
setnames(lvotype, grepout("^T|N|^S|^M", colnames(lvotype)),
  paste0("value.", grepout("^T|N|^S|^M", colnames(lvotype))))
lvotype[is.na(LivestockType)|LivestockType == "", LivestockType := "Other"]
lvotype[grepl("cow", LivestockType), LivestockType := "Cow/Ox"]
lvotypel ← reshape(lvotype, direction = "long",
  idvar = c("Arm", "LivestockType", "Year"),
  varying = grepout("val", colnames(lvotype)))
lvotypel ← lvotypel[grepl("Cow", LivestockType) & grepl("Mean|Tot|^N", time), ]
lvotypel ← lvotypel[!is.na(Year), ]
setkey(lvotypel, Arm, Year, LivestockType)
lvotypel[, Variable := time]
lvotypel[grepl("N", time), Variable := "Number of owners"]
lvotypel[, Variable := factor(Variable, levels = c("Mean", "Total", "Number of owners"))]
g ← ggplot(data = lvotypel, aes(Year, value)) +
  geom_col(data = lvotypel[grepl("Total", Variable), ]) +
  geom_col(data = lvotypel[grepl("Mean", Variable), ]) +
  geom_col(data = lvotypel[grepl("N", Variable), ]) +
  xlab("Year") +
  theme(
   axis.text.x = element_text(size = 5, angle = 90, vjust = 1, hjust = 1),
   axis.text.y = element_text(size = 5),
   axis.title = element_text(size = 6),
   strip.text.x = element_text(color = "blue", size = 5,
     margin = margin(0, .5, 0, .5, "cm")),
   strip.text.y = element_text(color = "blue", size = 4,
     margin = margin(.5, 0, .5, 0, "cm"))) +
  facet_grid(Variable ~ Arm, scale = "free_y")
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo3/NumberOfCowsByYear.png"),
  g,
  width = 12, height = 6, units = "cm",
  dpi = 300
 )
```

Figure 9: Number of cows/oxen by year



Source: Survey data.

Note:

Finding III.2 Figure 7 shows increasing livestock accumulation in all arms but traditional. Figure 9 shows increasng cow ownership relative to traditional in the bottom panel while the holding per owner is similar across all arms. This is evidence of an acceleration of becoming a large livestock owner for the large sized arms relative to the small size arm. Given that the number of cows per owner remains the similar, it does not provide evidence for accelerated growth of livestock after becoming an owner.

III.5 Assets+Livestock

```
#ass ← readRDS(paste0(pathsaveHere, "AssetAdminDataUsedForEstimation.rds"))
ass ← readRDS(paste0(pathsaveHere, DataFileNames[4], "InitialSample.rds"))
if (Only800) ass ← ass[o800 == 1L, ]
# creaditstatus != yes are pure controls
table0(ass[survey == 1,.(BorrowerStatus, creditstatus)])
```

```
                  creditstatus
BorrowerStatus     Yes  No
  borrower         597   0
  pure saver         0   0
  quit membership    0 199
```

```
table0(ass[survey == 1,.(Mstatus, creditstatus)])
```

```
              creditstatus
Mstatus        Yes  No
  gErosion       0  40
  gRejection     0  70
  iRejection     0  89
  iReplacement   0   0
  newGroup       0   0
  oldMember    597   0
```

```
ass[, grepout("Loan|UD|Forced", colnames(ass)) := NULL]
CovStrings <- "^groupid$|hhid|tee|^dummy.*[a-z]$|Floo|Time\\.?.|With|.Size|Head|^creditsta
ass <- ass[!(hhid == 7043715 & HAssetAmount == 0), ]
ass1 <- ass[, grepout(paste0(CovStrings, "^HAsse"), colnames(ass)), with = F]
ass1R <- ass[, grepout(paste0(CovStrings, "^HAsse|RM"), colnames(ass)), with = F]
ass2 <- ass[, grepout(paste0(CovStrings, "^PAsse"), colnames(ass)), with = F]
ass2R <- ass[, grepout(paste0(CovStrings, "^PAsse|RM"), colnames(ass)), with = F]
# before-after style 2 time point data. Choose tee == 2 as baseline because there are many
#ass <- readRDS(paste0(pathsaveHere, "AssetAdminDataUsedForEstimation.rds"))
ass <- readRDS(paste0(pathsaveHere, DataFileNames[4], "InitialSample.rds"))
if (Only800) ass <- ass[o800 == 1L, ]
ass <- ass[!(hhid == 7043715 & HAssetAmount == 0), ]
ass[, grepout("Time|Loan", colnames(ass)) := NULL]
ass3 <- ass[tee == 2 | tee == 4, grepout(paste0(CovStrings, "^HAsse"), colnames(ass)), wit
ass3R <- ass[tee == 2 | tee == 4, grepout(paste0(CovStrings, "^HAsse|RM"), colnames(ass)),
ass4 <- ass[tee == 2 | tee == 4, grepout(paste0(CovStrings, "^PAsse"), colnames(ass)), wit
ass4R <- ass[tee == 2 | tee == 4, grepout(paste0(CovStrings, "^PAsse|RM"), colnames(ass)),
datas0 <- paste0("ass", rep(1:4, each = 2), c("", "R"))
datas <- paste0("as", rep(1:4, each = 2), c("", "R"))
ddatas <- paste0("d", datas)
ddatasd <- paste0(ddatas, "d")
for (i in 1:length(datas)) {
#   dl <- prepFDData(get(datas0[i]), Group = "^hhid$", TimeVar = "tee", Cluster = "groupic
#     # before considering pure control contrast
#     #LevelCovariates = "^dummy|Floo|^Time\\..$|Head",
#     # after considering pure control contrast
#     LevelCovariates = "^dummy|Floo|^Time\\..$|Head|^cred.*s$",
#     drop.if.NA.in.differencing = T, LevelPeriodToKeep = "last",
#     use.var.name.for.dummy.prefix = F, print.messages = F)
   dl <- FirstDiffPanelData(X = get(datas0[i]),
     Group = "^hhid$", TimeVar = "tee", Cluster = "groupid",
     LevelCovariates = "^dummy|Head|^Time\\..$|Female$|Floo|Eldest|^cred.*s$|xid$|SchPa|^A
  dat <- dl$diff
  dat[, grepout("^en$", colnames(dat)) := NULL]
  # create PureControl*Time2, Time3 interactions and drop creditstatus
  if (grepl("ass[12]", datas0[i]) & any(grepl("cred.*s$", colnames(dat)))) {
    dat[, PureControl := 0L]
    dat[!grepl("es$", creditstatus), PureControl := 1L]
    dat[, creditstatus := NULL]
    dat[, c("PureControl.Time3", "PureControl.Time4") :=
      .(PureControl * Time.3, PureControl * Time.4)]
  }
  assign(ddatas[i], dl)
  assign(ddatasd[i], dat)
}
```

```
Dropped 64 obs due to T<2.
Dropped 735 obs due to NA.
Dropped 64 obs due to T<2.
Dropped 1604 obs due to NA.
Dropped 64 obs due to T<2.
Dropped 735 obs due to NA.
Dropped 64 obs due to T<2.
Dropped 1604 obs due to NA.
Dropped 69 obs due to T<2.
Dropped 666 obs due to NA.
Dropped 69 obs due to T<2.
```

```
Dropped 721 obs due to NA.
Dropped 69 obs due to T<2.
Dropped 666 obs due to NA.
Dropped 69 obs due to T<2.
Dropped 721 obs due to NA.
```

```
das1Rd ← das1Rd[tee > 2, ]
das2Rd ← das2Rd[tee > 2, ]
das1d[, Tee := .N, by = hhid]
das2d[, Tee := .N, by = hhid]

#lvo ←  readRDS(paste0(pathsaveHere, ”LivestockAdminDataUsedForEstimation.rds”))
lvo ← readRDS(paste0(pathsaveHere, DataFileNames[5], ”InitialSample.rds”))
if (Only800) lvo ← lvo[o800 == 1L, ]
table0(lvo[, .(tee, Arm)])
```

```
   Arm
tee traditional large large grace cow
  1         199   200         189 200
  2         168   195         188 195
  3         163   192         173 190
  4         143   188         164 170
```

```
table0(lvo[grepl(”ow”, LivestockCode), .(tee, Arm)])
```

```
   Arm
tee traditional large large grace cow
  1          31    44          36  32
  2          88   137         137 159
  3         119   169         156 163
  4          99   157         136 145
```

```
# xid ← readRDS(paste0(path1234, ”ID.rds”))
# xidlv ← xid[,.(Mstatus, AssignOriginal, groupid, hhid, survey, year)]
# setnames(xidlv, ”AssignOriginal”, ”Arm”)
# setkey(lvo, Arm, groupid, hhid, survey, Mstatus)
# setkey(xidlv, Arm, groupid, hhid, survey, Mstatus)
# lvo ← merge(lvo, xidlv, by = key(xidlv), all = T)
lvo[, grepout(”Loan|UD|Forced”, colnames(lvo)) := NULL]
lvostrings ← ”^groupid$|hhid|^Arm$|tee|^dummy[TLCMUWS]|creditst|^TotalIm|Floo|Time\\.|liv
lvoR ← lvo[, grepout(paste0(lvostrings, ”|RM”), colnames(lvo)), with = F]
lvo ← lvo[, grepout(lvostrings, colnames(lvo)), with = F]
lvo3 ← lvo[tee == 2 | tee == 4, ]
lvoR3 ← lvoR[tee == 2 | tee == 4, ]
datas ← c(”lvo”, ”lvoR”, ”lvo3”, ”lvoR3”)
ddatas ← paste0(”d”, datas)
ddatasd ← paste0(ddatas, ”d”)
for (i in 1:length(datas)) {
#   dl ← prepFDData(get(datas[i]), Group = ”^hhid$”, TimeVar = ”tee”, Cluster = ”groupid’
#     LevelCovariates = ”^dummy|^Arm$|Floo|^Time\\..$|Head|Cows|liv.*de$|credits”,
#     drop.if.NA.in.differencing = T, LevelPeriodToKeep = ”last”,
#     use.var.name.for.dummy.prefix = F, print.messages = F)
   dl ← FirstDiffPanelData(X = get(datas[i]),
     Group = ”^hhid$”, TimeVar = ”tee”, Cluster = ”groupid”,
     LevelCovariates = ”^dummy|^Arm$|Floo|^Time\\..$|Head|Cows|liv.*de$|credits|xid$|SchPa
  dat ← dl$diff
```

```
  dat[, grepout("^en$", colnames(dat)) := NULL]
  assign(ddatas[i], dl)
  assign(ddatasd[i], dat)
}
```

```
Dropped 64 obs due to T<2.
Dropped 735 obs due to NA.
Dropped 64 obs due to T<2.
Dropped 1604 obs due to NA.
Dropped 81 obs due to T<2.
Dropped 665 obs due to NA.
Dropped 81 obs due to T<2.
Dropped 720 obs due to NA.
```

```
dlvoRd ← dlvoRd[tee > 1, ]
```

```
#ass ←  readRDS(paste0(pathsaveHere, "RosterAssetAdminOriginalHHsDataUsedForEstimation.rc
ass ← readRDS(paste0(pathsaveHere, DataFileNames[4], "InitialSample.rds"))
if (Only800) ass ← ass[o800 == 1L, ]
ass[, grepout("Loan|UD|Forced", colnames(ass)) := NULL]
assstrings ← "^Arm$|^groupid$|hhid|tee|^.Asse|^dummy.*[a-z]$|Floo|Time\\.?.|Head|With|.Si
lvostrings ← "^groupid$|hhid|tee|^TotalIm|Cows|^Arm$|BSta"
ass1 ← ass[, grepout(assstrings, colnames(ass)), with = F]
ass1R ← ass[, grepout(paste0(assstrings, "|RM"), colnames(ass)), with = F]
# before-after style 2 time point data. Choose tee == 2 as baseline because there are many
#ass ←  readRDS(paste0(pathsaveHere, "RosterAssetAdminOriginalHHsDataUsedForEstimation.rc
#lvo ←  readRDS(paste0(pathsaveHere, "RosterLivestockAdminOriginalHHsDataUsedForEstimatic
lvo ← readRDS(paste0(pathsaveHere, DataFileNames[5], "InitialSample.rds"))
if (Only800) lvo ← lvo[o800 == 1L, ]
lvo[, grepout("Loan|UD|Forced", colnames(lvo)) := NULL]
lvo1 ← lvo[, grepout(lvostrings, colnames(lvo)), with = F]
# merge
#commonstrings ← "^groupid$|hhid|^Arm|tee|Floo|Time\\.?.|Head"
commoncols ← intersect(colnames(ass1), colnames(lvo1))
AL1 ← merge(ass1, lvo1, by = commoncols, All = T)
AL1[is.na(TotalImputedValue), TotalImputedValue := 0]
AL1[, TotalValue := TotalImputedValue + HAssetAmount + PAssetAmount]
AL1[, c("TotalImputedValue", "HAssetAmount", "PAssetAmount") := NULL]
AL1 ← unique(AL1)
AL2 ← AL1[tee == 2 | tee == 4, ]
AL2[, grepout("Time", colnames(AL2)) := NULL]

commoncols ← intersect(colnames(ass1R), colnames(lvo1))
AL1R ← merge(ass1R, lvo1, by = commoncols, All = T)
AL1R[is.na(TotalImputedValue), TotalImputedValue := 0]
AL1R[, TotalValue := TotalImputedValue + HAssetAmount + PAssetAmount]
ALfig ← AL1R[, .(Arm, groupid, hhid, dummyUltraPoor, tee, TotalValue)]
setnames(ALfig, "dummyUltraPoor", "UltraPoor")
ALfig[, povertystatus := "ultra poor"]
ALfig[UltraPoor == 0L, povertystatus := "moderately poor"]
ALfig[, povertystatus := factor(povertystatus,
  levels = c("ultra poor","moderately poor"))]
ALfig[, UltraPoor := NULL]
AL1R[, c("TotalImputedValue", "HAssetAmount", "PAssetAmount") := NULL]
AL1R ← unique(AL1R)
AL2R ← AL1R[tee == 2 | tee == 4, ]
AL2R[, grepout("Time", colnames(AL2)) := NULL]
```

```
Warning in `[.data.table`(AL2R, , `:=`(grepout("Time", colnames(AL2)), NULL)): length(LHS
```

```
datas <- c(paste0("AL", 1:2), paste0("AL", 1:2, "R"))
ddatas <- paste0("d", datas)
ddatasd <- paste0(ddatas, "d")
for (i in 1:length(datas)) {
  dl <- prepFDData(get(datas[i]), Group = "^hhid$", TimeVar = "tee", Cluster = "groupid",
    LevelCovariates = "^dummy|^Arm|Floo|^Time\\..$|Head|Cows|BSta",
    drop.if.NA.in.differencing = T, LevelPeriodToKeep = "last",
    use.var.name.for.dummy.prefix = F, print.messages = F)
  dat <- dl$diff
  if (i == 1) {
    # Recreate Time.4 which is dropped when kept only 1:(T-1) obs.
    #dat[, c("Time.2", "Time.3", "Time.4") := 0L]
    #dat[tee == 1, Time.2 := 1L]
    #dat[tee == 2, Time.3 := 1L]
    #dat[tee == 3, Time.4 := 1L]
    dat[, grepout("Time.?2", colnames(dat)) := NULL]
  }
  assign(ddatas[i], dl)
  assign(ddatasd[i], dat)
}
dAL1Rd <- dAL1Rd[tee > 2, ]

FileName <- "AssetLivestock"
FileNameHeader <-
  paste0(c("", "Grace", "PovertyStatus", "Size", "Attributes",
    "TInt", "TIntGrace", "TIntSize", "Rd24Diff", "Rd24DiffGrace",
    "Rd24DiffPovertyStatus", "Rd24DiffSize", "Rd24DiffAttributes"), "OriginalHHs")
alsuffixes <- c("", "G", "P", "S", "a", "T", "TG", "TS", "D", "DG", "DP", "DS", "Da")
listheader <- paste0("al", alsuffixes)
DataToUse1 <- rep("dAL1d", 6)
DataToUse2 <- rep("dAL2d", 6)
Addseparatingcols <- NULL; Separatingcolwidth <- NULL
Separatingcoltitle <- NULL
Regressands <- rep("TotalValue", 6)
tableboxwidth <- 4.5

source(paste0(pathprogram, "AssetLivestockCovariateSelection.R"))

exclheader <- paste0("excl", alsuffixes)
source(paste0(pathprogram, "FDEstimationFile.R"))
saveRDS(fdplist, paste0(pathsave, "FD_assetslivestock.rds"))

library(ggplot2)
g <- ggplot(data = subset(ALfig, !is.na(Arm)), aes(group = tee)) +
#  geom_point(size = .1, position = position_dodge(width = .5)) +
#  geom_smooth(span = .5, aes(colour = Arm, group = Arm)) +
  #scale_x_log10(breaks = c(1, 100, 1000, 10000, 20000, 30000, 50000)) +
  geom_boxplot(aes(x= tee, y = TotalValue, colour = Arm))+
  #scale_y_log10(breaks = c(1, 1000, 5000, 10000, 20000, 50000, 100000, 500000)) +
  scale_y_continuous(breaks = seq(0, 100000, 10000), limits = c(0, 100000)) +
  theme(axis.text.x = element_text(angle = 90, vjust = 1, hjust = 1),
   strip.text.y = element_text(colour = "blue"), legend.position = "none") +
  facet_grid(. ~ Arm)
```

```
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo3/TotalAssets.png"),
  g,
  width = 10, height = 4, units = "cm",
  dpi = 300
)
```

```
# dummy chunk
```

Table 22: FD estimation of total assets, original HHs

covariates	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	11745.7*** (1069.4)	20645.4*** (1713.6)	21376.0*** (1841.5)	21977.1*** (1842.9)	23363.2*** (1914.7)	21896.3*** (1827.9)
Large	5295.2** (2070.4)	7434.8*** (2336.4)	7702.6*** (2348.6)	7935.1*** (2361.1)	8117.1*** (2360.1)	7943.6*** (2359.1)
LargeGrace	2859.5* (1701.1)	4071.3** (1836.9)	3925.7** (1814.7)	4029.3** (1793.3)	4112.1** (1786.4)	4047.2** (1771.6)
Cow	2543.2 (1743.1)	4880.4* (2714.2)	4985.7* (2692.2)	4986.3* (2633.5)	5030.1* (2611.3)	4940.2* (2632.9)
rd 2 - 3		−10562.2*** (2737.0)	−10460.2*** (2755.6)	−10458.7*** (2756.6)	−13428.4*** (3011.1)	−10457.0*** (2756.1)
Large × rd 2 - 3		−8049.8 (6468.7)	−7556.3 (6444.7)	−7615.0 (6459.6)	−8595.3 (6389.6)	−7615.2 (6458.9)
LargeGrace × rd 2 - 3		−436.4 (6266.2)	−419.9 (6263.0)	−439.7 (6263.7)	−897.1 (6186.2)	−454.2 (6262.2)
Cow × rd 2 - 3		−12684.5 (8193.9)	−12827.8 (8310.8)	−12856.6 (8315.6)	−13008.1 (8190.4)	−12863.6 (8316.0)
rd 3 - 4		−21002.1*** (2250.7)	−21048.4*** (2231.3)	−21055.9*** (2230.2)	−22508.8*** (2239.2)	−21065.9*** (2226.2)
Large × rd 3 - 4		−10252.2* (5445.8)	−10677.1* (5454.3)	−10762.3** (5476.6)	−11305.4** (5439.7)	−10754.1** (5471.8)
LargeGrace × rd 3 - 4		−8479.6** (3356.6)	−8519.0** (3351.1)	−8557.5** (3350.9)	−8803.8*** (3282.0)	−8563.6** (3351.1)
Cow × rd 3 - 4		−10619.9 (6558.2)	−10497.3 (6455.7)	−10633.2* (6447.7)	−10743.3* (6315.3)	−10668.2* (6434.0)
HadCows				−3805.4** (1582.0)	−11695.5*** (3730.5)	
HadCows × rd 2 - 3					15844.0*** (5235.4)	
HadCows × rd 3 - 4					7754.0 (6031.2)	
NumCowsOwnedAtRd1						−2553.3** (1282.7)
FloodInRd1			−1527.2 (1101.2)	−1548.7 (1096.6)	−1528.5 (1097.1)	−1488.1 (1111.8)
Head literate			−425.2 (1539.4)	−156.7 (1544.6)	−160.9 (1546.1)	−166.7 (1563.1)
$T=2$	16	16	16	16	16	16
$T=3$	52	52	50	50	50	50
$T=4$	665	665	665	665	665	665
$\bar{R}^2$	0.001	0.056	0.057	0.058	0.062	0.058
$\hat{\rho}$	−0.167	−0.155	−0.152	−0.162	−0.163	−0.158
$\Pr[\hat{\rho}=0]$	0.000	0.000	0.000	0.000	0.000	0.000
N	2115	2115	2111	2111	2111	2111

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Household assets do not include livestock. Regressions (1)-(3), (5)-(6) use only arm and calendar information. (4) and (7) use previous six month repayment and saving information which is lacking in rd 1, hence starts from rd 2.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

Table 23: FD estimation of total assets by attributes

covariates	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	11745.7***	20645.4***	21376.0***	21977.1***	23442.2***	21896.3***
	(1069.4)	(1713.6)	(1841.5)	(1842.9)	(1910.2)	(1827.9)
Upfront	5295.2**	7434.8***	7702.6***	7935.1***	7945.0***	7943.6***
	(2070.4)	(2336.4)	(2348.6)	(2361.1)	(2370.2)	(2359.1)
WithGrace	−2435.6	−3363.5	−3777.0	−3905.8	−3893.4	−3896.3
	(2212.0)	(2453.7)	(2514.8)	(2509.1)	(2518.7)	(2505.4)
InKind	−316.3	809.1	1060.0	957.0	867.0	893.0
	(1909.1)	(2815.8)	(2823.0)	(2763.1)	(2676.3)	(2758.7)
rd 2 - 3		−10562.2***	−10460.2***	−10458.7***	−13354.8***	−10457.0***
		(2737.0)	(2755.6)	(2756.6)	(2993.4)	(2756.1)
Upfront × rd 2 - 3		−8049.8	−7556.3	−7615.0	−8574.2	−7615.2
		(6468.7)	(6444.7)	(6459.6)	(6397.3)	(6458.9)
WithGrace × rd 2 - 3		7613.3	7136.5	7175.3	7797.9	7161.0
		(6885.1)	(6856.4)	(6863.0)	(6754.3)	(6858.8)
InKind × rd 2 - 3		−12248.0	−12407.9	−12416.9	−11968.0	−12409.4
		(8526.5)	(8636.1)	(8636.3)	(8250.7)	(8635.4)
rd 3 - 4		−21002.1***	−21048.4***	−21055.9***	−22467.8***	−21065.9***
		(2250.7)	(2231.3)	(2230.2)	(2219.3)	(2226.2)
Upfront × rd 3 - 4		−10252.2*	−10677.1*	−10762.3**	−11042.7**	−10754.1**
		(5445.8)	(5454.3)	(5476.6)	(5264.1)	(5471.8)
WithGrace × rd 3 - 4		1772.6	2158.0	2204.8	2387.9	2190.4
		(5561.0)	(5569.0)	(5576.6)	(5427.7)	(5572.3)
InKind × rd 3 - 4		−2140.3	−1978.3	−2075.7	−1659.6	−2104.6
		(6654.3)	(6554.9)	(6535.4)	(6109.9)	(6525.1)
HadCows				−3805.4**	−11909.0***	
				(1582.0)	(3555.1)	
HadCows × rd 2 - 3					15927.8***	
					(5031.6)	
HadCows × rd 3 - 4					8170.2	
					(5722.2)	
NumCowsOwnedAtRd1						−2553.3**
						(1282.7)
FloodInRd1			−1527.2	−1548.7	−1610.3	−1488.1
			(1101.2)	(1096.6)	(1104.2)	(1111.8)
Head literate			−425.2	−156.7	39.5	−166.7
			(1539.4)	(1544.6)	(1563.5)	(1563.1)
HadCows × WithGrace					−4688.7	
					(4156.0)	
HadCows × WithGrace × rd 2 - 3					−19239.6*	
					(11288.4)	
HadCows × WithGrace × rd 3 - 4					−3554.5	
					(11845.8)	
HadCows × InKind					−2058.8	
					(4606.7)	
HadCows × InKind × rd 2 - 3					35785.5**	
					(16256.4)	
HadCows × InKind × rd 3 - 4					23359.9*	
					(13978.8)	
$T = 2$	16	16	16	16	16	16
$T = 3$	52	52	50	50	50	50
$T = 4$	665	665	665	665	665	665
$\bar{R}^2$	0.001	0.056	0.057	0.058	0.064	0.058
$\hat{\rho}$	−0.167	−0.155	−0.152	−0.162	−0.170	−0.158
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000
N	2115	2115	2111	2111	2111	2111

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. LargeSize is an indicator function if the arm is of large size, WithGrace is an indicator function if the arm is with a grace period, InKind is an indicator function if the arm provides a cow. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Household assets do not include livestock. Regressions (1)-(3), (5)-(6) use only arm and calendar information. (4) and (7) use previous six month repayment and saving information which is lacking in rd 1, hence starts from rd 2.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

III.6 Assets+Livestock-Debt

Tabulation in ass for Mstatus, BorrowerStatus, creditstatus.

```
#ass ← readRDS(paste0(pathsaveHere, "AssetAdminDataUsedForEstimation.rds"))
ass ← readRDS(paste0(pathsaveHere, DataFileNames[4], "InitialSample.rds"))
```

```
if (Only800) ass ← ass[o800 == 1L, ]
# creaditstatus != yes are pure controls
table0(ass[survey == 1,.(BorrowerStatus, creditstatus)])
```

```
                 creditstatus
BorrowerStatus    Yes  No
  borrower        597   0
  pure saver        0   0
  quit membership   0 199
```

```
table0(ass[survey == 1,.(Mstatus, creditstatus)])
```

```
              creditstatus
Mstatus         Yes  No
  gErosion        0  40
  gRejection      0  70
  iRejection      0  89
  iReplacement    0   0
  newGroup        0   0
  oldMember     597   0
```

```
ass[, grepout("Loan|UD|Forced", colnames(ass)) := NULL]
CovStrings ← "^groupid$|hhid|tee|^dummy.*[a−z]$|Floo|Time\\.?.|With|.Size|Head|^creditsta
ass ← ass[!(hhid == 7043715 & HAssetAmount == 0), ]
ass1 ← ass[, grepout(paste0(CovStrings, "^HAsse"), colnames(ass)), with = F]
ass1R ← ass[, grepout(paste0(CovStrings, "^HAsse|RM"), colnames(ass)), with = F]
ass2 ← ass[, grepout(paste0(CovStrings, "^PAsse"), colnames(ass)), with = F]
ass2R ← ass[, grepout(paste0(CovStrings, "^PAsse|RM"), colnames(ass)), with = F]
# before-after style 2 time point data. Choose tee == 2 as baseline because there are many
#ass ← readRDS(paste0(pathsaveHere, "AssetAdminDataUsedForEstimation.rds"))
ass ← readRDS(paste0(pathsaveHere, DataFileNames[4], "InitialSample.rds"))
if (Only800) ass ← ass[o800 == 1L, ]
ass ← ass[!(hhid == 7043715 & HAssetAmount == 0), ]
ass[, grepout("Time|Loan", colnames(ass)) := NULL]
ass3 ← ass[tee == 2 | tee == 4, grepout(paste0(CovStrings, "^HAsse"), colnames(ass)), wit
ass3R ← ass[tee == 2 | tee == 4, grepout(paste0(CovStrings, "^HAsse|RM"), colnames(ass)),
ass4 ← ass[tee == 2 | tee == 4, grepout(paste0(CovStrings, "^PAsse"), colnames(ass)), wit
ass4R ← ass[tee == 2 | tee == 4, grepout(paste0(CovStrings, "^PAsse|RM"), colnames(ass)),
datas0 ← paste0("ass", rep(1:4, each = 2), c("", "R"))
datas ← paste0("as", rep(1:4, each = 2), c("", "R"))
ddatas ← paste0("d", datas)
ddatasd ← paste0(ddatas, "d")
for (i in 1:length(datas)) {
#   dl ← prepFDData(get(datas0[i]), Group = "^hhid$", TimeVar = "tee", Cluster = "groupic
#     # before considering pure control contrast
#     #LevelCovariates = "^dummy|Floo|^Time\\..$|Head",
#     # after considering pure control contrast
#     LevelCovariates = "^dummy|Floo|^Time\\..$|Head|^cred.*s$",
#     drop.if.NA.in.differencing = T, LevelPeriodToKeep = "last",
#     use.var.name.for.dummy.prefix = F, print.messages = F)
   dl ← FirstDiffPanelData(X = get(datas0[i]),
     Group = "^hhid$", TimeVar = "tee", Cluster = "groupid",
     LevelCovariates = "^dummy|Head|^Time\\..$|Female$|Floo|Eldest|^cred.*s$|xid$|SchPa|^A
  dat ← dl$diff
  dat[, grepout("^en$", colnames(dat)) := NULL]
  # create PureControl*Time2, Time3 interactions and drop creditstatus
```

```
  if (grepl("ass[12]", datas0[i]) & any(grepl("cred.*s$", colnames(dat)))) {
    dat[, PureControl := 0L]
    dat[!grepl("es$", creditstatus), PureControl := 1L]
    dat[, creditstatus := NULL]
    dat[, c("PureControl.Time3", "PureControl.Time4") :=
      .(PureControl * Time.3, PureControl * Time.4)]
  }
  assign(ddatas[i], dl)
  assign(ddatasd[i], dat)
}
```

```
Dropped 64 obs due to T<2.
Dropped 735 obs due to NA.
Dropped 64 obs due to T<2.
Dropped 1604 obs due to NA.
Dropped 64 obs due to T<2.
Dropped 735 obs due to NA.
Dropped 64 obs due to T<2.
Dropped 1604 obs due to NA.
Dropped 69 obs due to T<2.
Dropped 666 obs due to NA.
Dropped 69 obs due to T<2.
Dropped 721 obs due to NA.
Dropped 69 obs due to T<2.
Dropped 666 obs due to NA.
Dropped 69 obs due to T<2.
Dropped 721 obs due to NA.
```

```
das1Rd <- das1Rd[tee > 2, ]
das2Rd <- das2Rd[tee > 2, ]
das1d[, Tee := .N, by = hhid]
das2d[, Tee := .N, by = hhid]
```

```
#lvo <-  readRDS(paste0(pathsaveHere, "LivestockAdminDataUsedForEstimation.rds"))
lvo <- readRDS(paste0(pathsaveHere, DataFileNames[5], "InitialSample.rds"))
if (Only800) lvo <- lvo[o800 == 1L, ]
table0(lvo[, .(tee, Arm)])
```

```
   Arm
tee traditional large large grace cow
  1         199   200         189 200
  2         168   195         188 195
  3         163   192         173 190
  4         143   188         164 170
```

```
table0(lvo[grepl("ow", LivestockCode), .(tee, Arm)])
```

```
   Arm
tee traditional large large grace cow
  1          31    44          36  32
  2          88   137         137 159
  3         119   169         156 163
  4          99   157         136 145
```

```
# xid <- readRDS(paste0(path1234, "ID.rds"))
# xidlv <- xid[,.(Mstatus, AssignOriginal, groupid, hhid, survey, year)]
# setnames(xidlv, "AssignOriginal", "Arm")
# setkey(lvo, Arm, groupid, hhid, survey, Mstatus)
```

```
# setkey(xidlv, Arm, groupid, hhid, survey, Mstatus)
# lvo ← merge(lvo, xidlv, by = key(xidlv), all = T)
lvo[, grepout("Loan|UD|Forced", colnames(lvo)) := NULL]
lvostrings ← "^groupid$|hhid|^Arm$|tee|^dummy[TLCMUWS]|creditst|^TotalIm|Floo|Time\\.|liv
lvoR ← lvo[, grepout(paste0(lvostrings, "|RM"), colnames(lvo)), with = F]
lvo ← lvo[, grepout(lvostrings, colnames(lvo)), with = F]
lvo3 ← lvo[tee == 2 | tee == 4, ]
lvoR3 ← lvoR[tee == 2 | tee == 4, ]
datas ← c("lvo", "lvoR", "lvo3", "lvoR3")
ddatas ← paste0("d", datas)
ddatasd ← paste0(ddatas, "d")
for (i in 1:length(datas)) {
#   dl ← prepFDData(get(datas[i]), Group = "^hhid$", TimeVar = "tee", Cluster = "groupid"
#     LevelCovariates = "^dummy|^Arm$|Floo|^Time\\..$|Head|Cows|liv.*de$|credits",
#     drop.if.NA.in.differencing = T, LevelPeriodToKeep = "last",
#     use.var.name.for.dummy.prefix = F, print.messages = F)
   dl ← FirstDiffPanelData(X = get(datas[i]),
     Group = "^hhid$", TimeVar = "tee", Cluster = "groupid",
     LevelCovariates = "^dummy|^Arm$|Floo|^Time\\..$|Head|Cows|liv.*de$|credits|xid$|SchPa
  dat ← dl$diff
  dat[, grepout("^en$", colnames(dat)) := NULL]
  assign(ddatas[i], dl)
  assign(ddatasd[i], dat)
}
```

```
Dropped 64 obs due to T<2.
Dropped 735 obs due to NA.
Dropped 64 obs due to T<2.
Dropped 1604 obs due to NA.
Dropped 81 obs due to T<2.
Dropped 665 obs due to NA.
Dropped 81 obs due to T<2.
Dropped 720 obs due to NA.
```

```
dlvoRd ← dlvoRd[tee > 1, ]
```

```
#ass ←  readRDS(paste0(pathsaveHere, "RosterAssetAdminOriginalHHsDataUsedForEstimation.rc
ass ← readRDS(paste0(pathsaveHere, DataFileNames[4], "InitialSample.rds"))
arA ← readRDS(paste0(pathsaveHere, DataFileNames[2], "InitialSample.rds"))
ass[, grepout("Loan|UD|Forced", colnames(ass)) := NULL]
# merge debt outstanding to assets.
# arA has on avg 12 meetings per survey round. Which meeting in a survey round
# should I use? Merge both immediate past and future dates.
# First, reshape AssD to wide: hhid survey IntDate1, ..., IntDate4
# Second, merge with arA and find meetings immediately before and after IntDatX
# Third, keep only meetings immediately before and after IntDatX
arD ← arA[, .(hhid, survey, tee, Date, CumLoanAmount,
  CumEffectiveRepayment, CumRepaid, CumNetSaving, DebtOutstanding)]
assD ← ass[!is.na(IntDate), .(Arm, BStatus, hhid, survey, IntDate)]
assDW ← reshape(assD, direction = "wide", idvar = c("Arm", "BStatus", "hhid"),
  timevar = "survey", v.names = "IntDate")
setkey(assDW, hhid); setkey(arD, hhid)
arDebt ← assDW[arD]
arDebt[, c("PeriodPos", "SVY") := .(as.character(NA), as.integer(NA))]
for (i in 1:4) {
  arDebt[, DiffDays := Date - eval(parse(text=paste0("IntDate.", i)))]
```

```
  arDebt[, ImmedAfter := min(DiffDays[DiffDays ≥ 0], na.rm = T), by = hhid]
  arDebt[, ImmedBefore := max(DiffDays[DiffDays < 0], na.rm = T), by = hhid]
  arDebt[, (paste0(c("MtgBefore.", "MtgAfter."), i)) := 0L]
  arDebt[DiffDays == ImmedBefore, (paste0("MtgBefore.", i)) := 1L]
  arDebt[DiffDays == ImmedBefore, c("PeriodPos", "SVY") := .("before", as.integer(i))]
  arDebt[DiffDays == ImmedAfter, (paste0("MtgAfter.", i)) := 1L]
  arDebt[DiffDays == ImmedAfter, c("PeriodPos", "SVY") := .("after", as.integer(i))]
}
arDebt ← arDebt[eval(parse(text=
  paste(
    paste0(grepout("Mtg", colnames(arDebt)), collapse = "+")
  , "!=0")
  )), ]
arDebt[, grepout("^IntD.*[1-4]$|^Diff|^M..Diff|^Immed|^Mtg[AB]|survey", colnames(arDebt))
setnames(arDebt, "SVY", "survey")
arDebtW ← reshape(arDebt, direction = "wide", idvar = c("hhid", "survey"),
  timevar = "PeriodPos", v.names = grepout("Cum|Date|Deb|tee", colnames(arDebt)))
setkey(arDebtW, Arm, BStatus, hhid, survey)
setkey(ass, Arm, BStatus, hhid, survey)
ass ← arDebtW[ass]
# use before. using after gives many cases of NetValue > TotalValue
assstrings ← "^Arm$|^groupid$|hhid|tee|^.Asse|^dummy.*[a-z]$|Floo|Time\\.?.|Head|With|.Si
lvostrings ← "^groupid$|hhid|tee|^TotalIm|Cows"
if (Only800) ass ← ass[o800 == 1L, ]
ass1 ← ass[, grepout(assstrings, colnames(ass)), with = F]
ass1R ← ass[, grepout(paste0(assstrings, "|RM"), colnames(ass)), with = F]
lvo ← readRDS(paste0(pathsaveHere, DataFileNames[5], "InitialSample.rds"))
if (Only800) lvo ← lvo[o800 == 1L, ]
lvo[, grepout("Loan|UD|Forced", colnames(lvo)) := NULL]
lvo1 ← lvo[, grepout(lvostrings, colnames(lvo)), with = F]
# merge
commoncols ← intersect(colnames(ass1), colnames(lvo1))
NeA1 ← merge(ass1, lvo1, by = commoncols, NeAl = T)
NeA1[is.na(TotalImputedValue), TotalImputedValue := 0]
NeA1[, TotalValue := TotalImputedValue + HAssetAmount + PAssetAmount]
NeA1[, NetValue := TotalValue − a2b(DebtOutstanding.before, NA, 0)]
NeA1[, c("TotalImputedValue", "HAssetAmount",
  "PAssetAmount", "TotalValue") := NULL]
NeA1 ← unique(NeA1)
NeA1[, grepout("before", colnames(NeA1)) := NULL]
# before-after style 2 time point data. Choose tee == 2 as baseline because there are many
NeA2 ← NeA1[tee == 2 | tee == 4, ]
NeA2[, grepout("Time", colnames(NeA2)) := NULL]
commoncols ← intersect(colnames(ass1R), colnames(lvo1))
NeA1R ← merge(ass1R, lvo1, by = commoncols, NeAl = T)
NeA1R[is.na(TotalImputedValue), TotalImputedValue := 0]
NeA1R[, TotalValue := TotalImputedValue + HAssetAmount + PAssetAmount]
NeA1R[, NetValue := TotalValue − a2b(DebtOutstanding.before, NA, 0)]
NeAfig ← NeA1R[, .(Arm, groupid, hhid, dummyUltraPoor, tee, NetValue)]
setnames(NeAfig, c("NetValue", "dummyUltraPoor"), c("TotalValue", "UltraPoor"))
NeAfig[, povertystatus := "ultra poor"]
NeAfig[UltraPoor == 0L, povertystatus := "moderately poor"]
NeAfig[, povertystatus := factor(povertystatus,
  levels = c("ultra poor","moderately poor"))]
NeAfig[, UltraPoor := NULL]
```

```
NeA1R[, c("TotalImputedValue", "HAssetAmount",
  "PAssetAmount", "TotalValue") := NULL]
NeA1R[, grepout("before", colnames(NeA1R)) := NULL]
NeA1R <- unique(NeA1R)
NeA2R <- NeA1R[tee == 2 | tee == 4, ]
NeA2R[, grepout("Time", colnames(NeA2)) := NULL]

datas <- c(paste0("NeA", 1:2), paste0("NeA", 1:2, "R"))
ddatas <- paste0("d", datas)
ddatasd <- paste0(ddatas, "d")
for (i in 1:length(datas)) {
  dl <- prepFDData(get(datas[i]), Group = "^hhid$",
      TimeVar = "tee", Cluster = "groupid",
      LevelCovariates = "^dummy|^Arm|Floo|^Time\\..$|Head|Cows|BSta",
      drop.if.NA.in.differencing = T, LevelPeriodToKeep = "last",
      use.var.name.for.dummy.prefix = F, print.messages = F)
  dat <- dl$diff
  if (i == 1) {
    # Recreate Time.4 which is dropped when kept only 1:(T-1) obs.
    #dat[, c("Time.2", "Time.3", "Time.4") := 0L]
    #dat[tee == 1, Time.2 := 1L]
    #dat[tee == 2, Time.3 := 1L]
    #dat[tee == 3, Time.4 := 1L]
    dat[, grepout("Time.?2", colnames(dat)) := NULL]
  }
  assign(ddatas[i], dl)
  assign(ddatasd[i], dat)
}
dNeA1Rd <- dNeA1Rd[tee > 2, ]
saveRDS(NeA1, paste0(pathsaveHere, "NetAssets.rds"))
write.tablev(NeA1, paste0(pathsaveHere, "NetAssets.prn"), colnamestrue = F)

FileName <- "NetAsset"
FileNameHeader <-
  paste0(c("", "Grace", "PovertyStatus", "Size", "Attributes",
    "TInt", "TIntGrace", "TIntSize", "Rd24Diff", "Rd24DiffGrace",
    "Rd24DiffPovertyStatus", "Rd24DiffSize", "Rd24DiffAttributes"), "OriginalHHs")
neasuffixes <- c("", "G", "P", "S", "a", "T", "TG", "TS", "D", "DG", "DP", "DS", "Da")
listheader <- paste0("nea", neasuffixes)
DataToUse1 <- rep("dNeA1d", 6)
DataToUse2 <- rep("dNeA2d", 6)
Addseparatingcols <- NULL; Separatingcolwidth <- NULL
Separatingcoltitle <- NULL
Regressands <- rep("NetValue", 6)
tableboxwidth <- 4.5

source(paste0(pathprogram, "NetAssetCovariateSelection.R"))

exclheader <- paste0("excl", neasuffixes)
source(paste0(pathprogram, "FDEstimationFile.R"))
saveRDS(fdplist, paste0(pathsave, "FD_netassets.rds"))

library(ggplot2)
d1 <- subset(ALfig, !is.na(Arm))
d2 <- subset(NeAfig, !is.na(Arm))
ColourForPoints <- c("darkblue", "darkred")
```

```
g <- ggplot(data = subset(d2, tee == 1 & 0 <= TotalValue & TotalValue < 100000),
  aes(x=TotalValue, fill = povertystatus)) +
  geom_histogram(bins=50, alpha=.5, position="identity",
    aes(x = TotalValue, y = ..density..)) +
  scale_x_log10() +
  theme(
    axis.text.x = element_text(size = 6),
    axis.text.y = element_text(size = 6),
    axis.title = element_text(size = 7),
    legend.key.size = unit(.15, "cm"),
    legend.text = element_text(size = 6),
    legend.title = element_text(size = 6),
    legend.position = "bottom")
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo3/NetAssetsAtRd1.png"),
  g,
  width = 12, height = 6, units = "cm",
  dpi = 300
 )
# postscript does not support transparency.
# setEPS()
# postscript(file =
#   paste0(pathprogram,
#     "figure/ImpactEstimationOriginal1600Memo3/NetAssetsAtRd1.eps"),
#   , width = 5, height = 2.5, horizontal = F) # unit: inch
# print(g)
# dev.off()
pdf(file =
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo3/NetAssetsAtRd1.pdf"),
  , width = 8/2.54, height = 5/2.54, pointsize = 10) # native unit: inch
print(g)
dev.off()
```

```
pdf
  2
```

```
library(ggplot2)
d1 <- subset(ALfig, !is.na(Arm))
d2 <- subset(NeAfig, !is.na(Arm))
d1[, Type := "gross assets"]
d2[, Type := "net assets"]
dd <- rbindlist(list(d1, d2), use.names = T, fill = T)
dd[, Type := factor(Type, levels = c("gross assets", "net assets"))]
ddn <- subset(dd, grepl("net", Type))
g <- ggplot(data = ddn) +
  geom_boxplot(aes(x= factor(tee), y = TotalValue, colour = povertystatus),
    outlier.alpha = 0.1)+
  scale_x_discrete(name = "survey round") +
  scale_y_continuous(name = "asset values (Tk.)",
    breaks = seq(0, 100000, 10000), limits = c(0, 100000)) +
  theme(
   axis.text.x = element_text(size = 6),
   axis.text.y = element_text(size = 6),
   axis.title = element_text(size = 7),
```

```
    strip.text.x = element_text(color = "blue", size = 6,
      margin = margin(0, .5, 0, .5, "cm")),
    strip.text.y = element_text(color = "blue", size = 6,
      margin = margin(.5, 0, .5, 0, "cm")),
    legend.position = "bottom") +
  facet_grid(. ~ Arm)
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo3/NetAssets.png"),
  g,
  width = 12, height = 6, units = "cm",
  dpi = 300
 )
setEPS()
postscript(file =
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo3/NetAssets.eps"),
  , horizontal = F)
print(g)
dev.off()
```

```
pdf
  2
```

```
library(ggplot2)
ass <- readRDS(paste0(pathsaveHere, DataFileNames[4], "InitialSample.rds"))
assC <- ass[!grepl("^bo", BStatus), .(hhid, tee, povertystatus, BStatus, AssetAmount)]
setnames(assC, "AssetAmount", "TotalValue")
for (i in 1:3)
  for (j in (i+1):4) {
    assC1 <- reshape(assC[tee == i|tee == j, ], direction = "wide",
          idvar = c("hhid", "povertystatus"),
          timevar = "tee", v.names = "TotalValue")
    assC1[, c("before", "after") := .(i, j)]
    assign(paste0("a", i, j), assC1)
  }
d2W <- rbindlist(list(a12, a13, a14, a23, a24, a34))
setnames(d2W, c("TotalValue.1", "TotalValue.2"),
  c("TotalValue.before", "TotalValue.after"))
d2W <- d2W[!is.na(povertystatus), ]
ColourForPoints <- c("darkblue", "darkred")
CapitalType <- c("NonborrowerGrossAssets", "GrossAssets", "NetAssets")
j <- CapitalType[1]
g <- ggplot(data = d2W,
  aes(x= TotalValue.before, y = TotalValue.after,
    colour = povertystatus, group = povertystatus)) +
  geom_point(aes(fill = povertystatus), size = .01,
    position = position_dodge(width = .5), #colour = "transparent",
    alpha = .6) +
  geom_smooth(span = .5, size = .75,
    aes(colour = povertystatus, group = povertystatus)) +
  geom_abline(intercept = 0, slope = 1,
    aes(colour = "yellow", size = .75)) +
  scale_colour_manual(values = ColourForPoints) +
  scale_fill_manual(values = c("blue", "red")) +
  scale_x_continuous(name = "net assets in t (Tk)")+
```

```
  scale_y_continuous(name = "net assets in t+1 (Tk)")+
  theme(
    axis.text.x = element_text(size = 5, angle = 45, vjust = 1, hjust = 1),
    axis.text.y = element_text(size = 5),
    axis.title = element_text(size = 6),
    strip.text.x = element_text(color = "blue", size = 5,
      margin = margin(0, .5, 0, .5, "cm")),
    strip.text.y = element_text(color = "blue", size = 4,
      margin = margin(.5, 0, .5, 0, "cm")),
     legend.text = element_text(size = 6),
     legend.title = element_text(size = 7),
     legend.key = element_rect(fill = "white"),
     legend.key.size = unit(.5, "cm"),
    legend.position = "bottom")
g1 <- g + facet_wrap(before ~ after, scales = "free")
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo3/NonborrowerGrossAssetsDynamicsByPovertyStatu
  , g1, width = 12, height = 8, units = "cm", dpi = 300
 )
setEPS()
postscript(file =
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo3/NonborrowerGrossAssetsDynamicsByPovertyStat
  , horizontal = F)
print(g1)
dev.off()
```

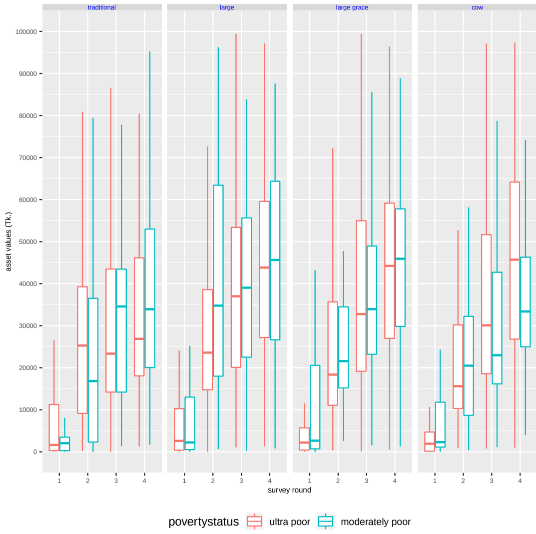
```
pdf
  2
```

```
for (j in CapitalType[-1]){
  if (grepl("et", j))
    d2 <- subset(NeAfig, !is.na(Arm)) else
    d2 <- subset(ALfig, !is.na(Arm))
  d2[, ArmSize := "large size"]
  d2[grepl("tra", Arm), ArmSize := "small size"]
  d2W <- reshape(d2, direction = "wide",
    idvar = c("hhid", "povertystatus"),
    timevar = "tee", v.names = "TotalValue")
  d2W <- d2W[!is.na(povertystatus), ]
  for (i in 1:2) {
    g <- ggplot(data = d2W,
      aes(x= !!sym(paste0("TotalValue.", i)), y = !!sym(paste0("TotalValue.", i+1)),
        colour = povertystatus, group = povertystatus)) +
      geom_point(aes(fill = povertystatus), size = .01,
        position = position_dodge(width = .5), #colour = "transparent",
        alpha = .6) +
      geom_smooth(span = .5, size = .75,
        aes(colour = povertystatus, group = povertystatus)) +
      geom_abline(intercept = 0, slope = 1,
        aes(colour = "yellow", size = .75)) +
      scale_colour_manual(values = ColourForPoints) +
      scale_fill_manual(values = c("blue", "red")) +
      scale_x_continuous(name = paste0("net assets in round", i, " (Tk)"),
        limits = c(0, 20000))+
```

```
#         breaks = seq(0, 100000, 10000), limits = c(0, 100000)) +
      scale_y_continuous(name = paste("net assets in round", i+1, "(Tk)"),
        limits = c(0, 20000))+
#         breaks = seq(0, 100000, 10000), limits = c(0, 100000)) +
      theme(
        axis.text.x = element_text(size = 6),
        axis.text.y = element_text(size = 6),
        axis.title = element_text(size = 7),
        strip.text.x = element_text(color = "blue", size = 6,
          margin = margin(0, .5, 0, .5, "cm")),
        strip.text.y = element_text(color = "blue", size = 6,
          margin = margin(.5, 0, .5, 0, "cm")),
        legend.position = "none")
    g1 <- g + facet_grid(. ~ povertystatus)
    g2 <- g + facet_grid(povertystatus ~ Arm)
    g3 <- g + facet_grid(povertystatus ~ ArmSize)
    ggsave(
      paste0(pathprogram,
        "figure/ImpactEstimationOriginal1600Memo3/", j,
        "DynamicsByPovertyStatusBaseRound", i, ".png")
      , g1, width = 12, height = 8, units = "cm", dpi = 300
    )
    ggsave(
      paste0(pathprogram,
        "figure/ImpactEstimationOriginal1600Memo3/", j,
        "DynamicsByArmAndPovertyStatusBaseRound", i, ".png")
      , g2, width = 12, height = 6, units = "cm", dpi = 300
    )
    ggsave(
      paste0(pathprogram,
        "figure/ImpactEstimationOriginal1600Memo3/", j,
        "DynamicsByArmSizeAndPovertyStatusBaseRound", i, ".png")
      , g3, width = 6, height = 6, units = "cm", dpi = 300
    )
  }
}
```

```
# dummy chunk
```

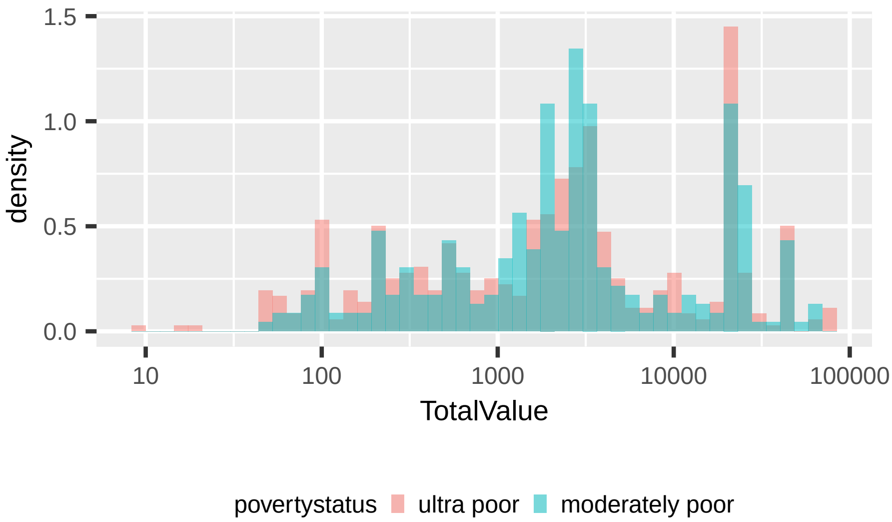
Figure 10: Total and net asset values



Source: Survey data.

Note: Top panel shows total gross asset values. Bottom panel shows total net asset values = total gross asset values - debt outstanding. Debt outstanding takes the value of the month immediately after the respective survey round interview.

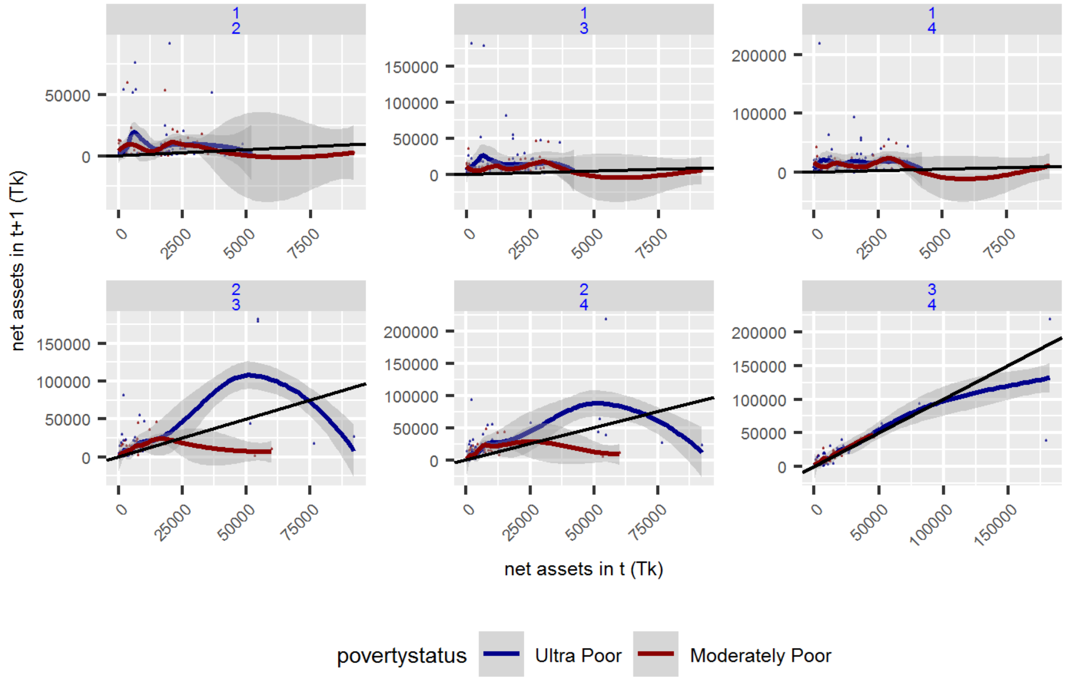
Figure 11: Net asset values at round 1



Source: Survey data.

Note: Net asset values = total gross asset values - debt outstanding. Debt outstanding takes the value of the month immediately after the respective survey round interview.

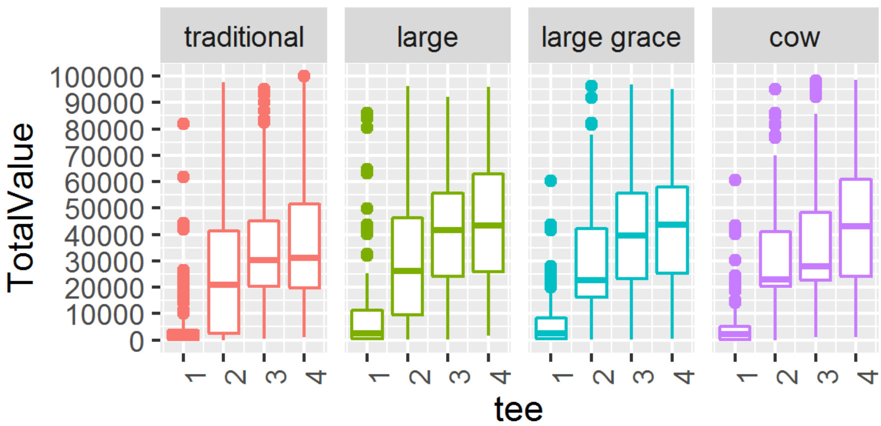
FIGURE 12: TOTAL ASSET DYNAMICS OF NONBORROWERS



Source: Survey data.

Note: Only for nonborrowers. Scatter plots contrast t vs. $t + 1$ comparison where t and $t + 1$ are given in strip ribbons of each panel.

FIGURE 13: FE ESTIMATES OF NET ASSET VALUES



Source: Survey data.

Note: Estimates on each arms and their period interactions. Net asset values = total gross asset values - debt outstanding.

TABLE 24: FD ESTIMATION OF NET ASSETS, ORIGINAL HHS

covariates	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	10994.2*** (1117.8)	14009.9*** (1785.7)	14855.4*** (1917.5)	15435.1*** (1908.8)	16725.2*** (1935.3)	15357.6*** (1896.4)
Large	6189.6*** (2093.7)	6660.8*** (2465.4)	6968.5*** (2472.1)	7192.6*** (2482.9)	7275.7*** (2503.5)	7201.0*** (2479.0)
LargeGrace	4018.1** (1766.5)	2594.3 (1865.4)	2421.9 (1823.6)	2521.8 (1801.5)	2709.1 (1799.7)	2539.2 (1782.4)
Cow	3573.7** (1800.1)	3760.9 (2635.1)	3869.8 (2602.8)	3870.4 (2542.7)	3987.4 (2503.3)	3825.9 (2542.8)
rd 2 - 3		575.9 (2734.4)	674.7 (2754.0)	676.1 (2755.3)	−2207.3 (2967.8)	677.8 (2754.6)
Large × rd 2 - 3		1488.2 (6979.8)	1984.5 (6957.6)	1928.0 (6973.9)	629.5 (6873.1)	1927.7 (6973.1)
LargeGrace × rd 2 - 3		15028.8** (6175.1)	15049.2** (6170.3)	15030.0** (6171.8)	14471.1** (6323.7)	15016.0** (6170.2)
Cow × rd 2 - 3		433.2 (7920.2)	272.3 (8047.4)	244.5 (8052.1)	−5.6 (7961.3)	237.7 (8052.7)
rd 3 - 4		−9331.3*** (2327.4)	−9379.7*** (2311.5)	−9387.0*** (2312.4)	−10780.2*** (2216.2)	−9396.6*** (2309.3)
Large × rd 3 - 4		−3819.5 (6095.8)	−4264.9 (6108.5)	−4347.1 (6132.4)	−4763.7 (5680.6)	−4339.2 (6127.9)
LargeGrace × rd 3 - 4		2197.5 (3299.8)	2154.3 (3293.8)	2117.2 (3297.7)	1668.0 (3141.7)	2111.3 (3298.4)
Cow × rd 3 - 4		−1415.1 (6641.4)	−1296.0 (6555.3)	−1427.1 (6555.5)	−1497.1 (6249.4)	−1460.9 (6546.4)
HadCows				−3670.0** (1560.9)	−11954.6*** (3430.6)	
HadCows × rd 2 - 3					15762.0*** (5075.5)	
HadCows × rd 3 - 4					8768.4 (5525.5)	
NumCowsOwnedAtRd1						−2464.7* (1260.1)
FloodInRd1			−1811.3 (1128.1)	−1832.1 (1123.2)	−1847.4 (1135.9)	−1773.5 (1137.6)
Head literate			−270.9 (1543.7)	−11.9 (1547.4)	191.8 (1540.4)	−21.3 (1564.2)
HadCows × Large					7347.4 (4468.3)	
HadCows × LargeGrace					814.7 (3648.4)	
HadCows × Large × rd 2 - 3					−3161.1 (11746.4)	
HadCows × LargeGrace × rd 2 - 3					−27220.9** (12581.0)	
HadCows × Large × rd 3 - 4					−21894.4 (15534.7)	
HadCows × LargeGrace × rd 3 - 4					−20640.0* (10622.1)	
$T = 2$	16	16	16	16	16	16
$T = 3$	52	52	50	50	50	50
$T = 4$	665	665	665	665	665	665
$\bar{R}^2$	0.002	0.02	0.02	0.021	0.028	0.021
$\hat{\rho}$	−0.173	−0.161	−0.162	−0.156	−0.174	−0.151
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000
N	2115	2115	2111	2111	2111	2111

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Household assets do not include livestock. Regressions (1)-(3), (5)-(6) use only arm and calendar information. (4) and (7) use previous six month repayment and saving information which is lacking in rd 1, hence starts from rd 2.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

TABLE 25: FD ESTIMATION OF NET ASSETS BY ATTRIBUTES

covariates	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	10994.2*** (1117.8)	14009.9*** (1785.7)	14855.4*** (1917.5)	15435.1*** (1908.8)	16773.0*** (1969.9)	15357.6*** (1896.4)
Upfront	6189.6*** (2093.7)	6660.8*** (2465.4)	6968.5*** (2472.1)	7192.6*** (2482.9)	7244.0*** (2510.0)	7201.0*** (2479.0)
WithGrace	−2171.5 (2237.3)	−4066.5 (2528.4)	−4546.6* (2586.7)	−4670.8* (2583.9)	−4568.4* (2622.4)	−4661.8* (2577.6)
InKind	−444.4 (1965.2)	1166.5 (2694.1)	1448.0 (2699.4)	1348.6 (2645.1)	1260.3 (2576.1)	1286.7 (2642.4)
rd 2 - 3		575.9 (2734.4)	674.7 (2754.0)	676.1 (2755.3)	−2235.7 (2980.1)	677.8 (2754.6)
Upfront × rd 2 - 3		1488.2 (6979.8)	1984.5 (6957.6)	1928.0 (6973.9)	844.9 (6858.5)	1927.7 (6973.1)
WithGrace × rd 2 - 3		13540.6* (7153.8)	13064.6* (7124.3)	13102.1* (7133.9)	13841.7** (6974.0)	13088.3* (7129.0)
InKind × rd 2 - 3		−14595.6* (8073.9)	−14776.8* (8194.5)	−14785.5* (8195.5)	−14364.8* (7866.0)	−14778.3* (8194.3)
rd 3 - 4		−9331.3*** (2327.4)	−9379.7*** (2311.5)	−9387.0*** (2312.4)	−10794.2*** (2225.6)	−9396.6*** (2309.3)
Upfront × rd 3 - 4		−3819.5 (6095.8)	−4264.9 (6108.5)	−4347.1 (6132.4)	−4675.3 (5703.9)	−4339.2 (6127.9)
WithGrace × rd 3 - 4		6017.0 (5898.6)	6419.2 (5909.8)	6464.3 (5921.3)	6431.7 (5544.5)	6450.4 (5916.2)
InKind × rd 3 - 4		−3612.6 (6460.9)	−3450.3 (6371.5)	−3544.2 (6360.2)	−3172.9 (5980.9)	−3572.2 (6352.2)
HadCows				−3670.0** (1560.9)	−11966.9*** (3426.1)	
HadCows × rd 2 - 3					15826.8*** (5044.2)	
HadCows × rd 3 - 4					8732.0 (5517.5)	
NumCowsOwnedAtRd1						−2464.7* (1260.1)
FloodInRd1			−1811.3 (1128.1)	−1832.1 (1123.2)	−1854.3 (1139.2)	−1773.5 (1137.6)
Head literate			−270.9 (1543.7)	−11.9 (1547.4)	184.4 (1542.9)	−21.3 (1564.2)
HadCows × Upfront					6337.8 (4968.5)	
HadCows × Upfront × rd 2 - 3					6114.5 (11668.1)	
HadCows × Upfront × rd 3 - 4					−19671.7 (16779.7)	
HadCows × WithGrace					−6532.2 (4859.2)	
HadCows × WithGrace × rd 2 - 3					−24060.1* (13095.5)	
HadCows × WithGrace × rd 3 - 4					1254.4 (15267.2)	
HadCows × InKind					−1655.4 (4293.7)	
HadCows × InKind × rd 2 - 3					35010.7** (16007.3)	
HadCows × InKind × rd 3 - 4					22307.7* (13545.5)	
$T = 2$	16	16	16	16	16	16
$T = 3$	52	52	50	50	50	50
$T = 4$	665	665	665	665	665	665
$\bar{R}^2$	0.002	0.02	0.02	0.021	0.028	0.021
$\hat{\rho}$	−0.173	−0.161	−0.162	−0.156	−0.170	−0.151
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000
N	2115	2115	2111	2111	2111	2111

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. LargeSize is an indicator function if the arm is of large size, WithGrace is an indicator function if the arm is with a grace period, InKind is an indicator function if the arm provides a cow. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Household assets do not include livestock. Regressions (1)-(3), (5)-(6) use only arm and calendar information. (4) and (7) use previous six month repayment and saving information which is lacking in rd 1, hence starts from rd 2.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

Table 26: FD estimation of net assets by attributes, round 2 and 4 comparison

covariates	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	16160.3***	16442.3***	18355.9***	18282.2***	18186.4***	17618.3***
	(2817.3)	(2971.2)	(3433.4)	(3534.2)	(3519.8)	(3467.8)
Upfront	13126.8**	13109.8**	13636.6**	13614.9**	13344.4**	13368.0**
	(5395.2)	(5435.3)	(5462.2)	(5409.9)	(5354.9)	(5360.9)
WithGrace	2622.0	2617.4	1624.7	1637.5	2114.0	1766.6
	(5894.4)	(5915.9)	(6035.1)	(5993.8)	(6064.9)	(5944.5)
InKind	−7966.6	−7934.0	−7345.8	−7327.5	−7171.1	−7014.3
	(5014.7)	(4963.5)	(4858.2)	(4852.1)	(4902.0)	(4829.1)
HadCows				433.9	520.1	
				(4829.3)	(4388.9)	
NumCowsOwnedAtRd1						3307.3
						(3629.4)
Head literate		−2372.9	−2368.0	−2397.4	−1626.9	−2689.2
		(7891.7)	(7887.4)	(7928.7)	(7944.1)	(7878.3)
FloodInRd1			−4025.3	−4022.6	−4074.7	−4047.5
			(3223.0)	(3227.0)	(3267.6)	(3192.4)
HadCows × Upfront					8973.3	
					(12988.0)	
HadCows × WithGrace					−25832.3**	
					(12932.2)	
HadCows × InKind					29303.1***	
					(10759.1)	
$\bar{R}^2$	0.013	0.012	0.012	0.011	0.017	0.013
N	665	665	665	665	665	665

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates between round 2 and 4. A first-difference is defined as $\Delta x_{t+k} \equiv x_{t+k} - x_t$ for $k = 1, 2, \ldots$. Saving and repayment misses are taken from administrative data and merged with survey data at Year-Month of survey interviews. Intercept terms are omitted in estimating equations. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Household assets do not include livestock. Regressions (1)-(3), (5)-(6) use only arm and calendar information. (4) and (7) use previous six month repayment and saving information which is lacking in rd 1, hence starts from rd 2.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

III.7 Incomes

```
source(paste0(pathprogram, "ReadTrimIncomeOriginalHHsFDData.R"))
```

```
Dropped 200 obs due to T<2.
Dropped 768 obs due to NA.
Dropped 200 obs due to T<2.
Dropped 1572 obs due to NA.
Dropped 55 obs due to T<2.
Dropped 53 obs due to NA.
Dropped 55 obs due to T<2.
Dropped 60 obs due to NA.
```

```
source(paste0(pathprogram, "ReadTrimIncomeOriginalHHsFDData.R"))
```

```
Dropped 200 obs due to T<2.
Dropped 768 obs due to NA.
Dropped 200 obs due to T<2.
Dropped 1572 obs due to NA.
Dropped 55 obs due to T<2.
Dropped 53 obs due to NA.
Dropped 55 obs due to T<2.
Dropped 60 obs due to NA.
```

Income sources are mainly labour incomes (lab) and farm revenues (far) with 2919 and 184 observations, respectively. After first-differencing, they become 1951 and 72 observations, with 1951 households observed for 1952 times.

Obs for survey labour income.

```
table(dlabd[, tee])
```

```
  2   3   4
607 678 666
```

Obs for survey labour income and admin repayment data.

```
table(dlabRd[, tee])
```

```
  3   4
549 598
```

```
table(dfarRd[, tee])
```

```
 3  4
33 36
```

Obs for survey farm revenue.

```
table(dfard[, tee])
```

```
 3  4
35 37
```

Obs for survey farm revenue and admin repayment data.

```
table(dfarRd[, tee])
```

```
 3  4
33 36
```

```
dlabRd <- dlabRd[tee > 2, ]
dfard <- dfard[tee > 2, ]
dfarRd <- dfarRd[tee > 2, ]

FileName <- "Incomes"
FileNameHeader <- paste0(c("", "Grace", "PovertyStatus", "Size", "Attributes"),
   "OriginalHHs")
lbsuffixes <- c("", "g", "p", "s", "a")
listheader <- paste0("lb", lbsuffixes)
Regressands <- c(rep("TotalHHLabourIncome", 4), rep("TotalRevenue", 3))
DataToUse1 <- DataToUse2 <- c(rep("dlabd", 3), "dlabRd", rep("dfard", 2), "dfarRd")
Addseparatingcols = 4; Separatingcolwidth = .2
Separatingcoltitle = c("Labour income (Tk)", "Farm income (Tk)")

source(paste0(pathprogram, "IncomeCovariateSelection.R"))

exclheader <- paste0("excl", lbsuffixes)
source(paste0(pathprogram, "FDEstimationFile.R"))
saveRDS(fdplist, paste0(pathsave, "FD_income.rds"))

#dummy chunk
```

Table 27: FD estimation of incomes

covariates	Labour income (Tk) (1)	(2)	(3)	(4)	Farm income (Tk) (5)	(6)	(7)
(Intercept)	5.85***	−0.45	−4.32	0.09	−8.30	−16.04	−14.75**
	(1.33)	(3.27)	(3.80)	(4.38)	(6.97)	(9.68)	(6.88)
Large	5.19	0.05	−1.30	16.37	8.71	10.69	14.53
	(5.58)	(3.98)	(3.52)	(13.27)	(7.16)	(7.78)	(9.53)
LargeGrace	−5.81	−15.41	−14.76	1.04	8.90	3.20	−16.55
	(5.21)	(12.98)	(12.54)	(5.37)	(7.08)	(10.24)	(20.01)
Cow	−0.97	−2.91	−3.60	6.15	3.60	4.39	−1.24
	(3.88)	(3.98)	(3.77)	(5.95)	(8.73)	(9.38)	(10.50)
rd 2 - 3		14.99***	15.07***	0.21		17.14	25.42
		(5.21)	(5.19)	(5.83)		(15.98)	(16.74)
Large × rd 2 - 3		6.30	6.12	−17.26		8.71	−1.87
		(5.81)	(5.78)	(14.99)		(12.40)	(35.81)
LargeGrace × rd 2 - 3		24.88	24.64	−3.08		100.34	50.89
		(19.42)	(19.32)	(8.28)		(65.08)	(47.95)
Cow × rd 2 - 3		4.54	4.99	−11.75		18.90	−58.04
		(7.47)	(7.45)	(8.98)		(11.76)	(77.08)
rd 3 - 4		15.59**	15.75**				
		(6.58)	(6.61)				
Large × rd 3 - 4		18.81	19.12				
		(14.81)	(14.89)				
LargeGrace × rd 3 - 4		20.74	21.07				
		(19.73)	(19.84)				
Cow × rd 3 - 4		5.07	5.81				
		(9.82)	(9.95)				
FloodInRd1			8.89***	5.90			−10.84
			(3.37)	(5.04)			(9.61)
Head literate			−1.81	−5.29			3.35
			(3.12)	(3.94)			(7.01)
6M repayment				1.82			48.51
				(15.56)			(57.54)
6M net saving				−46.21			122.38
				(41.67)			(119.02)
6M other member net saving				−71.38			−758.52
				(45.64)			(604.36)
6M other member Repaid				2.52			−44.82
				(16.13)			(60.82)
$T = 2$	108	108	107	110	30	30	29
$T = 3$	137	137	135	516	21	21	20
$T = 4$	523	523	523	0	0	0	0
$\bar{R}^2$	0	0.004	0.006	−0.004	−0.042	0.035	0.007
$\hat{\rho}$	−0.216	−0.237	−0.215	−0.225	−0.062	−0.648	−0.549
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.777	0.000	0.001
N	1951	1951	1946	1142	72	72	69

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Labour income is in 1000 Tk unit andis sum of all earned labour incomes. Farm revenue is total of agricultural produce sales.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

TABLE 28: FD ESTIMATION OF INCOMES BY ATTRIBUTES

	Labour income (Tk)				Farm income (Tk)		
covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	5.85***	−0.45	−4.32	0.09	−8.30	−16.04	−14.75**
	(1.33)	(3.27)	(3.80)	(4.38)	(6.97)	(9.68)	(6.88)
Upfront	5.19	0.05	−1.30	16.37	8.71	10.69	14.53
	(5.58)	(3.98)	(3.52)	(13.27)	(7.16)	(7.78)	(9.53)
WithGrace	−11.00	−15.46	−13.47	−15.32	0.18	−7.49	−31.08
	(7.40)	(13.06)	(12.30)	(11.72)	(2.03)	(6.90)	(23.46)
InKind	4.85	12.49	11.16	5.11	−5.30	1.19	15.31
	(6.22)	(13.06)	(12.47)	(6.40)	(5.39)	(8.67)	(19.58)
rd 2 - 3		14.99***	15.07***	0.21		17.14	25.42
		(5.21)	(5.19)	(5.83)		(15.98)	(16.74)
Upfront × rd 2 - 3		6.30	6.12	−17.26		8.71	−1.87
		(5.81)	(5.78)	(14.99)		(12.40)	(35.81)
WithGrace × rd 2 - 3		18.58	18.52	14.17		91.63	52.77
		(19.09)	(18.97)	(13.17)		(64.24)	(38.61)
InKind × rd 2 - 3		−20.34	−19.64	−8.67		−81.44	−108.94
		(19.65)	(19.46)	(7.53)		(64.12)	(86.93)
rd 3 - 4		15.59**	15.75**				
		(6.58)	(6.61)				
Upfront × rd 3 - 4		18.81	19.12				
		(14.81)	(14.89)				
WithGrace × rd 3 - 4		1.93	1.95				
		(23.54)	(23.52)				
InKind × rd 3 - 4		−15.67	−15.26				
		(20.76)	(20.65)				
FloodInRd1			8.89***	5.90			−10.84
			(3.37)	(5.04)			(9.61)
Head literate			−1.81	−5.29			3.35
			(3.12)	(3.94)			(7.01)
6M repayment				1.82			48.51
				(15.56)			(57.54)
6M net saving				−46.21			122.38
				(41.67)			(119.02)
6M other member net saving				−71.38			−758.52
				(45.64)			(604.36)
6M other member Repaid				2.52			−44.82
				(16.13)			(60.82)
$T = 2$	108	108	107	110	30	30	29
$T = 3$	137	137	135	516	21	21	20
$T = 4$	523	523	523	0	0	0	0
$\bar{R}^2$	0	0.004	0.006	−0.004	−0.042	0.035	0.007
$\hat{\rho}$	−0.216	−0.237	−0.215	−0.225	−0.062	−0.648	−0.549
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.777	0.000	0.001
N	1951	1951	1946	1142	72	72	69

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. LargeSize is an indicator function if the arm is of large size, WithGrace is an indicator function if the arm is with a grace period, InKind is an indicator function if the arm provides a cow. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Labour income is in 1000 Tk unit andis sum of all earned labour incomes. Farm revenue is total of agricultural produce sales.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

III.8 Consumption

```
#con ← readRDS(paste0(pathsaveHere, "RosterConsumptionAdminOriginalHHsDataUsedForEstimat
con ← readRDS(paste0(pathsaveHere, DataFileNames[9], "InitialSample.rds"))
if (Only800) con ← con[o800 == 1, ]
con[, ConsumptionBaseline := 0L]
con[as.Date(IntDate) < as.Date(DisDate1), ConsumptionBaseline := 1L]
con[, ConsumptionBaseline := as.integer(any(ConsumptionBaseline == 1L)),
  by = hhid]

table(con[, .(Arm, ConsumptionBaseline)])
```

```
            ConsumptionBaseline
```

```
Arm              0
  traditional 474
  large       573
  large grace 516
  cow         557
```

```
con ← con[, grepout("groupid|hhid|tee|^dummy[A-Z]|Floo|Tim|Size|With|Poo|RM|Expen|Head|HH
  colnames(con)), with = F]
expcol ← grepout("Exp", colnames(con))
con[, paste0("PC", expcol) := .SD/HHsize, .SDcols = expcol]
pcexpcol ← grepout("PC", colnames(con))
con[, c("PCExpenditure", "TotalExpenditure") :=
  .(eval(parse(text=paste(pcexpcol, collapse = "+"))),
    eval(parse(text=paste(expcol, collapse = "+"))))]
con[, grepout("Loan|UD|^Tota|Food|Ener|Soc|^Hygi|^Time$", colnames(con)) := NULL]
# drop Time 2 (period 1-2) and its iteractions, because data starts from t=2
#conR[, grepout("Time.?2|Time.?3|^Time$", colnames(con)) := NULL]
conR = copy(con)
conR[, grepout("Time.?2|^Time$", colnames(con)) := NULL]
con[, grepout("RM", colnames(con)) := NULL]
datas ← c("con", "conR")
ddatas ← paste0("d", datas)
ddatasd ← paste0(ddatas, "d")
for (i in 1:length(datas)) {
# a  dl ← prepFDData(get(datas[i]), Group = "^hhid$", TimeVar = "tee", Cluster = "groupic
# a    LevelCovariates = "^dummy[A-Z].*[a-z]$|Floo|^Time\\..$|Head|HH",
# a    drop.if.NA.in.differencing = T, LevelPeriodToKeep = "last",
# a    use.var.name.for.dummy.prefix = F, print.messages = F)
# a  dat ← dl$diff
  dl ← FirstDiffPanelData(get(datas[i]),
    Group = "^hhid$", TimeVar = "tee", Cluster = "groupid",
     LevelCovariates = "^dummy|Head|^Time\\..$|Female$|Floo|Eldest|HH|credits|xid$|SchPa|^
  dat ← dl$diff
  dat[, grepout("^en$", colnames(dat)) := NULL]
  # Recreate Time.4 which is dropped when kept only 1:(T-1) obs.
  dat[, grepout("Time.?2", colnames(dat)) := NULL]
  assign(ddatas[i], dl)
  assign(ddatasd[i], dat)
}
```

```
Dropped 16 obs due to T<2.
Dropped 718 obs due to NA.
Dropped 16 obs due to T<2.
Dropped 853 obs due to NA.
```

```
Warning in `[.data.table`(dat, , `:=`(grepout("Time.?2", colnames(dat)), : length(LHS)==0;
```

```
dcond[, Tee := .N, by = hhid]
```

Consumption is observed in rd 2-4. There are 2120 observations, with first-differencing, it becomes 1386 observations with 50, 1336 households observed for 2, 3 times.

```
source(paste0(pathprogram, "ReadTrimConsumptionOriginalHHsFDData.R"))
```

```
Dropped 16 obs due to T<2.
Dropped 718 obs due to NA.
Dropped 16 obs due to T<2.
Dropped 853 obs due to NA.
```

```
Warning in `[.data.table`(dat, , `:=`(grepout("Time.?2", colnames(dat)), : length(LHS)==0;
```

```
FileName <- "Consumption"
cnsuffixes <- c("", "g", "p", "s", "a")
listheader <- paste0("cn", cnsuffixes)
Regressands <- c(rep("PCExpenditure", 4), rep("PCHygieneExpenditure", 3))
DataToUse1 <- DataToUse2 <-
  c(rep("dcond", 3), "dconRd", rep("dcond", 2), "dconRd")
Addseparatingcols = 4; Separatingcolwidth = .2
Separatingcoltitle = c("Per capita consumption (Tk)",
  "Per capita hygiene consumption (Tk)")
```

```
source(paste0(pathprogram, "ConsumptionCovariateSelection.R"))
```

```
FileNameHeader <- paste0(c("", "Grace", "PovertyStatus", "Size", "Attributes"),
  "OriginalHHs")
exclheader <- paste0("excl", cnsuffixes)
source(paste0(pathprogram, "FDEstimationFile.R"))
saveRDS(fdplist, paste0(pathsave, "FD_consumption.rds"))
```

```
FileNameHeader <- paste0(FileNameHeader, "Robustness")
exclheader <- paste0("excl", cnsuffixes)
source(paste0(pathprogram, "FDEstimationFile.R"))
```

```
#dummy chunk
```

Table 29: FD estimation of consumption

	Per capita consumption (Tk)				Per capita hygiene consumption (Tk)		
covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	289.8***	482.7***	484.1***	529.6***	175.4***	213.5***	201.5***
	(34.8)	(50.6)	(51.0)	(71.0)	(20.0)	(30.3)	(37.8)
Large	52.1	82.8	87.3	21.5	31.1	57.3*	53.6
	(49.1)	(60.7)	(59.8)	(75.4)	(28.0)	(33.9)	(40.8)
LargeGrace	−1.1	−4.7	−7.3	−68.3	3.0	−5.0	8.5
	(47.8)	(56.3)	(54.6)	(70.6)	(30.0)	(32.0)	(36.2)
Cow	35.6	94.7	77.7	−2.3	9.5	46.4	38.1
	(51.5)	(59.4)	(57.3)	(76.6)	(30.7)	(35.4)	(39.3)
rd 3 - 4		−438.9***	−415.5***	−405.4***		−108.0**	−57.5
		(78.3)	(76.5)	(84.0)		(42.0)	(43.5)
Large × rd 3 - 4		−105.6	−96.8	20.7		−140.4	−95.8
		(200.9)	(201.4)	(264.4)		(101.6)	(136.0)
LargeGrace × rd 3 - 4		84.2	87.5	233.4		48.2	96.4
		(234.1)	(233.9)	(267.9)		(132.1)	(152.7)
Cow × rd 3 - 4		−317.2	−242.0	−50.6		−219.5*	−140.4
		(210.0)	(199.2)	(239.7)		(114.9)	(136.4)
FloodInRd1			−35.7	−50.1			−30.6
			(28.2)	(36.1)			(22.8)
Head literate			68.5	51.6			36.5
			(43.2)	(46.0)			(34.2)
6M repayment				126.2			116.4
				(137.0)			(81.7)
6M net saving				−697.2			−254.5
				(428.9)			(172.7)
6M other member net saving				−432.6			494.0
				(1488.9)			(609.6)
6M other member Repaid				−63.1			−43.4
				(177.9)			(96.0)
$T = 2$	50	50	50	23	50	50	23
$T = 3$	668	668	665	611	668	668	611
$\bar{R}^2$	−0.001	0.064	0.062	0.06	−0.002	0.017	0.011
$\hat{\rho}$	−0.471	−0.412	−0.408	−0.406	−0.322	−0.270	−0.285
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	1386	1386	1380	1245	1386	1386	1245

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Consumption is annualised values.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

Table 30: FD estimation of consumption by attributes

	Per capita consumption (Tk)				Per capita hygiene consumption (Tk)		
covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	289.8*** (34.8)	482.7*** (50.6)	484.1*** (51.0)	529.6*** (71.0)	175.4*** (20.0)	213.5*** (30.3)	201.5*** (37.8)
Upfront	52.1 (49.1)	82.8 (60.7)	87.3 (59.8)	21.5 (75.4)	31.1 (28.0)	57.3* (33.9)	53.6 (40.8)
WithGrace	−53.1 (47.7)	−87.5 (61.2)	−94.5 (59.8)	−89.9 (71.4)	−28.1 (29.7)	−62.4** (31.5)	−45.1 (35.7)
InKind	36.6 (50.2)	99.4* (60.0)	85.0 (57.5)	66.0 (57.7)	6.5 (32.3)	51.5 (33.1)	29.6 (30.5)
rd 3 - 4		−438.9*** (78.3)	−415.5*** (76.5)	−405.4*** (84.0)		−108.0** (42.0)	−57.5 (43.5)
Upfront × rd 3 - 4		−105.6 (200.9)	−96.8 (201.4)	20.7 (264.4)		−140.4 (101.6)	−95.8 (136.0)
WithGrace × rd 3 - 4		189.8 (229.4)	184.2 (229.7)	212.8 (234.1)		188.5 (122.6)	192.1* (109.9)
InKind × rd 3 - 4		−401.4* (237.4)	−329.5 (227.6)	−284.1 (229.8)		−267.7** (133.8)	−236.8* (128.1)
FloodInRd1			−35.7 (28.2)	−50.1 (36.1)			−30.6 (22.8)
Head literate			68.5 (43.2)	51.6 (46.0)			36.5 (34.2)
6M repayment				126.2 (137.0)			116.4 (81.7)
6M net saving				−697.2 (428.9)			−254.5 (172.7)
6M other member net saving				−432.6 (1488.9)			494.0 (609.6)
6M other member Repaid				−63.1 (177.9)			−43.4 (96.0)
$T = 2$	50	50	50	23	50	50	23
$T = 3$	668	668	665	611	668	668	611
$\bar{R}^2$	−0.001	0.064	0.062	0.06	−0.002	0.017	0.011
$\hat{\rho}$	−0.471	−0.412	−0.408	−0.406	−0.322	−0.270	−0.285
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	1386	1386	1380	1245	1386	1386	1245

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. LargeSize is an indicator function if the arm is of large size, WithGrace is an indicator function if the arm is with a grace period, InKind is an indicator function if the arm provides a cow. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Consumption is annualised values.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

Table 31: FD estimation of consumption, moderately poor vs. ultra poor

	Per capita consumption (Tk)				Per capita hygiene consumption (Tk)		
covariates	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	314.2***	529.1***	512.5***	498.6***	197.4***	253.0***	226.5***
	(30.6)	(51.7)	(47.0)	(54.2)	(18.8)	(28.6)	(30.5)
UltraPoor	−1.8	−1.2	13.5	24.4	−16.2	−21.9	4.6
	(32.9)	(39.7)	(37.6)	(36.0)	(22.2)	(24.0)	(23.0)
rd 3 - 4		−437.1***	−413.7***	−406.7***		−106.0**	−61.8
		(79.7)	(77.3)	(87.2)		(43.5)	(45.0)
UltraPoor × rd 3 - 4		35.6	−13.5	−6.2		43.7	−0.5
		(119.5)	(110.3)	(121.9)		(64.6)	(68.8)
FloodInRd1			−26.8	−41.4			−28.5
			(29.6)	(34.8)			(22.5)
Head literate			72.8*	54.4			36.0
			(43.4)	(45.1)			(34.0)
6M repayment				113.1			97.1
				(132.3)			(83.7)
6M net saving				−690.2*			−298.0*
				(410.4)			(176.6)
6M other member net saving				−407.1			494.3
				(1234.6)			(531.5)
6M other member Repaid				−97.3			−51.3
				(172.7)			(86.0)
$T = 2$	50	50	50	23	50	50	23
$T = 3$	668	668	665	611	668	668	611
$\bar{R}^2$	−0.001	0.059	0.058	0.059	0	0.009	0.005
$\hat{\rho}$	−0.471	−0.407	−0.401	−0.403	−0.323	−0.294	−0.302
$\Pr[\hat{\rho} = 0]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	1386	1386	1380	1245	1386	1386	1245

Source: Estimated with GUK administrative and survey data.

Notes: 1. First-difference estimates using administrative and survey data. First-differenced ($\Delta x_{t+1} \equiv x_{t+1} - x_t$) regressands are regressed on categorical and time-variant covariates. Head age and literacy are from baseline survey data. ρ indicates the AR(1) coeffcient of first-difference residuals as suggested by Wooldridge (2010, 10.71) and $\Pr[\rho = 0]$ is its p value. 6M repayment, 6M net saving are mean lagged 6 month repayment and net saving. 6M other repayment, 6M other net saving are mean lagged 6 month repayment and net saving of other members in a group. UltraPoor is an indicator function if the household is classified as the ultra poor. Sample is continuing members and replacing members of early rejecters and received loans prior to 2015 Janunary. Consumption is annualised values.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

III.9 Counting observations used in FD estimation

```
setkey(ar, Arm, BStatus, o800, survey)
ar[, Num := 1:.N, by = .(survey, Arm, BStatus, o800)]
ar[o800==1, .(Num = Num, N = length(unique(hhid))),
  by = .(survey, Arm, BStatus)][Num==1, ]
```

```
    survey         Arm               BStatus Num   N
 1:      1 traditional              borrower   1 109
 2:      2 traditional              borrower   1  84
 3:      3 traditional              borrower   1  84
 4:      4 traditional              borrower   1  83
 5:      1 traditional individual rejection   1  31
 6:      2 traditional individual rejection   1  26
 7:      3 traditional individual rejection   1  26
 8:      4 traditional individual rejection   1  25
 9:      1 traditional      group rejection   1  40
10:      2 traditional      group rejection   1  39
11:      3 traditional      group rejection   1  36
12:      4 traditional      group rejection   1  36
13:      1 traditional   rejection by flood   1  20
14:      2 traditional   rejection by flood   1  17
15:      3 traditional   rejection by flood   1  18
16:      1       large              borrower   1 171
17:      2       large              borrower   1 163
18:      3       large              borrower   1 165
19:      4       large              borrower   1 164
20:      1       large individual rejection   1   9
```

```
21:       2       large individual rejection   1   8
22:       3       large individual rejection   1   9
23:       4       large individual rejection   1   9
24:       1       large      group rejection   1  20
25:       2       large      group rejection   1  20
26:       3       large      group rejection   1  19
27:       4       large      group rejection   1  19
28:       1 large grace             borrower   1 167
29:       2 large grace             borrower   1 163
30:       3 large grace             borrower   1 163
31:       4 large grace             borrower   1 160
32:       1 large grace individual rejection   1  13
33:       2 large grace individual rejection   1   9
34:       3 large grace individual rejection   1  11
35:       4 large grace individual rejection   1  11
36:       1 large grace      group rejection   1  10
37:       1 large grace   rejection by flood   1  10
38:       1         cow             borrower   1 153
39:       2         cow             borrower   1 151
40:       3         cow             borrower   1 150
41:       4         cow             borrower   1 147
42:       1         cow individual rejection   1  37
43:       2         cow individual rejection   1  29
44:       3         cow individual rejection   1  30
45:       4         cow individual rejection   1  30
46:       1         cow   rejection by flood   1  10
47:       2         cow   rejection by flood   1  10
48:       3         cow   rejection by flood   1  10
    survey          Arm              BStatus Num   N
```

```
ar[, MaxTee := max(tee), by = hhid]
LostHHs ← ar[
  hhid %in% hhid[o800 == 1 & grepl("tra", Arm) & grepl("b", BStatus)
  & survey == 1] &
  !(hhid %in% hhid[o800 == 1 & grepl("tra", Arm) & grepl("b", BStatus)
  & survey == 2]) & tee == MaxTee, hhid]
summary(ass[hhid %in% LostHHs, .(Arm, TradGroup, BStatus,
  hhid, survey=factor(survey), AssetAmount)])
```

```
           Arm       TradGroup                    BStatus         hhid
 traditional:29   planned: 0   borrower            :25   Min.   : 7020816
 large      : 0   twice  : 0   pure saver          : 0   1st Qu.: 7042511
 large grace: 0   double : 0   individual rejection: 0   Median : 7042720
 cow        : 0   NA's   :29   group rejection     : 0   Mean   :12535652
                               rejection by flood  : 4   3rd Qu.: 8148210
                                                         Max.   :81710203
 survey  AssetAmount
 1:28   Min.   :     0
 3: 1   1st Qu.:   200
        Median :  1620
        Mean   :  5973
        3rd Qu.:  3200
        Max.   :123760
```

```
lvo[hhid %in% LostHHs, .(Arm, BStatus, hhid, survey, NumCows, number_owned)]
```

```
            Arm             BStatus    hhid survey NumCows number_owned
 1: traditional            borrower 7020816      1       0            0
 2: traditional            borrower 7031513      1       1            1
```

```
 3: traditional           borrower  7042502      1       2            2
 4: traditional           borrower  7042503      1       0            0
 5: traditional           borrower  7042504      1       0            0
 6: traditional           borrower  7042508      1       0            0
 7: traditional           borrower  7042509      1       0            3
 8: traditional           borrower  7042511      1       0            4
 9: traditional           borrower  7042516      1       0            0
10: traditional           borrower  7042519      1       0            0
11: traditional           borrower  7042520      1       0            0
12: traditional           borrower  7042703      1       0            0
13: traditional           borrower  7042717      1       0            0
14: traditional           borrower  7042719      1       0            0
15: traditional           borrower  7042720      1       0            0
16: traditional rejection by flood  7054408      1       0            0
17: traditional rejection by flood  7054413      1       0            0
18: traditional           borrower  7065011      1       1            1
19: traditional           borrower  8148201      1       0            0
20: traditional           borrower  8148202      1       0            5
21: traditional           borrower  8148208      1       0            0
22: traditional           borrower  8148210      1       0            8
23: traditional           borrower  8148212      1       0            0
24: traditional           borrower  8148213      1       0            5
25: traditional           borrower  8148216      1       0            5
26: traditional           borrower  8148217      1       1            1
27: traditional           borrower  8148218      1       0            5
28: traditional rejection by flood 81710203      1       2            2
29: traditional rejection by flood 81710203      3       2            2
            Arm            BStatus     hhid survey NumCows number_owned
```

```
con[hhid %in% LostHHs, .(BStatus, hhid, tee)]
```

```
             BStatus     hhid tee
1: rejection by flood 81710203   1
```

```
ass[o800==1 & grepl("tr", Arm), .(Num = 1:.N, N = length(unique(hhid))),
  by = .(survey, BStatus)][Num==1, ]
```

```
   survey              BStatus Num   N
 1:      1             borrower   1 109
 2:      2             borrower   1  84
 3:      3             borrower   1  84
 4:      4             borrower   1  83
 5:      1 individual rejection   1  30
 6:      2 individual rejection   1  26
 7:      3 individual rejection   1  26
 8:      4 individual rejection   1  25
 9:      1      group rejection   1  40
10:      2      group rejection   1  39
11:      3      group rejection   1  36
12:      4      group rejection   1  36
13:      1   rejection by flood   1  20
14:      2   rejection by flood   1  17
15:      3   rejection by flood   1  18
```

```
# Di: Data before estimation
Di0 ← lapply(1:length(DataFileNames), function(i)
  readRDS(paste0(pathsaveHere, DataFileNames[i], "InitialSample.rds")))
Di0 ← lapply(Di0, function(x) x[o800 == 1, ])
FDfilenames ← c("saving", "schooling", "assets", "livestock",
```

```
  "assetslivestock", "netassets", "income", "consumption")
# Dr: Data used in estimation, last period
Dr00 ← lapply(1:length(FDfilenames), function(i)
  readRDS(paste0(pathsave, "FD_", FDfilenames[i], ".rds")))
names(Dr00) ← FDfilenames
# Dr0: Last regression specification in Dr00
Dr0 ← lapply(
    #get the last element for a given element in Dr00
  lapply(Dr00, function(x) x[[length(x)]] )
  ,
  # then pick the element with the name "data"
  function(z) z$data)
names(Dr0) ← FDfilenames
# for assets and consumption,
#  last entry with 6M covariates has only 3 rounds (T=2, 3)
# so use [[3]]rd regression specification
Dr0[["assets"]] ← Dr00[["assets"]][[3]]$data
Dr0[["consumption"]] ← Dr00[["consumption"]][[3]]$data
arid ← unique(arA[, .(hhid, Arm, BStatus)])
# only some lack BStatus
#Dr0 ← lapply(Dr0, function(z) merge(z, arid, by = "hhid", all.x= T))
#Dr0[[1]] ← merge(Dr0[[1]], arid, by = "hhid", all.x= T)
#Dr0[[6]] ← merge(Dr0[[6]], arid, by = "hhid", all.x= T)
Dr0[[2]][, hhid := as.numeric(gsub("\\..*", "", HHMid))]
saveRDS(Dr0, paste0(pathsaveHere, "DataInList_UsedInEstimation.rds"))
#arid ← unique(arA[, .(hhid, Arm)])
#Dr0[-c(1, 6)] ← lapply(Dr0[-c(1, 6)], function(x) merge(x, arid, by = "hhid", all.x= T))
#lapply(Dr0, function(x) grepout("B|Arm", colnames(x)))
# Dr: Sample size in period 1
picktee ← function(Period, x) switch(Period, Min = min(x), Max = max(x))
picktee("Min", 1:10)
```

```
[1] 1
```

```
picktee("Max", 1:10)
```

```
[1] 10
```

```
for (k in 1:2) {
  Dr ← lapply(Dr0, function(x) {
    x0 ← addmargins(
      table0(x[tee == picktee(c("Min", "Max")[k], tee), .(BStatus, Arm)]),
        1:2, sum, quiet = T)
    x1 ← data.frame(as.matrix.data.frame(x0))
    dxr ← dimnames(x0)[[1]]; dxr[is.na(dxr)] ← "NA"
    dxc ← dimnames(x0)[[2]]; dxc[is.na(dxc)] ← "NA"
    dimnames(x1) ← list(dxr, dxc)
    x1 ← data.table(x1)
    x1[, BStatus := dxr]
    return(x1)
    })
  Dr ← lapply(1:length(Dr), function(i)Dr[[i]][, File := FDfilenames[i]])
  Dr ← rbindlist(Dr, use.names = T, fill = T)
  setcolorder(Dr, c("File", "BStatus", arms, "sum"))
  Dr ← Dr[!grepl("pure", BStatus), ]
```

```
  assign(paste0("Dr", k), Dr)
  write.tablev(
   latextab(as.matrix(Dr),
       hleft = c(rep("\\footnotesize\\hfill", 2), rep("\\hfil\\footnotesize$", ncol(Dr)-2)),
       hcenter = c(rep(2.2, 2), rep(.95, ncol(Dr)-2)),
       hright = c("", "", rep("$", ncol(Dr)-2)),
       alternatecolorManualColor = "gray90",
       alternatecolorManual = c(seq(7, nrow(Dr)+2, 10), seq(8, nrow(Dr)+2, 10),
         seq(9, nrow(Dr)+2, 10), seq(10, nrow(Dr)+2, 10), seq(11, nrow(Dr)+2, 10)),
       addheaderAbove = paste0("(", letters[1:ncol(Dr)], ")"),
       headercolor = "paleblue")
     , paste0(pathprogram,
         "table/ImpactEstimationOriginal1600Memo3/NumObsByBStatusArmRegUsed",
         c("Min", "Max")[k], ".tex")
     , colnamestrue = F)
  saveRDS(Dr, paste0(pathsaveHere, "NumObsUsedInEstimation",
    c("Min", "Max")[k], ".rds"))
}
Di1 ← lapply(Di0, function(x) addmargins(table0(x[tee == min(tee) , .(BStatus, Arm)]),
  1:2, sum, quiet = T))
Di4 ← lapply(Di0, function(x) addmargins(table0(x[tee == max(tee) , .(BStatus, Arm)]),
  1:2, sum, quiet = T))
names(Di1) ← names(Di4) ← DataFileNames
Di ← lapply(Di0, function(x) {
  x0 ← addmargins(
    table0(x[tee == min(tee), .(BStatus, Arm)]), 1:2, sum, quiet = T)
  x1 ← data.frame(as.matrix.data.frame(x0))
  dxr ← dimnames(x0)[[1]]; dxr[is.na(dxr)] ← "NA"
  dxc ← dimnames(x0)[[2]]; dxc[is.na(dxc)] ← "NA"
  dimnames(x1) ← list(dxr, dxc)
  x1 ← data.table(x1)
  x1[, BStatus := dxr]
  return(x1)
  })
Di ← lapply(1:length(Di), function(i)Di[[i]][, File := DataFileNames[i]])
Di ← rbindlist(Di, use.names = T, fill = T)
Di[, File := c(File[1], rep("", .N-1)), by = File]
Di ← Di[!grepl("pu", BStatus), ]
setcolorder(Di, c("File", "BStatus", arms, "sum"))
write.tablev(
 latextab(as.matrix(Di),
     hleft = c(rep("\\footnotesize\\hfill", 2), rep("\\hfil\\footnotesize$", ncol(Di)-2)),
     hcenter = c(rep(2.8, 2), rep(.95, ncol(Di)-2)),
     hright = c("", "", rep("$", ncol(Di)-2)),
     alternatecolorManualColor = "gray90",
     alternatecolorManual = c(seq(7, nrow(Di)+2, 10), seq(8, nrow(Di)+2, 10),
       seq(9, nrow(Di)+2, 10), seq(10, nrow(Di)+2, 10), seq(11, nrow(Di)+2, 10)),
     addheaderAbove = paste0("(", letters[1:ncol(Di)], ")"),
     headercolor = "paleblue")
  , paste0(pathprogram,
       "table/ImpactEstimationOriginal1600Memo3/NumObsByBStatusArmFile.tex")
  , colnamestrue = F)
saveRDS(Di, paste0(pathsaveHere, "NumObs.rds"))
```

Table 32: Number of observations by borrower status and arm

(a) File	(b) BStatus	(c) traditional	(d) large	(e) large grace	(f) cow	(g) sum
Schooling	borrower	128	224	205	183	740
	individual rejection	23	9	16	41	89
	group rejection	54	13	17	0	84
	rejection by flood	27	0	13	11	51
	sum	232	246	251	235	964
AllMeetingsRepayment	borrower	85	171	167	153	576
	individual rejection	31	9	13	37	90
	group rejection	0	0	0	0	0
	rejection by flood	0	0	0	0	0
	sum	116	180	180	190	666
Repayment	borrower	109	171	167	153	600
	individual rejection	31	9	13	37	90
	group rejection	40	20	10	0	70
	rejection by flood	20	0	10	10	40
	sum	200	200	200	200	800
Asset	borrower	109	171	167	153	600
	individual rejection	30	9	13	37	89
	group rejection	40	20	10	0	70
	rejection by flood	20	0	10	10	40
	sum	199	200	200	200	799
Livestock	borrower	109	171	166	153	599
	individual rejection	30	9	13	37	89
	group rejection	40	20	0	0	60
	rejection by flood	20	0	10	10	40
	sum	199	200	189	200	788
LivestockProducts	borrower	109	171	167	153	600
	individual rejection	30	9	13	37	89
	group rejection	40	20	10	0	70
	rejection by flood	20	0	10	10	40
	sum	199	200	200	200	799
LabourIncome	borrower	109	171	167	153	600
	individual rejection	30	9	13	37	89
	group rejection	40	20	10	0	70
	rejection by flood	20	0	10	10	40
	sum	199	200	200	200	799
FarmIncome	borrower	9	38	24	23	94
	individual rejection	2	0	0	2	4
	group rejection	0	8	0	0	8
	rejection by flood	1	0	0	0	1
	sum	12	46	24	25	107
Consumption	borrower	84	166	166	152	568
	individual rejection	27	9	11	33	80
	group rejection	39	19	0	0	58
	rejection by flood	18	0	0	10	28
	sum	168	194	177	195	734

Source: Survey data.

Note:

Table 33: Number of observations used in estimation by borrower status and arm at period 1

(a) File	(b) BStatus	(c) traditional	(d) large	(e) large grace	(f) cow	(g) sum
saving	borrower	82	163	165	149	559
saving	individual rejection	0	0	0	0	0
saving	group rejection	0	0	0	0	0
saving	rejection by flood	0	0	0	0	0
saving	sum	82	163	165	149	559
schooling	borrower	79	160	156	139	534
schooling	individual rejection	15	5	8	25	53
schooling	group rejection	45	10	0	0	55
schooling	rejection by flood	17	0	0	10	27
schooling	sum	156	175	164	174	669
assets	borrower	83	161	155	145	544
assets	individual rejection	24	8	9	26	67
assets	group rejection	36	19	0	0	55
assets	rejection by flood	0	0	0	0	0
assets	sum	143	188	164	171	666
livestock	borrower	83	161	155	144	543
livestock	individual rejection	24	8	9	26	67
livestock	group rejection	36	19	0	0	55
livestock	rejection by flood	0	0	0	0	0
livestock	sum	143	188	164	170	665
assetslivestock	borrower	83	161	155	144	543
assetslivestock	individual rejection	24	8	9	26	67
assetslivestock	group rejection	36	19	0	0	55
assetslivestock	rejection by flood	0	0	0	0	0
assetslivestock	sum	143	188	164	170	665
netassets	borrower	83	161	155	144	543
netassets	individual rejection	24	8	9	26	67
netassets	group rejection	36	19	0	0	55
netassets	rejection by flood	0	0	0	0	0
netassets	sum	143	188	164	170	665
income	borrower	2	16	9	6	33
income	individual rejection	0	0	0	0	0
income	group rejection	0	0	0	0	0
income	rejection by flood	0	0	0	0	0
income	sum	2	16	9	6	33
consumption	borrower	84	164	163	150	561
consumption	individual rejection	26	9	11	30	76
consumption	group rejection	36	18	0	0	54
consumption	rejection by flood	17	0	0	10	27
consumption	sum	163	191	174	190	718

Source: Survey data.

Note:

Table 34: Number of observations used in estimation by borrower status and arm at last period

(a) File	(b) BStatus	(c) traditional	(d) large	(e) large grace	(f) cow	(g) sum
saving	borrower	85	171	167	153	576
saving	individual rejection	0	0	0	0	0
saving	group rejection	0	0	0	0	0
saving	rejection by flood	0	0	0	0	0
saving	sum	85	171	167	153	576
schooling	borrower	65	140	134	112	451
schooling	individual rejection	11	6	5	22	44
schooling	group rejection	38	9	0	0	47
schooling	rejection by flood	0	0	0	0	0
schooling	sum	114	155	139	134	542
assets	borrower	83	161	155	145	544
assets	individual rejection	24	8	9	26	67
assets	group rejection	36	19	0	0	55
assets	rejection by flood	0	0	0	0	0
assets	sum	143	188	164	171	666
livestock	borrower	83	161	155	144	543
livestock	individual rejection	24	8	9	26	67
livestock	group rejection	36	19	0	0	55
livestock	rejection by flood	0	0	0	0	0
livestock	sum	143	188	164	170	665
assetslivestock	borrower	83	161	155	144	543
assetslivestock	individual rejection	24	8	9	26	67
assetslivestock	group rejection	36	19	0	0	55
assetslivestock	rejection by flood	0	0	0	0	0
assetslivestock	sum	143	188	164	170	665
netassets	borrower	83	161	155	144	543
netassets	individual rejection	24	8	9	26	67
netassets	group rejection	36	19	0	0	55
netassets	rejection by flood	0	0	0	0	0
netassets	sum	143	188	164	170	665
income	borrower	4	15	10	7	36
income	individual rejection	0	0	0	0	0
income	group rejection	0	0	0	0	0
income	rejection by flood	0	0	0	0	0
income	sum	4	15	10	7	36
consumption	borrower	83	162	156	146	547
consumption	individual rejection	24	8	9	26	67
consumption	group rejection	36	18	0	0	54
consumption	rejection by flood	0	0	0	0	0
consumption	sum	143	188	165	172	668

Source: Survey data.

Note:

III.10 IGA

IGA info is from c:/data/GUK/received/cleaned_by_RA/GUKAdminstrativeData.dta.

```
adw2 ← readRDS(paste0(path1234, "admin_data_wide2.rds"))
iga ← adw2[, .(hhid, Arm, Date, iga1st, iga12nd, iga13rd)]
setnames(iga, c("hhid", "Arm", "Date", paste0("iga", 1:3)))
if (Only800) iga ← iga[hhid %in% ar[o800 == 1L, hhid], ]
#table0(iga[, iga1])
#table0(iga[, iga2])
#table0(iga[, iga3])
setkey(iga, hhid, Date)
iga[, NumIGA := sum(!is.na(iga1)) + sum(!is.na(iga2)) + sum(!is.na(iga3)), by = .(hhid, D
#iga[NumIGA == 0 & !is.na(iga1), ]
setkey(iga, NumIGA, iga1, iga2, iga3)
```

```
iga.unique <- unique(iga[, .(NumIGA, iga1, iga2, iga3)])
iga.unique <- iga[iga.unique, .N/48, by = .EACHI]
setnames(iga.unique, "V1", "N")
setorder(iga.unique, -NumIGA, -N, iga1, iga2, iga3)
setkey(iga, NumIGA, iga1, Arm)
igaArm.unique <- unique(iga[, .(NumIGA, iga1, Arm)])
igaArm.unique <- iga[igaArm.unique, .N/48, by = .EACHI]
setnames(igaArm.unique, "V1", "N")
setorder(igaArm.unique, -NumIGA, -N, iga1)
for (i in 1:3) {
  iga[, paste0("IGA.", i) := as.character(NA)]
  iga[grepl("Cow|oxen", eval(parse(text = paste0("iga", i)))),
    paste0("IGA.", i) := "cow"]
  iga[grepl("Goa|heep", eval(parse(text = paste0("iga", i)))),
    paste0("IGA.", i) := "goat sheep"]
  iga[grepl("small", eval(parse(text = paste0("iga", i)))),
    paste0("IGA.", i) := "small trade"]
  iga[grepl("house|land", eval(parse(text = paste0("iga", i)))),
    paste0("IGA.", i) := "house land"]
  iga[grepl("machi", eval(parse(text = paste0("iga", i)))),
    paste0("IGA.", i) := "machinery"]
  iga[grepl("addy|nut", eval(parse(text = paste0("iga", i)))),
    paste0("IGA.", i) := "paddy nuts corn"]
  iga[, paste0("IGA.", i) := factor(eval(parse(text = paste0("IGA.", i))),
    levels = c("cow", "goat sheep", "machinery", "small trade", "house land", "paddy nuts
}
setkey(iga, NumIGA, IGA.1, IGA.2, IGA.3, Arm)
iga.unique3 <- unique(iga[, .(NumIGA, IGA.1, IGA.2, IGA.3, Arm)])
iga.unique3 <- iga[iga.unique3, .N/48, by = .EACHI]
setnames(iga.unique3, "V1", "N")
setorder(iga.unique3, -NumIGA, -N, Arm, IGA.1, IGA.2, IGA.3)
iga.unique3[, NumIGA := factor(NumIGA, levels = 3:0)]
```

```
library(ggplot2)
p <- ggplot(data = iga.unique3[NumIGA != 0 & !is.na(IGA.1), ], aes(IGA.1, N)) +
  geom_col() +
  xlab("First IGA choices") +
  theme(axis.text.x = element_text(angle = 30, vjust = .5, hjust = 1),
    strip.text.y = element_text(colour = "blue"))+
  facet_grid(NumIGA ~ Arm, switch = "y")
setEPS()
postscript(file =
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/IGAChoices.eps"),
  , horizontal = F)
print(p)
dev.off()
```

```
pdf
  2
```

```
iga.unique3[, num := 1:.N]
igaUL <- reshape(iga.unique3, direction = "long", idvar = c("num", "NumIGA", "Arm", "N"),
  varying = paste0("IGA.", 1:3))
setnames(igaUL, "time", "rank")
setkey(igaUL, num, rank)
library(ggplot2)
```

```
p <- ggplot(data = igaUL[NumIGA != 0 & !is.na(IGA), ], aes(IGA, N)) +
  geom_col() +
  xlab("First IGA choices") +
  theme(axis.text.x = element_text(angle = 30, vjust = .5, hjust = 1),
    strip.text.y = element_text(colour = "blue"))+
  facet_grid(NumIGA ~ Arm, switch = "y")
setEPS()
postscript(file =
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/AllIGAChoices.eps"),
  , horizontal = F)
print(p)
dev.off()
```

```
pdf
  2
```

```
iga.unique3[, num := 1:.N]
igaUL <- reshape(iga.unique3, direction = "long", idvar = c("num", "NumIGA", "Arm", "N"),
  varying = paste0("IGA.", 1:3))
setnames(igaUL, "time", "rank")
setkey(igaUL, num, rank)
library(ggplot2)
p <- ggplot(data = igaUL[NumIGA != 0 & !is.na(IGA), ], aes(IGA, N)) +
  geom_col() +
  xlab("First IGA choices") +
  theme(axis.text.x = element_text(angle = 90, vjust = .5, hjust = 1),
    strip.text.y = element_text(colour = "blue"))+
  facet_grid(. ~ Arm, switch = "y")
setEPS()
postscript(file =
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/AllIGAChoicesCollapsed.eps
  , horizontal = F)
print(p)
dev.off()
```

```
pdf
  2
```

III.11 Cumulative impacts

```
# b <- rpois(3, 4)
# x <- matrix(rpois(3*100, 5), byrow = T, ncol = 3)
# y <- x%*%b + rnorm(100)
# dat <- data.table(cbind(y=y, x))
# setnames(dat, c("y", "trad", "large", "largegrace"))
# testlm <- lm(y ~ trad + large + largegrace, data = dat)
# Vb <- summary(testlm)$cov
library(car)
# linearHypothesis (testlm, "large - 2*largegrace = 1")
# lh1 <- linearHypothesis (testlm, "large - 2*largegrace = 1", vcov.=Vb/10)
# lh3 <- linearHypothesis (testlm, "(Intercept)+large - 2*largegrace = 1", vcov.=Vb/10)
# c(attributes(lh1)$value, attributes(lh1)$vcov)
# c(attributes(lh1)$value) +
#   c(0, -1.96*sqrt(attributes(lh1)$vcov), 1.96*sqrt(attributes(lh1)$vcov))
```

```
# library(multcomp)
# lh2 <- glht(model=testlm, linfct=matrix(c(0, 0, 1, -2), byrow = T, nrow=1),
#   rhs=1, alternative="two.sided", vcov.=Vb/10)
# summary(lh2)
# confint(lh2)$confint[1, ]
addthese <- c("2*(Intercept)", "2*dummyLargeSize",
  "Time.3", "dummyLargeSize.Time3")
lhcow <- linearHypothesis(lva2$reg,
  paste0(paste(addthese, collapse = "+"), "=0")
  , vcov. = lva2$V)
varlhcow <- attr(lhcow, "vcov")
#c(attr(lhcow, "value")) + c(0, -1.96*sqrt(varlhcow), 1.96*sqrt(varlhcow))
```

Cumulative effect sums. In the example of cow, all periods share the baseline changes of intercept+cow. Per period deviations from baseline is TimeX+cow.TimeX for period X. Then per period changes are:

$$\begin{aligned}
\Delta\text{1st period} &= \text{intercept} + \text{cow},\\
\Delta\text{2nd period} &= \text{intercept} + \text{cow} + \text{Time2} + \text{cow.Time2},\\
\Delta\text{3rd period} &= \text{intercept} + \text{cow} + \text{Time3} + \text{cow.Time3}.
\end{aligned}$$

So cumulative change is:

$$\begin{aligned}
\Delta\text{1st period} + \Delta\text{2nd period} &= 2(\text{intercept} + \text{cow}) + \text{Time2} + \text{cow.Time2},\\
\Delta\text{1st period} + \Delta\text{2nd period} + \Delta\text{3rd period} &= 3(\text{intercept} + \text{cow}) + \text{Time2} + \text{cow.Time2}\\
&\quad + \text{Time3} + \text{cow.Time3}.
\end{aligned}$$

covadd covariate names for impacts

- covadd.trad lists only traditional arm covariates
- covadd.nontrad lists all other arm covariates

per period deviation traditional TimeY.

- deviation from traditional XX.TimeY.

per period change .

- traditional intercept+TimeY.
- deviation from traditional intercept+XX+TimeY+XX.TimeY

cumulative change intercept+XX+TimeY-1+XX.TimeY-1+TimeY+XX.TimeY.

```
library(multcomp)
lattributes <- c("LargeSize", "WithGrace", "InKind")
covadd0 <- list(c("\\(Intercept\\)", "dummyXX"),
  c("Time.3", "dummyXX.Time3"),
  c("Time.4", "dummyXX.Time4"))
covaddsav <- list(c("\\(Intercept\\)", "dummyXX"),
  c("LY2", "dummyXX.LY2"),
  c("LY3", "dummyXX.LY3"),
  c("LY4", "dummyXX.LY4"))
# scY: school has variable names such as dummyHigh,
#  need to delete "dummy" from them
#  male*school ~ Arm
covaddsch <- list(
  # male, traditional
```

```r
  c("\\(Intercept\\)", "^dummyJunior$", "^dummyHigh$"),
  # female, traditional
  c("^Female$", "dummyJunior.Female", "dummyHigh.Female"),
  # male, other arms
  c("dummyXX$", "dummyXX.dummyJunior$", "dummyXX.dummyHigh$"),
  # female, other arms
  c("dummyXX.Female", "dummyXX.dummyJunior.Female",
    "dummyXX.dummyHigh.Female")
  )
reglists <- c(
  paste0("sva", c(2, 4:5, 7:8)),
  paste0("asa", c(2:3, 6:7)),
  paste0(rep(c("lva", "cowa"), each = 6), 2:7),
  paste0("neaa", 2:6),
  paste0("lba", 2:3),
  paste0("cna", 2:4)
  )
confi <- NULL
for (rr in reglists) {
  regobj <- get(rr)
  thisreg <- regobj$reg
  coeffvec <- thisreg$coeff
  thisV <- regobj$V
  # if saving,
  #  change to loan year: TimeX => LYX
  #  multiply with 12 (turn to monthly to yearly)
  if (grepl("sv", rr)) {
    covadd <- covaddsav
    Mult <- 12
  } else {
    covadd <- covadd0
    Mult <- 1
  }
  covadd.trad <- lapply(covadd, function(x) x[1])
  covadd.nontrad <- lapply(covadd, function(x) x[2])
  for (g in lattributes) {
    addcova <- lapply(covadd, function(x) gsub("XX", g, x))
    addcova.nontrad <- lapply(covadd.nontrad, function(x) gsub("XX", g, x))
    addcova.trad <- covadd.trad
    # Consumption: No rd1 so period= 1, 2. Drop period 3 variables.
    if (grepl("cn", rr)) {
      addcova <- addcova[-2]
      addcova.nontrad <- addcova.nontrad[-2]
      addcova.trad <- covadd.trad[-2]
    }
    # nontrad
    hypvec <- rep(0, length(coeffvec))
    for (i in 1:length(addcova)) {
      # diff.hypvec: picks covariates of per period changes
      #  [[1]]"\\(Intercept\\)", "dummyInKind" and
      # [[2]] "Time.4", "dummyInKind.Time4"
      diff.hypvec <- rep(0, length(coeffvec))
      diff.hypvec[grepl(
        paste(
          paste0("^", unique(unlist(addcova[c(1, i)])), "$")
```

```
        , collapse = "|")
        , names(coeffvec))] ← 1*Mult
      lhcow ← glht(model=thisreg, linfct = matrix(diff.hypvec, byrow = T, nrow=1),
        alternative="two.sided", vcov.=thisV)
      confi ← rbind(confi,
        c("changes", rr, g, i, confint(lhcow)$confint[1, ]))
      # hypvec collects all coefficients by far to compute cumulative sums
      hypvec ← hypvec + diff.hypvec
      lhcow ← glht(model=thisreg, linfct = matrix(hypvec, byrow = T, nrow=1),
        alternative="two.sided", vcov.=thisV)
      confi ← rbind(confi,
        c("cumulative", rr, g, i, confint(lhcow)$confint[1, ]))
     # diff.hypvec: picks period deviations (=deviations from tee = 1)
     #  addcova.nontrad[[2]] is "dummyInKind.Time4"
     #  =concurrent difference relative to traditional
      diff.hypvec ← rep(0, length(coeffvec))
      diff.hypvec[grepl(
        paste(
          paste0("^", addcova.nontrad[[i]], "$")
        , collapse = "|")
        , names(coeffvec))] ← 1*Mult
      lhcow ← glht(model=thisreg, linfct = matrix(diff.hypvec, byrow = T, nrow=1),
        alternative="two.sided", vcov.=thisV)
      confi ← rbind(confi,
        c("concurrent", rr, g, i, confint(lhcow)$confint[1, ]))
    }
  } # end: attribute g loop
  # traditional
  hypvec ← rep(0, length(coeffvec))
  for (i in 1:length(addcova.trad)) {
    diff.hypvec ← rep(0, length(coeffvec))
    diff.hypvec[grepl(
      paste(
        paste0("^", unique(unlist(addcova.trad[c(1, i)])), "$")
      , collapse = "|")
      , names(coeffvec))] ← 1
    lhcow ← glht(model=thisreg, linfct = matrix(diff.hypvec, byrow = T, nrow=1),
      alternative="two.sided", vcov.=thisV)
    confi ← rbind(confi,
      c("changes", rr, "traditional", i, confint(lhcow)$confint[1, ]))
    hypvec ← hypvec + diff.hypvec
    lhcow ← glht(model=thisreg, linfct = matrix(hypvec, byrow = T, nrow=1),
      alternative="two.sided", vcov.=thisV)
    confi ← rbind(confi,
      c("cumulative", rr, "traditional", i, confint(lhcow)$confint[1, ]))
   # traditional: period deviations (=deviation from tee = 1)
    diff.hypvec ← rep(0, length(coeffvec))
    diff.hypvec[grepl(
      paste(
        paste0("^", addcova.trad[[i]], "$")
      , collapse = "|")
      , names(coeffvec))] ← 1*Mult
    lhcow ← glht(model=thisreg, linfct = matrix(diff.hypvec, byrow = T, nrow=1),
      alternative="two.sided", vcov.=thisV)
    confi ← rbind(confi,
```

```
      c("concurrent", rr, "traditional", i, confint(lhcow)$confint[1, ]))
  } # end: addcova.trad i loop
}
# schooling
screglists ←  paste0("scDa", 2:3)
schlevels ← c("primary", "junior", "high")
covadd ← covaddsch
confis ← NULL
for (rr in screglists) {
  regobj ← get(rr)
  thisreg ← regobj$reg
  coeffvec ← thisreg$coeff
  thisV ← regobj$V
  for (g in lattributes) {
    addcova ← lapply(covadd, function(x) gsub("XX", g, x))
    # males
    addcovam.trad ← addcova[[1]]
    addcovam.nontrad ← addcova[[3]]
    # females
    addcovaf.trad ← addcova[[2]]
    addcovaf.nontrad ← addcova[[4]]
    # males, trad
    #  i: school level
      for (i in 1:length(addcovam.trad)) {
        hypvecm ← hypvecf ← rep(0, length(coeffvec))
        hypvecm[grepl(
          paste(
            unique(unlist(addcovam.trad[c(1, i)]))
          , collapse = "|")
          , names(coeffvec))] ← 1
        lhcow ← glht(model=thisreg, linfct = matrix(hypvecm, byrow = T, nrow=1),
          alternative="two.sided", vcov.=thisV)
        confis ← rbind(confis,
          c("male", "level", rr, "traditional", schlevels[i], confint(lhcow)$confint[1, ]))
       #  addcova.nontrad[[2]] is "dummyInKind.Time4"
       #  =concurrent difference relative to traditional
        diff.hypvecm ← rep(0, length(coeffvec))
        diff.hypvecm[grepl(
          paste(
            addcovam.nontrad[i]
          , collapse = "|")
          , names(coeffvec))] ← 1
        lhcow ← glht(model=thisreg, linfct = matrix(diff.hypvecm, byrow = T, nrow=1),
          alternative="two.sided", vcov.=thisV)
        confis ← rbind(confis,
          c("male", "concurrent", rr, g, schlevels[i], confint(lhcow)$confint[1, ]))
      # females, trad: male trad + female dummies
        hypvecf[grepl(
          paste(
            unique(unlist(addcovaf.trad[c(1, i)]))
          , collapse = "|")
          , names(coeffvec))] ← 1
        hypvecf ← hypvecf + hypvecm
        lhcow ← glht(model=thisreg, linfct = matrix(hypvecf, byrow = T, nrow=1),
          alternative="two.sided", vcov.=thisV)
```

```
        confis <- rbind(confis,
          c("female", "level", rr, "traditional", schlevels[i], confint(lhcow)$confint[1,
        diff.hypvecf <- rep(0, length(coeffvec))
        diff.hypvecf[grepl(
          paste(
            addcovaf.nontrad[i]
          , collapse = "|")
          , names(coeffvec))] <- 1
        lhcow <- glht(model=thisreg, linfct = matrix(diff.hypvecf, byrow = T, nrow=1),
          alternative="two.sided", vcov.=thisV)
        confis <- rbind(confis,
          c("female", "concurrent", rr, g, schlevels[i], confint(lhcow)$confint[1, ]))
       # nontrad level
        hypvecm <- hypvecm + diff.hypvecm
        lhcow <- glht(model=thisreg, linfct = matrix(hypvecm, byrow = T, nrow=1),
          alternative="two.sided", vcov.=thisV)
        confis <- rbind(confis,
          c("male", "level", rr, g, schlevels[i], confint(lhcow)$confint[1, ]))
        hypvecf <- hypvecf + diff.hypvecf
        lhcow <- glht(model=thisreg, linfct = matrix(hypvecf, byrow = T, nrow=1),
          alternative="two.sided", vcov.=thisV)
        confis <- rbind(confis,
          c("female", "level", rr, g, schlevels[i], confint(lhcow)$confint[1, ]))
      } # end: school level i loop
  } # end: attribute g loop
}
confi <- data.table(confi)
setnames(confi, c("sumtype", "regressions", "attributes", "period",
  "estimate", "lb", "ub"))
confis <- data.table(confis)
setnames(confis, c("gender", "sumtype", "regressions", "attributes", "school",
  "estimate", "lb", "ub"))
  # traditional has 4 same entries when computing interactions
confis <- confis[!duplicated(confis), ]
confi <-
rbindlist(list(confi, confis), use.names = T, fill = T)
numcols <- c("period", "estimate", "lb", "ub")
confi[, (numcols) := lapply(.SD, as.numeric), .SDcols = numcols]
faccols <- c("gender", "sumtype", "regressions", "attributes", "school")
confi[, (faccols) := lapply(.SD, as.factor), .SDcols = faccols]
confi[, sumtype := factor(sumtype, levels =
  c("cumulative", "changes", "level", "concurrent"))]
setcolorder(confi, c("gender", "sumtype", "regressions", "attributes", "period",
  "school", "lb", "estimate", "ub"))
confi[, attributes := factor(attributes,
  levels = c("traditional", "LargeSize", "WithGrace", "InKind"))]
confi[, attributes := factor(attributes,
  labels = c("traditional", "Upfront", "WithGrace", "InKind"))]
confi[grepl("cn", regressions), period := period + 1]
confi[, regressand := "livestock values"]
confi[grepl("cow", regressions), regressand := "number of cattle"]
confi[grepl("nea", regressions), regressand := "net asset values"]
confi[grepl("^as", regressions), regressand := "non-livestock asset values"]
confi[grepl("lb", regressions), regressand := "labour incomes"]
confi[grepl("cn", regressions), regressand := "consumption"]
```

```
confi[grepl("sv", regressions), regressand := "net saving"]
confi[grepl("sv.[45]", regressions), regressand := "repayment"]
confi[grepl("sv.[78]", regressions), regressand := "effective repayment"]
confi[grepl("sc", regressions), regressand := "schooling"]
confi[, regressand := factor(regressand)]
```

```
library(ggplot2)
confi1 <- confi[grepl("lv|cow|neaa", regressions), ]
cols <- c("regressions", "regressand")
confi1[, (cols) := droplevels(.SD), .SDcols = cols]
confi1[, regressand := factor(regressand, levels =
  c("livestock values", "number of cattle", "net asset values"))]
confi1[, regressand := factor(regressand, labels =
  c("livestock", "cattle", "net assets"))]
p <- ggplot(data = confi1, aes(x = factor(period), y = estimate)) +
  geom_pointrange(aes(
    colour = regressions, shape = regressand,
    ymin = lb, ymax = ub),
    stat = "identity", fatten = 1.75,
    position = position_dodge(width = .85))
p <- p + facet_grid(regressand+sumtype ~ attributes, scales = "free_y") +
  scale_y_continuous(name = "impacts" #,limits = c(-.35, .15)
  ) +
  scale_x_discrete(name = "periods", breaks = 1:3) +
  theme(
   axis.text.x = element_text(size = 5, angle = 0, vjust = 1, hjust = 1),
   axis.text.y = element_text(size = 6),
   axis.title = element_text(size = 6),
   strip.text.x = element_text(color = "blue", size = 8,
     margin = margin(0, 1.25, 0, 1.25, "cm")),
   strip.text.y = element_text(color = "blue", size = 8,
     margin = margin(1.5, 0, 1.5, 0, "cm")),
   legend.position="none") +
  xlab("periods") +
  guides(colour = guide_legend(title = "regression specifications", nrow = 3)) +
  geom_hline(aes(yintercept = 0), data = confi1, colour = "lightgreen")
ggsave(
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/LivestockCumulativeEffects
  p,
  width = 13, height = 12, units = "cm",
  dpi = 300
 )
setEPS()
postscript(file =
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/LivestockCumulativeEffects
  , horizontal = F)
print(p)
dev.off()
```

```
pdf
  2
```

```
library(ggplot2)
confi1 <- confi[grepl("neaa", regressions), ]
cols <- c("regressions", "regressand")
confi1[, (cols) := droplevels(.SD), .SDcols = cols]
```

```
confi1[, regressand := "net asset values"]
p ← ggplot(data = confi1, aes(x = factor(period), y = estimate)) +
  geom_pointrange(aes(
    colour = regressions, shape = regressand,
    ymin = lb, ymax = ub),
    stat = "identity", fatten = 1.75,
    position = position_dodge(width = .85))
p ← p + facet_grid(sumtype ~ attributes, scales = "free_y") +
  scale_y_continuous(name = "impacts" #,limits = c(-.35, .15)
  ) +
  scale_x_discrete(name = "periods", breaks = 1:3) +
  theme(
   axis.text.x = element_text(size = 5, angle = 0, vjust = 1, hjust = 1),
   axis.text.y = element_text(size = 6),
   axis.title = element_text(size = 6),
   strip.text.x = element_text(color = "blue", size = 8,
     margin = margin(0, 1.25, 0, 1.25, "cm")),
   strip.text.y = element_text(color = "blue", size = 8,
     margin = margin(1.5, 0, 1.5, 0, "cm")),
   legend.position="none") +
  xlab("periods") +
  guides(colour = guide_legend(title = "regression specifications", nrow = 3)) +
  geom_hline(aes(yintercept = 0), data = confi1, colour = "lightgreen")
ggsave(
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/NetAssetsCumulativeEffects
  p,
  width = 12, height = 7, units = "cm",
  dpi = 300
 )
setEPS()
postscript(file =
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/NetAssetsCumulativeEffect
  , horizontal = F)
print(p)
dev.off()
```

```
pdf
  2
```

```
library(ggplot2)
confi2 ← subset(confi, !grepl("cumu", sumtype) & grepl("lb|cn", regressions))
cols ← c("sumtype", "regressand")
confi2[, (cols) := droplevels(.SD), .SDcols = cols]
p ← ggplot() + layer(data = confi2,
  mapping = aes(
  colour = regressions, shape = regressand,
  x = factor(period), y = estimate, ymin = lb, ymax = ub),
  position = position_dodge(width = .5),
  geom = "pointrange", stat = "identity")
p ← p + facet_grid(regressand+sumtype ~ attributes, scales = "free_y") +
  scale_y_continuous(name = "impacts") +
  scale_x_discrete(name = "periods", breaks = 1:3) +
  theme(
   axis.text.x = element_text(size = 5, angle = 0, vjust = 1, hjust = 1),
   axis.text.y = element_text(size = 6),
   axis.title = element_text(size = 6),
```

```
    strip.text.x = element_text(color = "blue", size = 8,
      margin = margin(0, 1.25, 0, 1.25, "cm")),
    strip.text.y = element_text(color = "blue", size = 8,
      margin = margin(1.5, 0, 1.5, 0, "cm")),
    legend.position="none") +
  xlab("periods") +
  guides(colour = guide_legend(title = "regression specifications", nrow = 3),
  shape = guide_legend(title = "regression specifications", nrow = 2)) +
  geom_hline(aes(yintercept = 0), colour = "lightgreen", data = confi2)
ggsave(
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/IncomeConsumptionEffects.p
  p,
  width = 13, height = 10, units = "cm",
  dpi = 300
 )
setEPS()
postscript(file =
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/IncomeConsumptionEffects.e
  , horizontal = F)
print(p)
dev.off()
```

```
pdf
  2
```

```
library(ggplot2)
confis2 <- subset(confi, grepl("sc", regressions))
cols <- c("sumtype", "regressand", "school")
confis2[, (cols) := droplevels(.SD), .SDcols = cols]
confis2[, school := factor(school, levels = c("primary", "junior", "high"))]
p <- ggplot(data = confis2, aes(x = factor(gender), y = estimate)) +
  geom_pointrange(aes(
    colour = school, shape = regressions,
    ymin = lb, ymax = ub),
    stat = "identity", fatten = 1.75,
    position = position_dodge(width = .25))
p <- p + facet_grid(school*sumtype ~ attributes, scales = "free_y") +
  scale_y_continuous(name = "impacts") +
  scale_x_discrete(name = "gender") +
  theme(
    axis.text.x = element_text(size = 7, angle = 0, vjust = 1, hjust = 1),
    axis.text.y = element_text(size = 7),
    axis.title = element_text(size = 6),
    strip.text.x = element_text(color = "blue", size = 8,
      margin = margin(0, 1.25, 0, 1.25, "cm")),
    strip.text.y = element_text(color = "blue", size = 8,
      margin = margin(1.5, 0, 1.5, 0, "cm")),
    legend.position="none") +
  xlab("periods") +
  guides(colour = guide_legend(title = "regression specifications", nrow = 3),
  shape = guide_legend(title = "regression specifications", nrow = 2)) +
  geom_hline(aes(yintercept = 0), colour = "lightgreen", data = confis2)
ggsave(
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/SchoolingEffects.png"),
  p,
  width = 12, height = 10, units = "cm",
```

```
  dpi = 300
 )
setEPS()
postscript(file =
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/SchoolingEffects.eps"),
  , horizontal = F)
print(p)
dev.off()
```

```
pdf
  2
```

```
library(ggplot2)
confi2 <- subset(confi, grepl("repay|savi", regressand) & grepl("a[247]", regressions))
# I will have saving in one panel and repayment and effective repayment
# in one panel for scale similarity. To do so, I will change
# regressand: effective repaymen => repayment
confi2[grepl(7, regressions), regressand := "repayment"]
cols <- c("sumtype", "regressand")
confi2[, (cols) := droplevels(.SD), .SDcols = cols]
confi2[, regressand := factor(regressand, levels = c("net saving", "repayment"))]
p <- ggplot() + layer(data = confi2,
  mapping = aes(
  colour = regressions, shape = regressand,
  x = factor(period), y = estimate, ymin = lb, ymax = ub),
  position = position_dodge(width = .75),
  geom = "pointrange", stat = "identity")
p <- p + facet_grid(regressand+sumtype ~ attributes, scales = "free_y") +
  scale_y_continuous(name = "impacts") +
  scale_x_discrete(name = "loan year", breaks = 1:4) +
  theme(
   axis.text.x = element_text(size = 5, angle = 90, vjust = 1, hjust = 1),
   axis.text.y = element_text(size = 6),
   axis.title = element_text(size = 6),
   strip.text.x = element_text(color = "blue", size = 6,
     margin = margin(0, .75, 0, .75, "cm")),
   strip.text.y = element_text(color = "blue", size = 6,
     margin = margin(.75, 0, .75, 0, "cm")),
   legend.position="none") +
  xlab("periods") +
  guides(colour = guide_legend(title = "regression specifications", nrow = 3),
  shape = guide_legend(title = "regression specifications", nrow = 2)) +
  geom_hline(aes(yintercept = 0), colour = "lightgreen", data = confi2)
ggsave(
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/repayments.png"),
  p,
  width = 13, height = 12, units = "cm",
  dpi = 300
 )
setEPS()
postscript(file =
  paste0(pathprogram, "figure/ImpactEstimationOriginal1600Memo3/repayments.eps"),
  , horizontal = F)
print(p)
dev.off()
```

```
pdf
  2
```

- Randomisation went well at group level
- Loan rejection is related to flood and smaller household size in nontraditional arm, smaller livestock values for traditional arm
- Traditional arm rejecters have smaller livestock values but with similar household size as non-traditional rejecters, implying some unused capacity for them to raise more livestock, or participation to large sized lending if offered
- This hints that once household size and risk are mitigated, poverty trap may be overcome
- Less educated members attrited in traditional arm indicates there may be underestimation, if there is an attrition bias at all (so, no need to use Lee bounds, I think)
- Greater accumulation of assets (livestock, productive assets, household assets) for Upfront attribute
- No impacts of InKind on asset accumulation, rejecting the necessity of entrepreneurship, which is in contrast with the finding of existing studies that impacts are larger for the experienced borrowers ... everyone can be an entrepreneur at this level of skills?
- Lower repayment rates for traditional
- Greater asset accumulation and higher repayment rates for Upfront suggests nonconvex production, a poverty trap
- More diverse and smaller scale investment portfolio among traditional
- Large consumption increase in period 2, smaller consumption increase and larger increase in labour incomes in period 3, interpreting these as repayment burden
- Schooling of primary school aged girls increased but decreased for high school age girls for Upfront, nutrition/wealth effects for younger girls and stronger labour demand effects for older girls

III.12 Participation

The reasons behind nonparticipation are fundamental in understanding the outreach. Selective attrition may bias the estimates so we need to know attriter's characteristics. In this section, we check how participation and attrition are different between arms. To do so, we test if the household characteristics are different between participants and nonpariticipants, or attriters and nonattriters. We use permutation tests to examine if there is a difference in mean characteristics between any two groups. We use 100000 random draws from all admissible permutations.

Before examining participation decisions, we confirm randomisation balance. Despite there were rejections to participate at the group level, we see randomisation balance was reasonably achieved as there is no household characteristics whose p value exceeding 10% for the difference between intervention arms at the group level (Table **??** in Appendix **??**).

We examined the difference between various groups in Appendix **??**. In summary, group rejecters of traditional and non-traditional differ. Baseline flood and younger household head are associated with group rejection for non-traditional while low livestock values for traditional (Table **??**, Table **??**). Non-traditional group rejecter have more livestock values than traditional group rejecters (Table **??**). In contrast to group rejecters, individual rejecters have similar characteristics between these two groups (Table **??**), and the common factor associated with nonparticipation is small household size

Table 35: Permutation test results of group rejection in traditional arm vs. participants in non-traditional arm

variables	NonTradArm	TradArm	p-value.lower	p-value.mid	p-value.upper
HeadLiteracy	0.124	0.050	0.123	0.166	0.209
HeadAge	38.073	39.026	0.558	0.561	0.564
HHsize	4.236	4.200	0.859	0.882	0.905
FloodInRd1	0.465	0.275	0.013	0.017	0.021
HAssetAmount	804	872	0.505	0.507	0.509
PAssetAmount	1152	1362	0.489	0.489	0.489
LivestockValue	5958	1291	0.003	0.003	0.003
NumCows	0.267	0.037	0.005	0.005	0.005
NetValue	7924	3078	0.024	0.024	0.024
n	491	40	(rate: 0.075)		

Source: Estimated with GUK administrative and survey data.
Notes: 1. R's package coin is used for baseline group mean covariates to conduct approximate permutation tests. Number of repetition is set to 100000. Step-down method is used to adjust for multiple testing of a multi-factor grouping variable. TradArm is group-rejecters in traditional arm NonTradArm is borrowers in non-traditional arms. Both columns show means of each group.
2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

(Table ??), and for non-traditional arms, baseline flood exposure is also correlated (Table ??).

As for group rejecters, we observed that lower livestock values are associated in traditional arm while it was mostly flood exposure for non-traditional arms. Given randomisation, we conjecture that it is lack of liquidity, or lack of Upfront attribute, prevented smaller livestock holders of traditional arm because they cannot purchase cattle due to insufficient saving or resale value of livestock, when members of similar characteristics partcipated in non-traditional arms. In Table 35, group rejecters of traditional arm and borrowers of non-traditional arms are compared. It shows the former is less exposed to flood in baseline and has lower livestock values. This implies that, once large enough sum of loan is disbursed, a poverty trap at this level may be overcome once household size and negative asset shocks are accounted for.

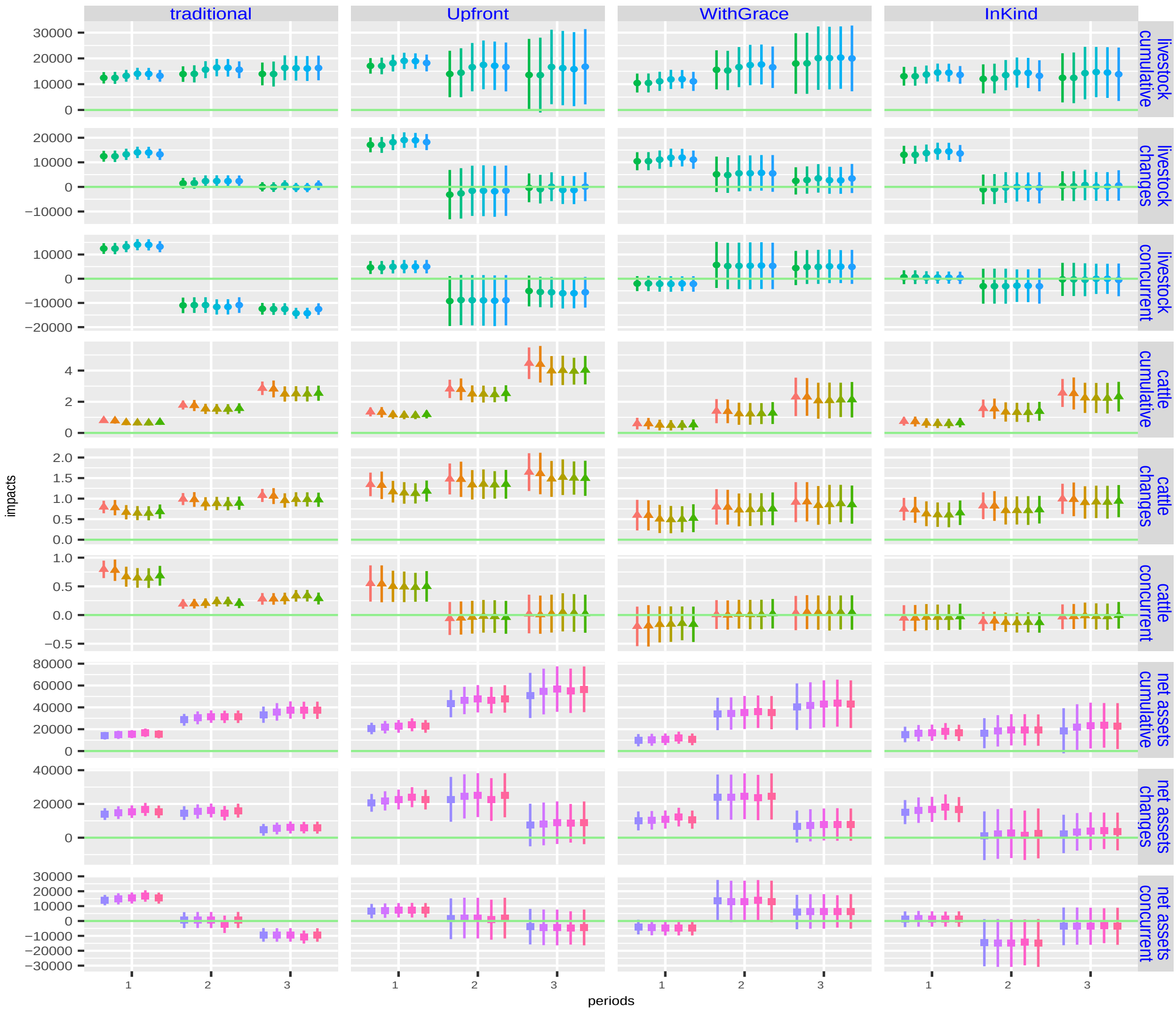
We see that households lacking labour resources and with a recent flood damage may opt out the borrowing. This is in contrast to the asset transfer programs where everyone participates. As some households who did not meet the conditions to raise cattle withheld themselves from participating, it may have caused the repayment rates to be higher than other programs targeting the poor.

The survey comes with a moderate rate of attrition. We checked for systematic differences between attriters and nonattriters in Table 36 (see more detailed attrition examination in Appendix ??). The attrition is not correlated with household level characteristics. As attrition rates differ between traditional and non-traditional arms, we compare them in Table 37. It shows that traditional arm attriters have a lower rate of head literacy while non-traditional arm attriters are more exposed to the flood. The traditional arm attriters may be less entrepreneurial, if anything, so their attrition may upwardly bias the positive gains of the arm, hence understate the relative impacts of non-traditional arm. So one can employ Lee bounds for stronger results, but doing so will give us less precision and require more assumptions.

III.13 Impacts

Figure 14 summarises estimation results as cumulative impact sums and additional impacts (see Appendix tables for full estimation results). There are three stock outcome variables, livestock values, number of cattle, and net asset values. For each outcome, there are three panels. First panel shows cumulative impacts up to period 1 (between survey rounds 1-2), period 2 (rounds 2-3), and period 3 (rounds 3-4) which are displayed along the horizontal axis. In each period, there are several estimation specifications which are bunched side-by-side. This is intended to show robustness to specification changes at a glance. One sees that there is little variation across specifications. As we multiply the estimates when we compute cumulative sums, it widens standard error bands in the later periods which unnecessarily clouds impact estimates. To assess the estimates in a less noisy way, the second panel shows the changes in each period, Δ1st period, Δ2nd period, Δ3rd period. In addition,

FIGURE 14: CUMULATIVE EFFECTS ON LIVESTOCK AND NET ASSETS



Source: Constructed from FD estimation results.

Note: For traditional arm, additional impact in a period relative to period 1, or a second-order difference, is given by $\Delta^2$2nd period = Period2, $\Delta^2$3rd period = Period3. For attribute X, Δ^2_X1st period = X, Δ^2_X2nd period = Period2 + X.Period2, Δ^2_X3rd period = Period3 + X.Period3. Per period changes in period 1 is Δ1st period = intercept for traditional, Δ_X1st period = intercept + X for other attributes, period 2 and 3 for traditional are Δ2nd period = Δ1st period + $\Delta^2$2nd period = intercept + Period2, Δ3rd period = Δ1st period + $\Delta^2$3rd period = intercept + Period3. For other attributes, Δ_X2nd period = Δ_X1st period + Δ^2_X2nd period = intercept + X + Period2 + X.Period2, Δ_X3rd period = Δ_X1st period + Δ^2_X3rd period = intercept + X + Period3 + X.Period3. Cumulative change sums are Δ1st period + Δ2nd period = 2intercept + Period2, Δ1st period + Δ2nd period + Δ3rd period = 3intercept + Period2 + Period3, Δ_X1st period + Δ_X2nd period = 2(intercept + X) + Period2 + X.Period2, Δ_X1st period + Δ_X2nd period + Δ_X3rd period = 3(intercept + X) + Period2 + X.Period2 + Period3 + X.Period3. For each outcome, top panel shows cumulative sums. Second panel shows per period changes Δ1st period, Δ2nd period, Δ3rd period. Third panel shows per period chanegs relative to period 1 change of traditional, $\Delta^2$2nd period, Δ^2_X2nd period, $\Delta^2$3rd period, Δ^2_X3rd period are plotted. For period 1, Δperiod 1 for traditional and Δ^1_X1st period for other attributes are shown. Bars show 95% confidence intervals using cluster robust standard errors.

Table 36: Permutation test results of attrition

variables	NonAttrited	Attrited	p-value.lower	p-value.mid	p-value.upper
HeadLiteracy	0.115	0.112	0.873	0.937	1.000
HeadAge	37.996	39.095	0.279	0.280	0.281
HHsize	4.178	4.267	0.537	0.548	0.559
Arm	0.789	0.517	0.000	0.000	0.000
FloodInRd1	0.493	0.496	0.920	0.960	1.000
HAssetAmount	774	705	0.210	0.210	0.210
PAssetAmount	1161	1266	0.665	0.665	0.665
LivestockValue	6069	5554	0.533	0.533	0.533
NumCows	0.271	0.262	0.813	0.832	0.850
NetValue	7722	7790	0.962	0.962	0.962
n	684	116	(rate: 0.145)		

Source: Estimated with GUK administrative and survey data.

Notes: 1. R's package coin is used for baseline mean covariates to conduct approximate permutation tests. Number of repetition is set to 100000. Step-down method is used to adjust for multiple testing of a multi-factor grouping variable. Attrited and Nonattrited columns show means of each group. For Arm, proportions of non-traditional arm are given.

2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

Table 37: Permutation test results of attriters between traditional and non-traditional arms

variables	NonTradArm	TradArm	p-value.lower	p-value.mid	p-value.upper
HeadLiteracy	0.125	0.028	0.096	0.150	0.205
HeadAge	40.175	38.694	0.582	0.585	0.588
HHsize	4.275	3.972	0.384	0.404	0.425
FloodInRd1	0.650	0.400	0.020	0.029	0.039
HAssetAmount	697	684	0.920	0.923	0.925
PAssetAmount	767	882	0.254	0.254	0.254
LivestockValue	3382	5094	0.244	0.244	0.244
NumCows	0.152	0.242	0.224	0.245	0.266
NetValue	4702	5375	0.815	0.815	0.815
n	40	36	(rate: 0.474)		

Source: Estimated with GUK administrative and survey data.

Notes: 1. R's package coin is used for baseline mean covariates to conduct approximate permutation tests. Number of repetition is set to 100000. Step-down method is used to adjust for multiple testing of a multi-factor grouping variable. NonTradArm and TradArm columns show means of each group. Attrition due to flood is dropped.

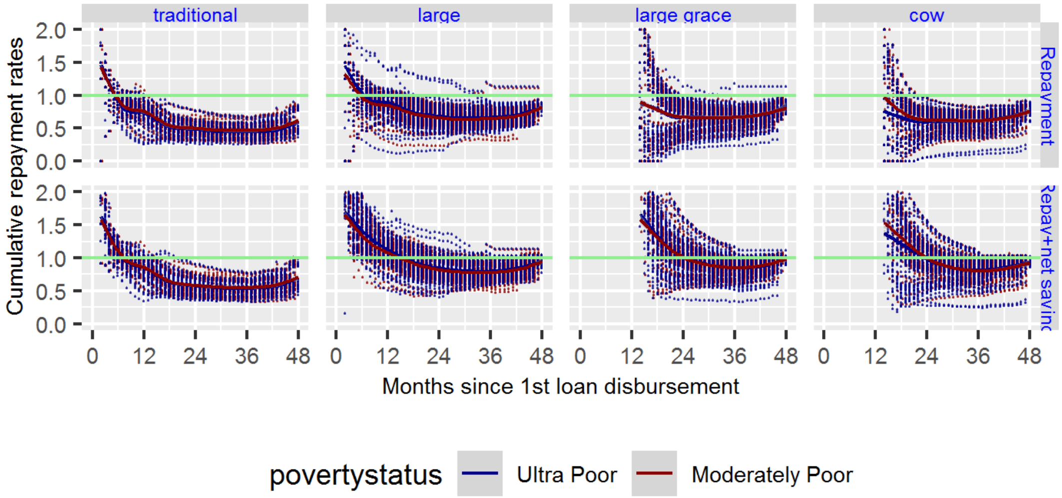
2. ***, **, * indicate statistical significance at 1%, 5%, 10%, respetively. Standard errors are clustered at group (village) level.

to make comparison easier against the traditional arm, the third panel shows changes relative to concurrent changes of traditional arm. For traditional arm in the third panel, they show changes in period 1, period 2 - period 1, and period 3 - period 1.

Figure 14 shows impacts on livestock holding values, cattle holding, and net asset values. One sees in livestock values, cumulative a sustained increase of livestock holding values in all arms. Second panel livestock values, changes, showing per period changes, indicates positive impacts only in period 1 for all attributes which reflects the loan receipt. When we convert these impacts to contemporaneous relative-to-traditional impacts in the third panel livestock values, contemporaneous, one sees that changes in period 2 and 3 cannot be statistically distinguishable from tradtional arm. This may not be surprising that all arms are receiving the equivalent sums by the beginning of period 3. At the same time, we acknowledge that the price information used to convert livestock holding to values, the median reported prices among survey respondents, is expected to have measurement errors. This may bias the results to any direction, so we use number of cattle holding as a proxy of livestock holding values in the second three panels. It is a reasonable proxy as the largest share of livestock value comes from cattle and goats and sheep are less popular in the area.

Expectedly, we see a sustained cumulative increase in all arms in number of cattle, cumulative panel. The relative additional impacts by period, shown in number of cattle, concurrent panel, are found to be large with the Upfront attribute especially in the first period. This is no surprise as a large liquid sum disbursed from the lender should face a relatively less obstacle in converting into livestock holding than in traditional arm while households may not have additional resource to buy more calf in period 2 or 3. The traditional arm members have increasing changes in the size of cattle holding in period 2 and 3, which can be explained by the second and third disbursements. Upfrontness does not lead to constant additional increase in period 3 as one sees the error bands cross the zero line. WithGrace attribute and InKind attribute received sustained cumulative impacts, yet the increaments relative to traditional are statistically zero for all periods.

Figure 15: Cumulative weekly repayment rates



Note: Each dot represents weekly observations. Only members who received loans are shown. Each panel shows ratio of cumulative repayment sum to cumulative due amount sum, ratio of sum of cumulative repayment and cumulative net saving (saving - withdrawal) sum to cumulative due amount sum, both are plotted against weeks after first disbursement. Value of 1 indicates the member is at per with repayment schedule. Horizontal lines has a Y intercept at 1. Lines are smoothed lines with a penalized cubic regression spline in ggplot2::geom_smooth function, originally from mgcv::gam with bs='cs'.

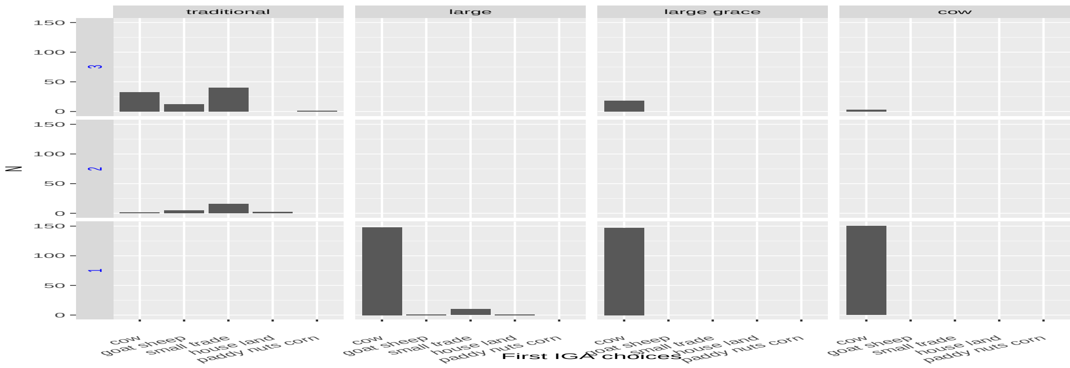
Net assets, defined by asset and livestock holding values less debt values, shows similar patterns as in livestock holding values, a sustained increase in assets, only that net assets have larger increments. This reflects that loan recipients accumulate household and productive assets. Livestock values did not change in period 2 and 3 for traditional arm, but the net asset values continue to increase in period 2 and 3, indicating sales of livestock. WithGrace attribute has relatively large increments in period 2 when one compares with contemporaneous traditional arm increments while the opposite is true in period 1. The latter is expected because debt does not decrease in period 1 for WithGrace arm when they do not repay, and the cattle valuation remains at the price of purchase, hence no increase, during the first year. Relative increases were larger in period 2 and 3 for WithGrace than traditional although the p values are around 10%. This suggests that having a grace period helps accumulate assets. The Upfront attribute has the larger asset accumulation relative to traditional in period 1. In all arms, net asset increments are large during first two periods, and smallest in the last period. We conjecture that this is due to loan repayment burden, which is consistent with what we observe in consumption and labour income patterns.

Traditional arm experienced a sustained increase in all outcomes. However, even they received an equivalent loan amount, the cumulative impacts on net assets are smaller than Upfront attribute. This is consistent with the nonconvex production technology for cattle under a liquidity constraint.

Looking at impacts of the InKind attribute on cattle holding, livestock values and net asset values, entrepreneurship (to the extent that is necessary for dairy livestock production) may not be an impediment for a microfinance loan uptake and successes among members. This is in contrast with the existing studies which observed larger impacts among the more experienced borrowers. Previous studies targeted the population with a richer set of investment possibilities in a more urbanised setting, which feeds impact heterogeneity. In the current study, the population resides in a remote area with cattle as the dominant production possibility, and this may drive impacts to be more homogenous. The dairy cattle farming that consists of feeding, grazing, pregnancy and calving may turn out not to be too demanding in terms of crystalised intelligence in comparison with micro scale production in urban areas.

Figure 15 shows ratio of cumulative repayment to cumulative due amount, ratio of sum of cumulative repayment and cumulative net saving (saving - withdrawal) to cumulative due amount, both are plotted against weeks after first disbursement. Each dot represents a member at each time point.

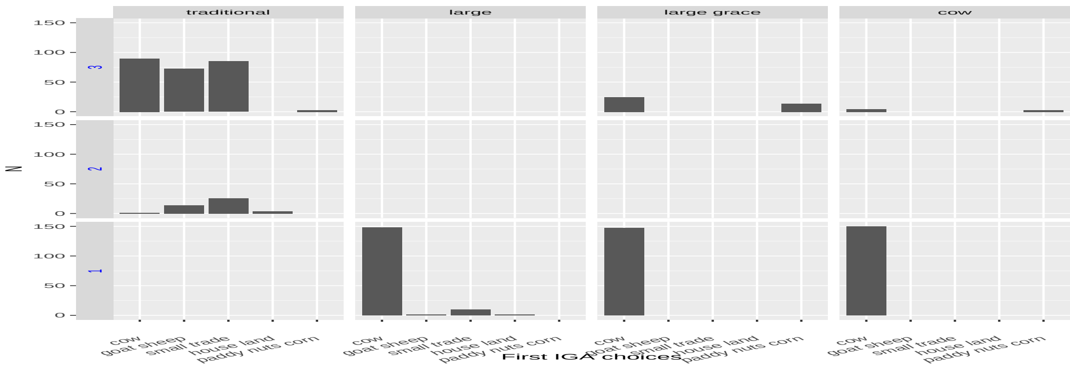
Figure 16: IGA choices



Source: Administrative data.

Note: Based on information reported at the weekly meeting.

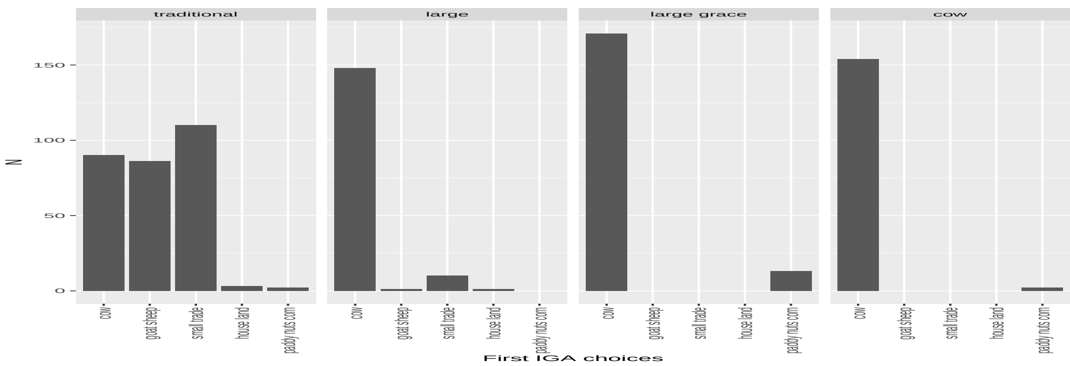
Figure 17: All IGA choices



Source: Administrative data.

Note: Based on information reported at the weekly meeting.

Figure 18: All IGA choices



Source: Administrative data.

Note: Based on information reported at the weekly meeting.

Value of 1, which is given by a horizontal line, indicates the member is at per with repayment schedule. One sees that repayment rates are above 1 at the beginning but stay below 1 for most of the time. The majority of borrowing members did not repay the loan by the 48th month with installments. One notes traditional arm has lower repayment rates of all arms. When a member does not reach the due amount with installments, they had to repay from net saving, an arrangement to which the lender and the borrowers agreed at the loan contract. Repayment rates after paying from net saving are 44.71, 93.57, 97.01, 95.42%, respectively, for traditional, large, large grace, cow arms and 87.85% for overall. [Abu-san: Why does the admin data continue up to the 48th month, not 36th?]

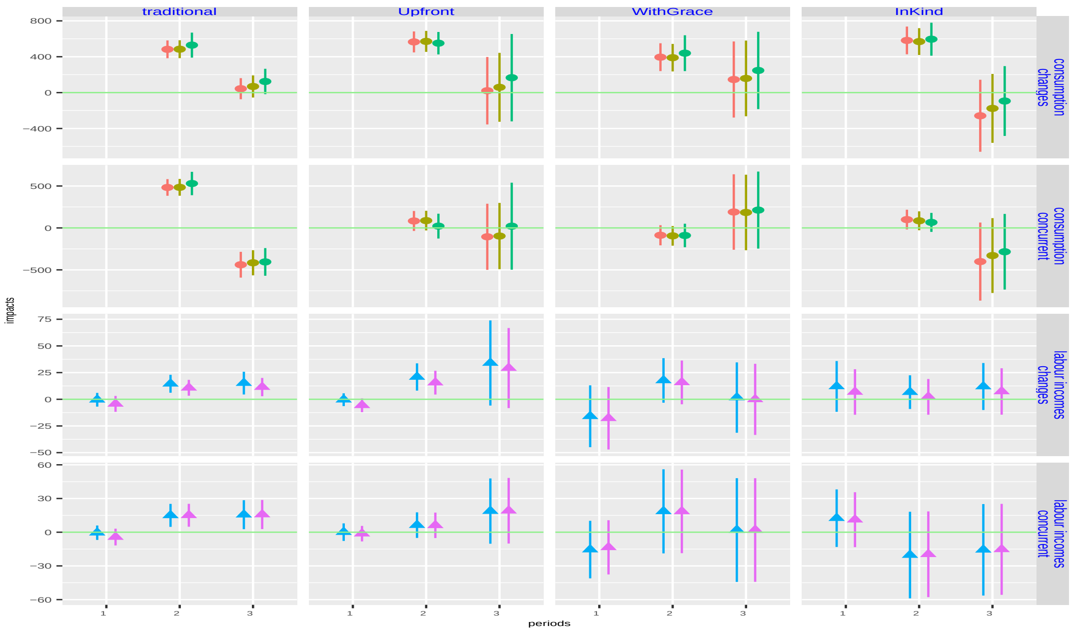
There is little difference in repayment rates by poverty classes. Figure 15 depicts both moderately poor and ultra poor. It is impossible to distinguish between them with eyeballs, and DID estimates also confirm this. This is in contrast to a popular belief that the ultra poor are the riskiest among all income classes. Poverty gradation through a participatory process, however, does not distinguish the moderately poor and the ultra poor on the observables. Figure 11 shows net asset values at baseline by poverty class, and Figure **??** shows initial livestock values at baseline by poverty class. Both show little difference in these observable characteristics. [Abu-san: Any ideas why?]

Smaller cumulative impacts and lower repayment rates of traditional arm members stand out once we acknowledge that they are receiving an equivalent amount and their contract differs with other arms only in the attributes we focus. These differences arise partly from the difference in investment choices. Figure 16, 17 show that almost no one of the traditional arm invested only in one project while only few members did so with the Upfront attribute. Goat/sheep and small trades are the top choices for the first income generating activities (IGAs) in traditional. This is consistent with convexity in the production technology of large domestic animals under a liquidity constraint. This also validates our supposition in experimental design that cattle production is the most preferred and probably the only economically viable investment choice. It reduces a concern that the cow arm may have imposed an unnecessary restriction in an investment choice by forcing to receive cattle. Figure 18 shows there are a significant number of cases in the traditional arm that members reportedly raise cows, yet they are also accompanied by pararell projects in smaller livestock production and small trades.

Figure 19 depicts estimates of consumption and labour incomes. As these are flow variables, we do not show cumulative impacts, and the top panel shows changes per period, the second panel shows changes relative to traditional. Consumption is not measured in the baseline, so we do not use it to understand welfare impacts but to understand how the members have dealt with the loan repayment. Consumption increased in period 3 and 4 except for InKind attribute. Increments were smaller in period 4 in all arms. As the repayment was delinquent after period 2, it is interesting that members increased the consumption while kept the loan repayment at sub-due level in period 3, but decreased the consumption and increased loan repayment in period 4. This hints naïveté of members who are not used to borrowing yet still conforming with the repayment discipline at the end. Labour income follows a pattern consistent with this interpretation of consumption that members increase their labour supply towards the end of loan cycle to aid repayment. The increased repayment in period 4 may thus have been born out of reduced consumption and increased wage labour.

In Figure 20, effects on child schooling are plotted. The impacts are on school enrollment probability changes, and concurrent panels are of interest as they show differences in enrollment changes between each attribute and traditional. One sees positive impacts on female primary school enrollments and negative impacts on female junior and high school enrollments with Upfront attribute. We interpret the former impact as nutrition/wealth effects of cattle rearing that children get to drink milk more. The reason, we conjecture, that only girls have positive impacts is that boys might have been drinking milk even in the absence of intervention. Negative impacts of elder girl's schooling may be due to stronger demand for cattle production in a household. Having cattle to take care of naturally shifts the relative prices in a household against child schooling, especially for elder girls as their returns on human capital are considered to be lower and task contents of cattle labour are less brawn intensive yet requires to be above primary school ages. This may be a downside of having

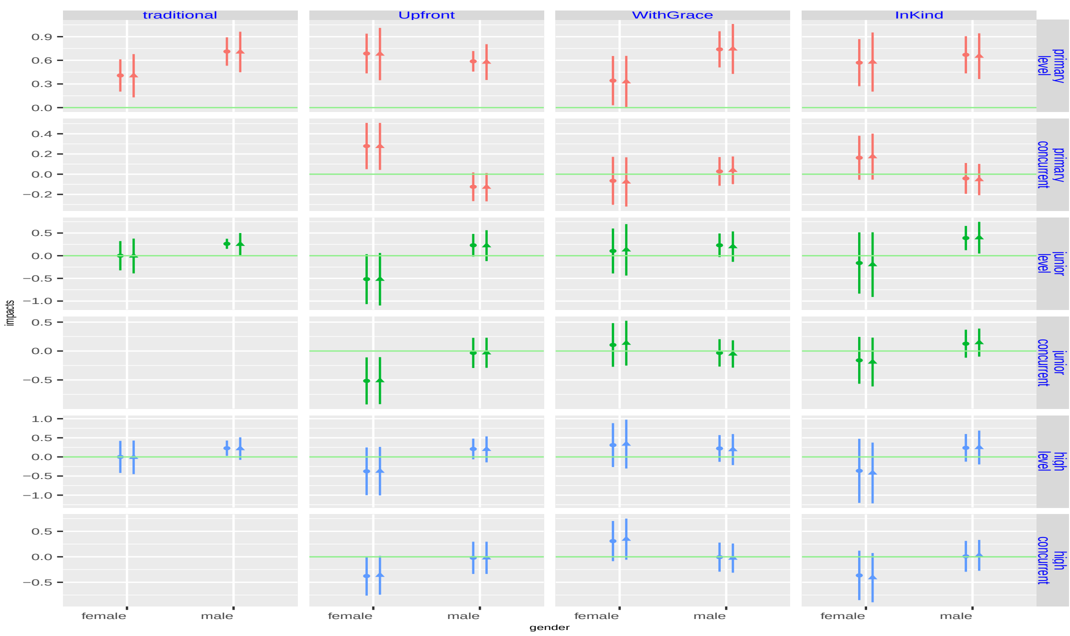
FIGURE 19: EFFECTS ON LABOUR INCOMES, CONSUMPTION



Source: Constructed from FD estimation results.

Note: Top panel shows additional impacts by period which are obtained by Δ1st period = intercept + X, Δ2nd period = intercept + X + Period2 + X.Period2, Δ3rd period = intercept + X + Period3 + X.Period3. Second panel shows changes relative to traditional which is obtained by X, X.Period2, X.Period3. Bars show 95% confidence intervals using cluster robust standard errors.

FIGURE 20: EFFECTS ON SCHOOLING



Source: Constructed from FD estimation results.

Note: Top panel shows additional impacts by period which are obtained by Δ1st period = intercept + X, Δ2nd period = intercept + X + Period2 + X.Period2, Δ3rd period = intercept + X + Period3 + X.Period3. Second panel shows changes relative to traditional which is obtained by X, X.Period2, X.Period3. Bars show 95% confidence intervals using cluster robust standard errors.

more household production with cattle.

> Finding III.3 FIGURE 16, 17 show that there are very few members who chose to invest in more than one project for the "large" arms, while in the traditional arm, almost no one invested only in one project. Goat/sheep and small trades are the top choices for the first IGA in traditional. This indicates the exitence of both a liquidity constraint and convexity in the production technology of large domestic animals. This also validates our supposition that dairy livestock production is the most preferred and probably the only economically viable investment choice. It reduces a concern that the cow arm may have imposed an unnecessary restriction in an investment choice by forcing to receive a cow. FIGURE 18 shows there are a significant number of cases in the traditional arm that members reportedly raise cows, yet they are also accompanied by pararell projects in smaller livestock production and small trades. Contrasting large, large grace with cow arms, it suggests that entrepreneurship (to the extent that is necessary for dairy livestock production) may not be an impediment for a microfinance loan uptake among members.

Together with TABLE ?? showing smaller net saving and repayment among traditional, the restriction on a project choice induced by a smaller loaned sum resulted in smaller returns.

III.14 Project cycle

```
library(readstata13)
pc1 ← read.dta13(paste0(path234E, "S21AProjectCycle.dta")
  , generate.factors = T, nonint.factors = T)
pc1 ← data.table(pc1)
pc2 ← read.dta13(paste0(path234E, "S21BProjectCycle.dta")
  , generate.factors = T, nonint.factors = T)
pc2 ← data.table(pc2)
setnames(pc1, c("id", "strat_year", "project_typf"),
  c("hhid", "start_year", "project_type"))
setnames(pc2, "id", "hhid")
xid ← readRDS(paste0(path1234, "ID.rds"))
xid[, tee := 1:.N, by = hhid]
xid1 ← xid[tee == 1, ]
xid1[, tee := NULL]
setkey(xid1, hhid); setkey(pc1, hhid); setkey(pc2, hhid)
pc1 ← pc1[xid1]
pc2 ← pc2[xid1]
arA ← readRDS(
    paste0(pathsaveHere, DataFileNames[2], "InitialSample.rds")
  )
arid ← unique(arA[, .(groupid, hhid, Mgroup, Mstatus, BStatus, creditstatus,
  Arm, o800)])
setkey(pc1, groupid, hhid, Mgroup, Mstatus)
setkey(arid, groupid, hhid, Mgroup, Mstatus)
pc1 ← pc1[arid]
if (Only800) {
  pc1 ← pc1[hhid %in% ar[o800 == 1L, hhid], ]
  pc2 ← pc2[hhid %in% ar[o800 == 1L, hhid], ]
}
# Entries with no info
pc1 ← pc1[!is.na(iga1_1st), ]
```

```
pc1[, Arm := factor(Arm, levels = arms)]
# Define Project as a more organised summary of project_type
pc1[, Project := as.character(NA)]
pc1[grepl("ow", project_type), Project := "cow"]
pc1[grepl("Ox", project_type), Project := "ox"]
pc1[grepl("Other", project_type) & grepl("goat|ram|sheep", project_type_others),
  Project := "goat/sheep"]
pc1[grepl("Land", project_type), Project := "land"]
pc1[grepl("busi|trad|tail", project_type_others), Project := "business/trade"]
pc1[, Project := factor(Project, levels = c("cow", "ox", "goat/sheep", "business/trade",
  "land", NA))]
# summarise igas
pc1[, IGA1 := tolower(gsub("^machi.*", "machine", iga1_1st))]
pc1[, IGA1 := gsub("^sheep.*", "goat", IGA1)]
pc1[, IGA1 := gsub("^cow.*", "cow", IGA1)]
pc1[, IGA1 := gsub("^ox.*", "ox", IGA1)]
pc1[, IGA1 := gsub("^smal.*", "trade", IGA1)]
pc1[, IGA1 := gsub("^paddy.*", "land", IGA1)]
pc1[, IGA1 := gsub("^(.*?) .*", "\\1", IGA1)]
pc1[, IGA2 := tolower(gsub("^machi.*", "machine", iga1_2nd))]
pc1[, IGA2 := gsub("^sheep.*", "goat", IGA2)]
pc1[, IGA2 := gsub("^cow.*", "cow", IGA2)]
pc1[, IGA2 := gsub("^ox.*", "ox", IGA2)]
pc1[, IGA2 := gsub("^smal.*", "trade", IGA2)]
pc1[, IGA2 := gsub("^paddy.*", "land", IGA2)]
pc1[, IGA2 := gsub("^(.*?) .*", "\\1", IGA2)]
pc1[, IGA3 := tolower(gsub("^machi.*", "machine", iga1_3rd))]
pc1[, IGA3 := gsub("^sheep.*", "goat", IGA3)]
pc1[, IGA3 := gsub("^cow.*", "cow", IGA3)]
pc1[, IGA3 := gsub("^ox.*", "ox", IGA3)]
pc1[, IGA3 := gsub("^smal.*", "trade", IGA3)]
pc1[, IGA3 := gsub("^paddy.*", "land", IGA3)]
pc1[, IGA3 := gsub("^(.*?) .*", "\\1", IGA3)]
pc1[, IGA13 := paste(IGA1, IGA2, IGA3, sep= "-")]
tabiga13 <- function(x) {
  tb <- table(unlist(base::strsplit(x, "-")))
  if (any(tb>1))
    paste0(tb[tb>1], " ", names(tb)[tb>1], "s,", names(tb)[tb==1]) else
    paste(names(tb)[order(tb)], collapse = ",")
}
pc1[, IGAs := gsub("-NA|NA-", "", IGA13)]
pc1[, IGAs := gsub(",", "", IGAs)]
pc1[, IGAs := lapply(IGAs, tabiga13), by = hhid]
pc1[, c("ProjNum", "TotalProj") := .(1:.N, .N), by = hhid]
tb <- table(pc1[, hhid])
# Members reporting multiple projects with multiple rows
#summary(pc1[hhid %in% names(tb)[tb>1],
#  .(hhid, project_type, IGAs=factor(IGAs), start_year, start_month,
#  end_year, end_month)])
#table0(pc1[hhid %in% names(tb)[tb>1], .(project_type, IGAs)])
# Conflicting info between Project and IGAs
tb <- table0(pc1[
#hhid %in% names(tb)[tb>1] &
  !((grepl("ow|ox", Project) & grepl("cow|ox", IGAs)) |
  (grepl("oat", Project) & grepl("oat", IGAs)) |
```

```
  (grepl("tra", Project) & grepl("tra", IGAs)) |
  (grepl("land", Project) & grepl("land", IGAs))), .(IGAs, Project)])
tb2 ← table(pc1[o800==1, hhid])
tb2 ← table0(pc1[
  hhid %in% names(tb2)[tb2>1] &
  !((grepl("ow|ox", Project) & grepl("cow|ox", IGAs)) |
    (grepl("oat", Project) & grepl("oat", IGAs)) |
    (grepl("tra", Project) & grepl("tra", IGAs)) |
    (grepl("land", Project) & grepl("land", IGAs))), .(IGAs, Project)])
tb3 ← table0(pc1[
  hhid %in% names(tb2)[tb2>1] &
  !((grepl("ow|ox", Project) & grepl("cow|ox", IGAs)) |
    (grepl("oat", Project) & grepl("oat", IGAs)) |
    (grepl("tra", Project) & grepl("tra", IGAs)) |
    (grepl("land", Project) & grepl("land", IGAs))), .(IGAs, TotalProj)])
```

There are issues with the project cycle data.

- There are 94 members who report multiple entries (rows). This is the intended way of reporting multiple projects. However, 12 members report IGAs (iga1_1st, etc.) that do not match with respective project_type. Among all members, project_type is less in details ("cow") and IGAs are more detailed ("cow, trade, goat"). In the majority cases, the former is a subset of the latter. In other cases, they simply differ: There are 96 unmatching members of which 60 with NAs in project_type. Given that there are (a relatively small number of) 36 cases of nonNAs in project type and detailed IGAs, I will use information only in igaX_Y and ignore project_type.
- There is one piece of information that may not to be dropped with project_type where 0 members report ox in their project while IGAs report cows. I will overwrite cow as IGA with ox.
- igaX_Y supposedly indicates X-th income generating activity in Y-th most recent project. But year_Y shows that igaX_Y is Y-th oldest project. year_2nd (all 2014), year_3rd (all 2015) are reported only for traditional indicates that year_Y refers to disbursement years, not necessarily the project starting year. This is further supported by no year_2nd is recorded for other arms. Information exists in iga1_1st, iga1_2nd, iga1_3rd (most, 2nd most, 3rd most recent igas), but not in iga2_1st, iga2_2nd, iga2_3rd, iga3_1st, iga3_2nd, iga3_3rd.

```
# subset cases
addmargins(table0(pc1[
  ((grepl("ow", Project) & grepl("cow", IGAs)) |(grepl("ox", Project) & grepl("ox", IGAs))
  (grepl("oat", Project) & grepl("oat", IGAs)) |(grepl("tra", Project) & grepl("tra", IGA
  (grepl("land", Project) & grepl("land", IGAs))), .(IGAs, Project)]),
  1:2, sum, quiet = T)
```

```
                   Project
IGAs                cow  ox goat/sheep business/trade land sum
  2 cows,goat         0   0          2              0    0   2
  2 cows,land         6   0          0              0    0   6
  2 cows,trade        5   0          0              3    0   8
  2 goats,cow         3   0          4              0    0   7
  2 goats,trade       0   0          3              2    0   5
  2 trades,cow        2   0          0              2    0   4
  2 trades,goat       0   0          0              1    0   1
  cow               327   0          0              0    0 327
  cow,goat,land       1   0          0              0    0   1
  cow,goat,trade      4   0          7              2    0  13
  cow,land,nutcorn    9   0          0              0    0   9
```

```
  cow,land,trade      3   0          0                0    0   3
  land                0   0          0                0    2   2
  ox                  0   1          0                0    0   1
  trade               0   0          0                1    0   1
  sum               360   1         16               11    2 390
```

```
# unmatching cases
addmargins(table0(pc1[!((grepl("ow", Project) & grepl("cow", IGAs)) |
  (grepl("ox", Project) & grepl("ox", IGAs)) |
  (grepl("oat", Project) & grepl("oat", IGAs)) |
  (grepl("tra", Project) & grepl("tra", IGAs)) |
  (grepl("land", Project) & grepl("land", IGAs))), .(IGAs, Project)]),
  1:2, sum, quiet = T)
```

```
                    Project
IGAs                 cow  ox goat/sheep business/trade land <NA> sum
  2 cows,goat          0   3          0              0    0    0   3
  2 cows,land          0   4          1              0    0    0   5
  2 cows,nutcorn       0   1          0              0    0    0   1
  2 cows,trade         0   5          3              0    0    3  11
  2 goats,cow          0   5          0              0    0    0   5
  2 goats,trade        2   1          0              0    0    7  10
  2 trades,cow         0   0          3              0    0    4   7
  2 trades,goat        0   1          0              0    0    2   3
  cow                  0 179          5              1    1   34 220
  cow,goat,trade       0   5          0              0    0    1   6
  cow,land,nutcorn     0   8          0              0    0    1   9
  cow,land,trade       0   1          0              0    0    2   3
  goat                 0   0          0              0    0    1   1
  house                0   0          0              0    0    1   1
  land                 5   1          0              0    0    4  10
  ox                   1   0          0              0    0    0   1
  trade                6   5          1              0    0    0  12
  sum                 14 219         13              1    1   60 308
```

```
setkey(pc1, hhid, start_year, start_month)
table0(pc1[!is.na(iga1_2nd), .(year_1st, year_2nd)])
```

```
        year_2nd
year_1st  0 2014
    2013 27   95
```

```
table0(pc1[!is.na(iga1_3rd), .(year_1st, year_3rd)])
```

```
        year_3rd
year_1st  0 2015
    2013 27   95
```

```
# members multiple igas but reporting only 1 date seem to have multiple projects,
# just not having multiple start dates (they started earlier than this research?)
summary(pc1[!is.na(iga1_2nd) & year_2nd == 0,
  .(Arm, BStatus = droplevels(BStatus), IGAs = droplevels(factor(IGAs)),
    Project = droplevels(Project))])
```

```
          Arm          BStatus                    IGAs     Project
 traditional: 0   borrower:27   2 cows,land      : 8   cow :14
 large      : 0                 2 cows,nutcorn   : 1   ox  :12
 large grace:22                 cow,land,nutcorn:18   NA's: 1
 cow        : 5
```

```
# members with multiple igas reporting more than 1 date
summary(pc1[!is.na(iga1_2nd) & year_2nd != 0,
  .(Arm=droplevels(Arm), BStatus = droplevels(BStatus),
    IGAs = droplevels(factor(IGAs)),
    Project = droplevels(Project),
    year_2nd = factor(year_2nd), year_3rd= factor(year_3rd))])
```

```
          Arm         BStatus                  IGAs             Project
 traditional:95   borrower:95   2 cows,trade   :19   cow            :21
                                cow,goat,trade:19   ox             :22
                                2 goats,trade  :15   goat/sheep     :23
                                2 goats,cow    :12   business/trade:10
                                2 trades,cow   :11   NA's           :19
                                cow,land,trade: 6
                                (Other)        :13
 year_2nd   year_3rd
 2014:95    2015:95
```

```
summary(pc1[!is.na(iga1_2nd) & year_2nd == 0,
  .(Arm=droplevels(Arm), BStatus = droplevels(BStatus),
    IGAs = droplevels(factor(IGAs)),
    Project = droplevels(Project),
    year_3rd= factor(year_3rd))])
```

```
          Arm         BStatus                    IGAs     Project    year_3rd
 large grace:22   borrower:27   2 cows,land      : 8   cow :14    0:27
 cow        : 5                 2 cows,nutcorn   : 1   ox  :12
                                cow,land,nutcorn:18   NA's: 1
```

```
# Overwrite cow with ox
pc1[grepl("^cow$", IGAs) & grepl("ox", Project), IGAs := "ox"]
```

Tabulation of loan projects shows that there is no member invested all in goats and goats are not the members' main assets. Among the 85 tradtional loan recipients who report their loan projects, there are 27 members who report to have purchased a goat twice and 15 who have invested in a retail trade twice. It is also puzzling that, among traditional arm members, 27 report to have invested in a cow twice, which seems unlikely with their purchasing powers.

```
table0(pc1[o800 == 1 & grepl("tra", Arm), IGAs])
```

```

   2 cows,goat     2 cows,land    2 cows,trade     2 goats,cow  2 goats,trade
             5               3              19              12             15
  2 trades,cow  2 trades,goat  cow,goat,land cow,goat,trade cow,land,trade
            11               4               1              19              6
```

```
# tb ← as.data.frame.matrix(table0(pc1[grepl("bor", BStatus), .(IGA13, Arm)]))
# tb ← data.table(cbind(IGA13 = rownames(tb), tb))
# tb[, IGA13 := as.character(IGA13)]
# setorder(tb, -traditional)
# tb
```

Number of reported IGAs by arm shows that traditional members report a project everytime they receive a loan, hence all have 3 IGAs. Interestingly, none has three goats.

```
#tbprjnum ← addmargins(table0(pc1[o800==1, .(N=.N), by = .(Arm, hhid)][,
#  .(Arm, N)]), 2, sum)
tbprjnum ← addmargins(table0(pc1[o800==1,
```

```
  .(NumIGAs = as.numeric(!is.na(IGA1)) + as.numeric(!is.na(IGA2)) + as.numeric(!is.na(IGA3
  by = .(Arm, hhid)][, .(Arm, NumIGAs)]), 2, sum)
cbind(round((tbprjnum[, 1:2]/tbprjnum[, 3])*100, 2), sum = tbprjnum[, 3])
```

```
                    1      3 sum
traditional    0.00 100.00  95
large        100.00   0.00 217
large grace   88.83  11.17 197
cow           97.35   2.65 189
```

```
table0(pc1[o800 == 1 & grepl("tra", Arm), IGAs])
```

```

  2 cows,goat    2 cows,land   2 cows,trade    2 goats,cow  2 goats,trade
            5              3             19             12             15
 2 trades,cow  2 trades,goat  cow,goat,land cow,goat,trade cow,land,trade
           11              4              1             19              6
```

Goat holding size and total holding increase by the final round but the number of holders is decreasing, indicating a limited number of expansion in goat holding. Interestingly, it is only traditional arm holding that are increasing while all ther arms reduce the goat holding size.

```
lvo <- readRDS(paste0(pathsaveHere, DataFileNames[5], "InitialSample.rds"))
lvo[, Num := .N, by = hhid]
table0(lvo[, .(Arm, Num)])
```

```
               Num
Arm                1    2    3    4
  traditional    115   14  114  952
  large           11   10   21 1508
  large grace     48    8   54 1320
  cow             22   26  114 1308
```

```
# HHs with single observations
# summary(lvo[hhid %in% hhid[Num==1],
#   .(Arm, hhid, survey = factor(survey), Livestock = factor(LivestockCode),
#   NumCows = factor(NumCows), ObPattern)])
lvow <- reshape(lvo, direction = "wide", idvar = c("Arm", "BStatus", "o800", "hhid"),
  v.names = grepout("Live|NumC|owned|sales|val|cost", colnames(lvo)),
  timevar = "survey")
```

```
Warning in reshapeWide(data, idvar = idvar, timevar = timevar, varying = varying, : some c
```

```
lvo <- reshape(lvow, direction = "long")
lvo[, N := .N, by = .(Arm, BStatus, o800, survey)]
```

```
Warning in `[.data.table`(lvo, , `:=`(N, .N), by = .(Arm, BStatus, o800, : Invalid .intern
```

```
# HHs with single observations
summary(lvo[hhid %in% hhid[Num==1] & survey == 1,
  .(Arm, hhid, survey = factor(survey), Livestock = factor(LivestockCode),
  NumCows = factor(NumCows), ObPattern)])
```

```
          Arm            hhid            survey          Livestock   NumCows
 traditional:115   Min.   : 7010103   1:196                    :90   0:167
 large      : 11   1st Qu.: 7031403          Chicken/duck:68   1: 18
 large grace: 48   Median : 7043012          Goat/Sheep  : 9   2:  8
```

```
 cow         : 22   Mean   : 7630719           cow/ox       :29   3:  3
                    3rd Qu.: 7127117
                    Max.   :81710316

 ObPattern
 0111:  1
 1000: 91
 1010:  1
 1011:  0
 1100:  1
 1110:  0
 1111:102
```

```
addmargins(table0(lvo[hhid %in% hhid[Num<4] & survey == 1, .(Arm, BStatus)]),
  1:2, sum, T)
```

```
             BStatus
Arm            borrower individual rejection group rejection rejection by flood
  traditional      107                    8               5                 40
  large             19                    2               2                  0
  large grace       23                    7              20                 20
  cow               27                   26               0                 20
  sum              176                   43              27                 80
             BStatus
Arm             sum
  traditional 160
  large        23
  large grace  70
  cow          73
  sum         326
```

```
addmargins(table(lvo[o800 == 1, .(N = .N), by = .(Arm, hhid)][, .(Arm, N)]),
  1:2, sum, quiet = T)
```

```
             N
Arm             4 sum
  traditional 199 199
  large       200 200
  large grace 200 200
  cow         200 200
  sum         799 799
```

```
addmargins(table0(lvo[o800 == 1 & survey == 4, .(Arm, BStatus)]),
  1:2, sum, quiet = T)
```

```
             BStatus
Arm            borrower individual rejection group rejection rejection by flood
  traditional      109                   30              40                 20
  large            171                    9              20                  0
  large grace      167                   13              10                 10
  cow              153                   37               0                 10
  sum              600                   89              70                 40
             BStatus
Arm             sum
  traditional 199
  large       200
  large grace 200
  cow         200
  sum         799
```

```
lvo[grepl("ow|ox", LivestockCode), c("CowObs", "Cowtee") := .(.N, 1:.N),
  by = hhid]
addmargins(table0(lvo[o800 == 1 & grepl("ow|ox", LivestockCode)
  & Cowtee == 1,
  .(Arm, CowObs)]),
  1:2, sum, quiet = T)
```

```
               CowObs
Arm               1   2   3   4 sum
  traditional    23  39  52  20 134
  large          15  49  82  37 183
  large grace    11  46  86  26 169
  cow            12  25 115  23 175
  sum            61 159 335 106 661
```

```
addmargins(table0(lvo[o800 == 1 & grepl("ow|ox", LivestockCode),
  .(tee, NumCows)]),
  1:2, sum, quiet = T)
```

```
     NumCows
tee      0    1    2    3    4    5    6    7    8    9 <NA>  sum
  1     14  963  560  140   41    7    6    2    3    2   69 1807
  2      0    1    0    0    0    0    0    0    0    0    0    1
  sum   14  964  560  140   41    7    6    2    3    2   69 1808
```

Attach 0 cattle ownership when nothing is reported.

```
lvo[grepl("ow|ox", LivestockCode) & is.na(NumCows), NumCows := 0]
addmargins(table0(lvo[o800 == 1 & grepl("ow|ox", LivestockCode)& survey == 1,
  .(Arm, NumCows)]),
  1:2, sum, quiet = T)
```

```
               NumCows
Arm               1   2   3   4   5 sum
  traditional    22   7   2   0   0  31
  large          31   8   2   2   0  43
  large grace    25   9   1   0   1  36
  cow            24   7   1   0   0  32
  sum           102  31   6   2   1 142
```

```
addmargins(table0(lvo[o800 == 1 & grepl("ow|ox", LivestockCode)& survey == 4,
  .(Arm, NumCows)]),
  1:2, sum, quiet = T)
```

```
               NumCows
Arm               0   1   2   3   4   5   6   8   9 sum
  traditional     2  58  30   8   2   0   0   0   0 100
  large           0  62  67  21   4   3   2   0   1 160
  large grace     4  61  58  11   5   1   0   1   0 141
  cow             2  68  61  16   2   0   0   0   0 149
  sum             8 249 216  56  13   4   2   1   1 550
```

```
nocow ← lvo[Arm == "cow" & grepl("ow", LivestockCode) & o800 == 1 &
  Year > 2013,
  hhid[
    (is.na(number_owned) | number_owned==0) &
    (is.na(nowned_cow) | nowned_cow == 0) &
    (is.na(nowned_ox) | nowned_ox == 0)
  ]]
```

There are 0 members in cow arm who do not report cattle ownership at least on one date after receiving the cows. Total holding size and holders may be too low. Below gives holding size of cattle among cow arm in 2015.

```
setkey(lvo, Arm, hhid, IntDate)
table0(lvo[Arm == "cow" & grepl("ow", LivestockCode) &
  o800 == 1 & Year == 2015,
  number_owned])
```

```
integer(0)
```

Members of traditional arm have the smallest cattle holding. In Table 38, ANOVA and Kruskal-Wallis tests indicate that means of cattle holding are different between arms in 2017. Tukey HST gives test results that account for multiple testing and shows that there is a difference between traditional and large, and other arms are in between yet their standard errors are too large to be considered statistically different from both extremes.

```
#  aovdat <- lvo[grepl(lvstk[1], LivestockCode) & o800==1 &
#    hhid %in% arid[, hhid] & grepl("bo", BStatus) & Year == 2017,
#      .(Arm, number_owned)]
table0(lvo[grepl("ow|ox", LivestockCode), .(NumCows, number_owned)])
```

```
       number_owned
NumCows    0    1    2    3    4    5    6    7    8    9   10   12   15 <NA>
     0    24    0    0    0    0    0    0    0    0    0    0    0    0  110
     1     0 1849    0    0    0    0    0    0    0    0    0    0    0    0
     2     0    0 1073    0    0    0    0    0    0    0    0    0    0    0
     3     0    0    0  272    0    0    0    0    0    0    0    0    0    0
     4     0    0    0    0   89    0    0    0    0    0    0    0    0    0
     5     0    0    0    0    0   32    0    0    0    0    0    0    0    0
     6     0    0    0    0    0    0   14    0    0    0    0    0    0    0
     7     0    0    0    0    0    0    0    6    0    0    0    0    0    0
     8     0    0    0    0    0    0    0    0    4    0    0    0    0    0
     9     0    0    0    0    0    0    0    0    0    3    0    0    0    0
     10    0    0    0    0    0    0    0    0    0    0    2    0    0    0
     12    0    0    0    0    0    0    0    0    0    0    0    1    0    0
     15    0    0    0    0    0    0    0    0    0    0    0    0    1    0
```

```
table0(lvo[grepl("ow|ox", LivestockCode) & Year ≥ 2014,
  .(NumCows, number_owned)])
```

```
       number_owned
NumCows 1 4
      1 2 0
      4 0 2
```

```
lvo[!grepl("cow", Arm) &
  hhid %in% hhid[
    any(is.na(NumCows)) &
    (!is.na(NumCows) & NumCows > 0 & survey < 2)] &
        hhid %in% pc1[grepl("cow", pc1[, IGA13]), hhid],
  .(Arm, hhid, survey, NumCows, LivestockCode, number_owned)]
```

```
           Arm    hhid survey NumCows LivestockCode number_owned
 1: traditional 7021103      2       1        cow/ox            1
 2: traditional 7021103      3       1        cow/ox            1
 3: traditional 7021103      4       1        cow/ox            1
 4: traditional 7021103      1       1        cow/ox            1
```

```
  5: traditional 7065003      2       2        cow/ox           2
 ---
308: large grace 8169809      1       2        cow/ox           2
309: large grace 8169813      2       1        cow/ox           1
310: large grace 8169813      3       0        cow/ox          NA
311: large grace 8169813      4       0   Chicken/duck          4
312: large grace 8169813      1       1        cow/ox           1
```

```
aovdat ← lvo[o800==1 & survey == 4, .(Arm, NumCows)]
NCowDestat ← rbindlist(
lapply(by(aovdat[, NumCows], aovdat[, Arm], destat), data.table)
)
NCowDestat[, Arms := arms]
setcolorder(NCowDestat, c(ncol(NCowDestat), 1:(ncol(NCowDestat)-1)))
addmargins(table0(aovdat), 1:2, sum, quiet = T)
```

```
             NumCows
Arm             0   1   2   3   4   5   6   8   9 <NA> sum
  traditional  46  58  30   8   2   0   0   0   0   55 199
  large        32  62  67  21   4   3   2   0   1    8 200
  large grace  34  61  58  11   5   1   0   1   0   29 200
  cow          30  68  61  16   2   0   0   0   0   23 200
  sum         142 249 216  56  13   4   2   1   1  115 799
```

```
# non-Cow arm: Assign 1 to NA if
#  NumCows is positive before 2014
#  IGA13 includes cow
lvo[!grepl("cow", Arm) &
  hhid %in% hhid[
    any(is.na(NumCows)) &
    (!is.na(NumCows) & NumCows > 0 & survey == 1)] &
  hhid %in% pc1[grepl("cow", pc1[, IGA13]), hhid] &
  survey ≥ 2, NumCows := NumCows[!is.na(NumCows)][1], by = hhid]
aovdat1 ← lvo[o800==1 & survey == 4, .(Arm, NumCows)]
aovdat3 ← lvo[o800==1 & survey == 3, .(Arm, NumCows)]
aovdat4 ← lvo[o800==1 & survey == 2, .(Arm, NumCows)]
aovdat5 ← lvo[o800==1 & survey == 1, .(Arm, NumCows)]
```

Cow arm: add a cow for borrowers if NumCows is NA or zero after rd 1.

```
lvo[grepl("cow", Arm) & (is.na(NumCows) | (!is.na(NumCows)  & NumCows == 0))
   & survey ≥ 2 & grepl("bo", BStatus), NumCows := 1]
aovdat2 ← lvo[o800==1 & survey == 4, .(Arm, NumCows)]
NCowDestat ← rbindlist(
lapply(by(aovdat2[, NumCows], aovdat[, Arm], destat), data.table)
)
NCowDestat[, Arms := arms]
setcolorder(NCowDestat, c(ncol(NCowDestat), 1:(ncol(NCowDestat)-1)))
addmargins(table0(aovdat2), 1:2, sum, quiet = T)
```

```
             NumCows
Arm             0   1   2   3   4   5   6   8   9 <NA> sum
  traditional  46  54  35   7   3   0   0   0   0   54 199
  large        34  66  64  20   4   2   1   0   1    8 200
  large grace  33  61  60  10   5   0   0   2   0   29 200
  cow          15  89  61  16   2   0   0   0   0   17 200
  sum         128 270 220  53  14   2   1   2   1  108 799
```

```
# aovdat1: raw data in 2017
# aovdat2: NA => 0 for cow arm after 2013, 2017
# aovdat3: raw data in 2015-16
# aovdat4: raw data in 2014
# aovdat5: raw data in 2012
aovfilenames ← c("_beforeDataEdit", "", "_3", "_2", "_1")
for (k in 1:length(aovfilenames)) {
  aovdat ← get(paste0("aovdat", k))
  NCowDestat ← rbindlist(
  lapply(by(aovdat[, NumCows], aovdat[, Arm], destat), data.table)
  )
  NCowDestat[, Arms := arms]
  setcolorder(NCowDestat, c(ncol(NCowDestat), 1:(ncol(NCowDestat)-1)))
  tb ← addmargins(table0(aovdat), 2, sum)
  round(tb/tb[, ncol(tb)], 2)
  summary(res.aov ← aov(NumCows ~ Arm, data = aovdat))
  tuk ← TukeyHSD(res.aov)
  #plot(res.aov, 1)
  (res.KWaov ← kruskal.test(NumCows ~ Arm, data = aovdat))
  anova.res ← rbind(
    c("ANOVA", rep("", 3),
      formatC(summary(res.aov)[[1]][1, 5], digits = 4, format = "f"))
    , c("Kruskal-Wallis", rep("", 3),
      formatC(res.KWaov$p.val, digits = 4, format = "f"))
    , cbind(paste0("\\hspace{.5em}", rownames(tuk$Arm)),
       formatC(tuk$Arm, digits = 4, format = "f"))
  )
  colnames(anova.res) ← c("Test", "Mean diff", "lower", "upper", "$p$ value")
  assign(paste0("anovares", k), anova.res)
  write.tablev(
   latextab(anova.res,
     hleft = c("\\footnotesize\\hfill", rep("\\hfil\\footnotesize$", ncol(anova.res)-1)),
     hcenter = c(3.5, rep(1, ncol(anova.res)-1)),
     hright = c("", rep("$", ncol(anova.res)-1)),
     alternatecolor = "gray90",
     lastDiffVariable = "^AN",
     SepLineText = "Tukey HST", inter.with = ""),
    paste0(pathprogram,
     "table/ImpactEstimationOriginal1600Memo3/anovaCow",
     aovfilenames[k], ".tex"),
    colnamestrue = F)
}
anovares ← rbindlist(
  lapply(list(anovares1, anovares2, anovares3, anovares4, anovares5),
    function(x) data.table(x[, c(2, 5), drop = F]))
  )
setnames(anovares, c("difference", "pval"))
anovares[, Tests := rep(anovares1[, 1], length(aovfilenames))]
anovares[!grepl("AN|Kru", Tests), pval := paste0("(", pval, ")")]
anovm ← matrix(c(t(anovares[, 1:2])), byrow = F, nrow = 2)
anovm ← data.table(matrix(c(anovm), byrow = F, ncol = length(aovfilenames)))
anovm ← anovm[V1 != "", ]
anovm[, Tests := c(anovares1[1:2, 1], c(t(cbind(anovares1[-(1:2), 1], "")))))]
setcolorder(anovm, c("Tests", paste0("V", 1:5)))
setnames(anovm, c("Tests", "rd4", "rd4 edited", "rd3", "rd2", "rd1"))
```

```
write.tablev(
 latextab(as.matrix(anovm),
    hleft = c("\\footnotesize\\hfill", rep("\\hfil\\footnotesize$", ncol(anovm)-1)),
    hcenter = c(3.5, rep(1, ncol(anovm)-1)),
    hright = c("", rep("$", ncol(anovm)-1)),
    alternatecolorManualColor = "gray90",
    alternatecolorManual = c(seq(7, nrow(anovm)+2, 4), seq(8, nrow(anovm)+2, 4)),
    addheaderAbove = "num",
    addheaderBelow = letters[1:6],
    headercolor = "paleblue",
    adjustlineskip = "-.5ex", adjlskiprows = seq(3, nrow(anovm), 2),
    lastDiffVariable = "^AN", SepLineText = "Tukey HST", inter.with = "")
  , paste0(pathprogram,
      "table/ImpactEstimationOriginal1600Memo3/anovaCowResults.tex")
  , colnamestrue = F)
addmargins(table0(lvo[o800==1 & NumCows > 4 & survey == 4,
  .(Arm, groupid)]), 1:2, sum)
```

```
Margins computed over dimensions
in the following order:
1: Arm
2: groupid
```

```
              groupid
Arm             70203 70210 70538 70962 sum
  traditional       0     0     0     0   0
  large             1     0     1     2   4
  large grace       0     2     0     0   2
  cow               0     0     0     0   0
  sum               1     2     1     2   6
```

Table 38: Anova results for cattle holding equality by arm

Tests	(1) rd4	(2) rd4 edited	(3) rd3	(4) rd2	(5) rd1
a	b	c	d	e	f
ANOVA	0.0016	0.0008	0.0075	0.0000	0.3082
Kruskal-Wallis	0.0011	0.0003	0.0132	0.0001	0.3768
Tukey HST					
large-traditional	0.4537	0.4537	0.3535	0.5438	0.0955
	(0.0009)	(0.0007)	(0.0065)	(0.0000)	(0.3909)
large grace-traditional	0.3617	0.3617	0.2627	0.2582	0.0452
	(0.0173)	(0.0142)	(0.0862)	(0.1142)	(0.8774)
cow-traditional	0.3071	0.3763	0.1338	0.2826	−0.0050
	(0.0571)	(0.0083)	(0.6093)	(0.0600)	(0.9998)
large grace-large	−0.0920	−0.0920	−0.0908	−0.2856	−0.0503
	(0.8517)	(0.8435)	(0.8311)	(0.0517)	(0.8396)
cow-large	−0.1466	−0.0774	−0.2198	−0.2613	−0.1005
	(0.5659)	(0.8951)	(0.1527)	(0.0777)	(0.3443)
cow-large grace	−0.0546	0.0146	−0.1290	0.0244	−0.0503
	(0.9658)	(0.9992)	(0.6266)	(0.9963)	(0.8396)

Source: Survey data.

Note: Each column uses respective year cattle ownership information. For ANOVA and Kruskal-Wallis, each entry indicates p values. ANOVA tests for the null of equality of means under normality. Kruskal-Wallis tests for the null of no stochastic dominance among samples without using the normality assumption. Tukey's honest significant tests show difference in means and p values in parenthesis that account for multiple testing under normality. In column 2, we edited data by assigning 1 to members of cow arm at dates after disbursement if reported holding is NA or zero.

```
# goat holding
tb <- table(lvo[number_owned > 0 & grepl("oat", LivestockCode) &
  o800==1,
  .(survey, number_owned)])
```

```
tb <- cbind(addmargins(tb, 2, sum),
  total = tb[, 1] + tb[, 2]*2 + tb[, 3]*3 + tb[, 4]*4 + tb[, 5]*5 + tb[, 6]*6)
cbind(tb, HoldingSize = round(tb[, "total"]/tb[, "sum"], 2))
```

```
   1 2 3 4 5 6 sum total HoldingSize
1 10 9 1 0 0 0  20    31        1.55
2  7 3 0 2 0 0  12    21        1.75
3  1 3 1 1 2 0   8    24        3.00
4  0 1 0 5 2 2  10    44        4.40
```

```
setorder(lvo, Arm, BStatus, survey, Year)
# number of holders
lvstk <- c("ow|ox", "oat")
lvstkName <- c("cattle", "goat")
lvstkCounts <- c("NumCows", "number_owned")
lvstkSummary <- NULL
for (k in 1:2) {
  if (k == 1)
  lvoc <- lvo[o800==1 ,
    .(Holders = sum(!is.na(NumCows) & NumCows > 0)
    , Holding = sum(NumCows, na.rm = T)
    ),
    by = .(survey, Arm, BStatus, N)][,
    .(Arm, BStatus, survey, Holding, Holders
    , HoldingSize = Holding/Holders, N)] else
  lvoc <- lvo[o800==1 & grepl("oat", LivestockCode),
    .(Holders = sum(!is.na(number_owned) & number_owned > 0)
    , Holding = sum(number_owned, na.rm = T)
    ),
    by = .(survey, Arm, BStatus, N)][,
    .(Arm, BStatus, survey, Holding, Holders
    , HoldingSize = Holding/Holders, N)]
  lvoc[, PerCapitaHolding := Holding/N]
  setnames(lvoc, c("HoldingSize", "Holding", "Holders", "PerCapitaHolding"),
    paste0("value.", c("HoldingSize", "Holding", "Holders", "PerCapitaHolding")))
  lvocL <- reshape(lvoc, direction = "long", idvar = c("Arm", "BStatus", "survey", "N"),
    varying = grepout("^val", colnames(lvoc)))
  setnames(lvocL, "time", "variables")
  lvocL[, Livestock := lvstkName[k]]
  lvstkSummary <- rbind(lvstkSummary, lvocL)
}
```

```
Warning in `[.data.table`(lvocL, , `:=`(Livestock, lvstkName[k])): Invalid .internal.selfr
```

```
Warning in `[.data.table`(lvocL, , `:=`(Livestock, lvstkName[k])): Invalid .internal.selfr
```

Given the misreporting in large loans arms, the power may get affected and only large seems to stand out from all other arms, while large grace, cow are not different in terms of cattle ownership against traditional.

```
# number of loan recipients in each arm: Data of plot panel info and their N
ArmSizeData <- lvo[o800==1 & survey == 1, .(N = .N), by = .(Arm, BStatus)]
ArmSizeData2 = copy(ArmSizeData)
ArmSizeData3 = copy(ArmSizeData)
ArmSizeData4 = copy(ArmSizeData)
ArmSizeData[, variables := "Holders"]
```

```
ArmSizeData2[, variables := "Holding"]
ArmSizeData3[, variables := "HoldingSize"]
ArmSizeData3[, N := NA]
ArmSizeData4[, variables := "PerCapitaHolding"]
ArmSizeData4[, N := NA]
ArmSizeData <- rbindlist(list(ArmSizeData, ArmSizeData2,
  ArmSizeData3, ArmSizeData4), use.names = T)
library(ggplot2)
g <- ggplot(data = subset(lvstkSummary, grepl("cattle", Livestock)),
    aes(x = survey, y = value)) +
  geom_col() +
  scale_x_continuous(name = "round", breaks = 1:4) +
  ylab("counts") +
  theme(
    legend.position = "none",
    axis.title = element_text(size = 7),
    axis.text.x = element_text(size = 6, angle = 90, vjust = 0, hjust = .5),
    axis.text.y = element_text(size = 6, hjust = 1),
    strip.text.x = element_text(color = "blue", size = 6,
      margin = margin(0, .5, 0, .5, "cm")),
    strip.text.y = element_text(color = "blue", size = 6,
      margin = margin(.5, 0, .5, 0, "cm"))
  ) +
  facet_grid(variables ~ Arm*BStatus, scales = "free_y") +
  geom_hline(data = ArmSizeData, aes(yintercept = N, color = "red"))
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo3/CowHoldingByArmBStatus.png"),
  g,
  width = 14, height = 8, units = "cm",
  dpi = 300
 )
```

```
library(ggplot2)
g <- ggplot(data = subset(lvstkSummary, grepl("goat", Livestock)),
    aes(x = survey, y = value)) +
  geom_col() +
  scale_x_continuous(name = "round", breaks = 1:4) +
  ylab("counts") +
  theme(
    axis.title = element_text(size = 7),
    axis.text.x = element_text(size = 5, angle = 90, vjust = .5, hjust = 1),
    axis.text.y = element_text(size = 6, hjust = 1),
    strip.text.x = element_text(color = "blue", size = 6,
      margin = margin(0, .5, 0, .5, "cm")),
    strip.text.y = element_text(color = "blue", size = 6,
      margin = margin(.5, 0, .5, 0, "cm"))
  ) +
  facet_grid(variables ~ Arm*BStatus, scales = "free_y")
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo3/GoatHoldingByArmBStatus.png"),
  g,
  width = 14, height = 8, units = "cm",
  dpi = 300
 )
```

```
library(ggplot2)
g ← ggplot(data = subset(pc1, creditstatus == "Yes"), aes(Project)) +
  geom_histogram(stat = "count") +
  xlab("project choices") +
  scale_y_continuous(labels = scales::percent_format(accuracy = 1),
    name = "percentage in sample")+
  aes(y=stat(count)/sum(stat(count))) +
  theme(
    legend.position="bottom",
    legend.text = element_text(size = 7),
    legend.title = element_text(size = 9),
    legend.key = element_rect(fill = "white"),
    legend.key.size = unit(.5, "cm"),
    axis.text.x = element_text(size = 6, angle = 30, vjust = 1, hjust = 1),
    axis.text.y = element_text(size = 7, vjust = .5, hjust = 1),
    axis.title = element_text(size = 7),
    strip.text.x = element_text(color = "blue", size = 6,
      margin = margin(0, .5, 0, .5, "cm")),
    strip.text.y = element_text(color = "blue", size = 6,
      margin = margin(.5, 0, .5, 0, "cm"))
  ) +
  facet_grid(. ~ AssignOriginal, switch = "y")
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo2/ProjectChoices.png"),
  g,
  width = 10, height = 4, units = "cm",
  dpi = 300
)
```

```
library(ggplot2)
g ← ggplot(data = subset(pc2, size_sequence == 1), aes(cost_once_amount_taka)) +
  geom_histogram() +
  xlab("amount (Tk.)") +
  scale_y_continuous()+
  theme(
    legend.position="bottom",
    legend.text = element_text(size = 7),
    legend.title = element_text(size = 9),
    legend.key = element_rect(fill = "white"),
    legend.key.size = unit(.5, "cm"),
    axis.text = element_text(size = 5),
    axis.title = element_text(size = 7),
    strip.text.x = element_text(color = "blue", size = 6,
      margin = margin(0, .5, 0, .5, "cm")),
    strip.text.y = element_text(color = "blue", size = 6,
      margin = margin(.5, 0, .5, 0, "cm"))
  ) +
  facet_grid(. ~ AssignOriginal, switch = "y")
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo2/FixedInvestmentAmount.png"),
  g,
  width = 10, height = 4, units = "cm",
  dpi = 300
)
```

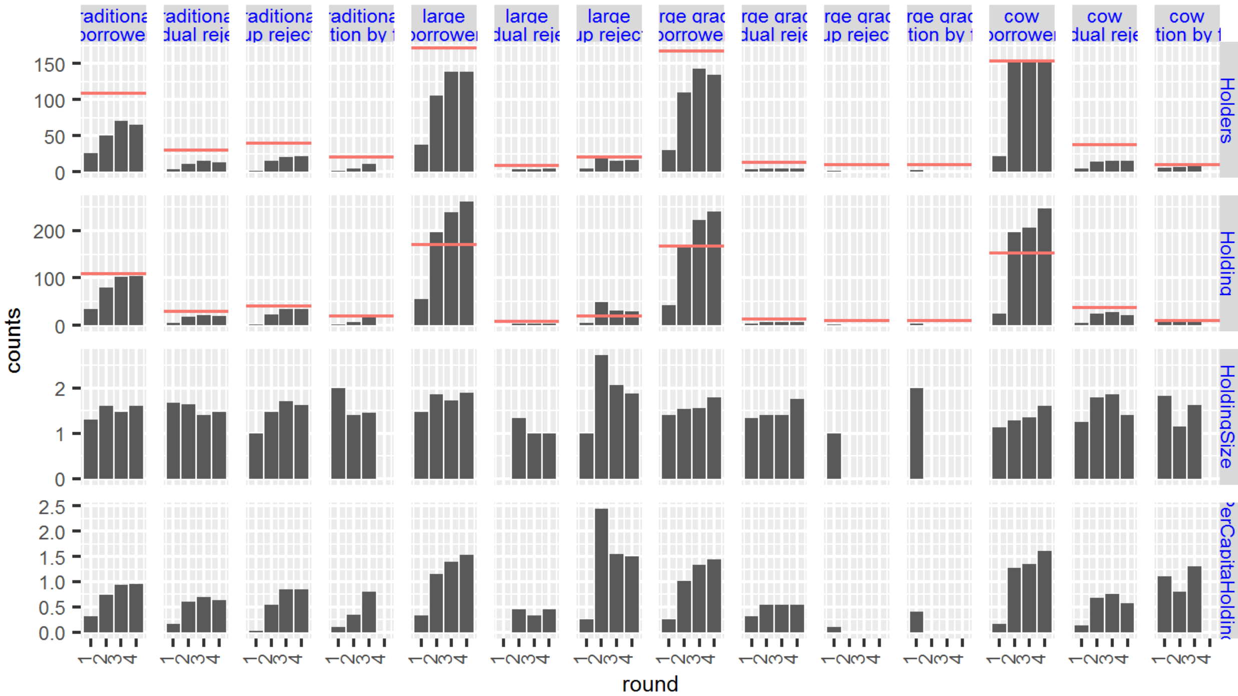
```
library(ggplot2)
pc21 ← pc2[!is.na(cost_once_when_year) & !is.na(cost_once_amount_taka) &
  size_sequence == 1, ]
setorder(pc21, hhid, cost_once_when_year)
pc21[, Seq := 1:.N, by = hhid]
pc21[Seq == 1, SeqString := "first"]
pc21[Seq == 2, SeqString := "second"]
pc21[Seq == 3, SeqString := "third"]
pc21[, SeqString := factor(SeqString)]
g ← ggplot(data = subset(pc21, size_sequence == 1),
  aes(cost_once_amount_taka)) +
  geom_histogram() +
  xlab("amount") +
  scale_y_continuous()+
  scale_x_continuous(limits = c(0, 30000))+
  theme(
    legend.position="bottom",
    legend.text = element_text(size = 7),
    legend.title = element_text(size = 9),
    legend.key = element_rect(fill = "white"),
    legend.key.size = unit(.5, "cm"),
    axis.text = element_text(size = 5),
    axis.title = element_text(size = 7),
    strip.text.x = element_text(color = "blue", size = 6,
      margin = margin(0, .5, 0, .5, "cm")),
    strip.text.y = element_text(color = "blue", size = 6,
      margin = margin(.5, 0, .5, 0, "cm"))
  )+
  #facet_grid(cost_once_when_year ~ AssignOriginal)
  facet_grid(SeqString ~ AssignOriginal, scales = "free_y")
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo2/FixedInvestmentAmountBySequence.png"),
  g,
  width = 12, height = 7, units = "cm",
  dpi = 300
)
```

```
library(ggplot2)
g ←
ggplot(data = subset(pc21, size_sequence == 1 & Seq == 1 & !is.na(DistDate1)),
  aes(cost_once_amount_taka)) +
  geom_histogram() +
  xlab("amount") +
  scale_y_continuous()+
  scale_x_continuous(limits = c(0, 30000))+
  theme(
    legend.position="bottom",
    legend.text = element_text(size = 7),
    legend.title = element_text(size = 9),
    legend.key = element_rect(fill = "white"),
    legend.key.size = unit(.5, "cm"),
    axis.text = element_text(size = 5),
    axis.title = element_text(size = 7),
    strip.text.x = element_text(color = "blue", size = 6,
      margin = margin(0, .5, 0, .5, "cm")),
```

```
    strip.text.y = element_text(color = "blue", size = 6,
      margin = margin(.5, 0, .5, 0, "cm"))
  )+
  facet_grid( ~ AssignOriginal)
ggsave(
  paste0(pathprogram,
    "figure/ImpactEstimationOriginal1600Memo2/FirstFixedInvestmentAmountByYear.png"),
  g,
  width = 10, height = 3, units = "cm",
  dpi = 300
 )
```

```
setkey(arid, Arm)
```

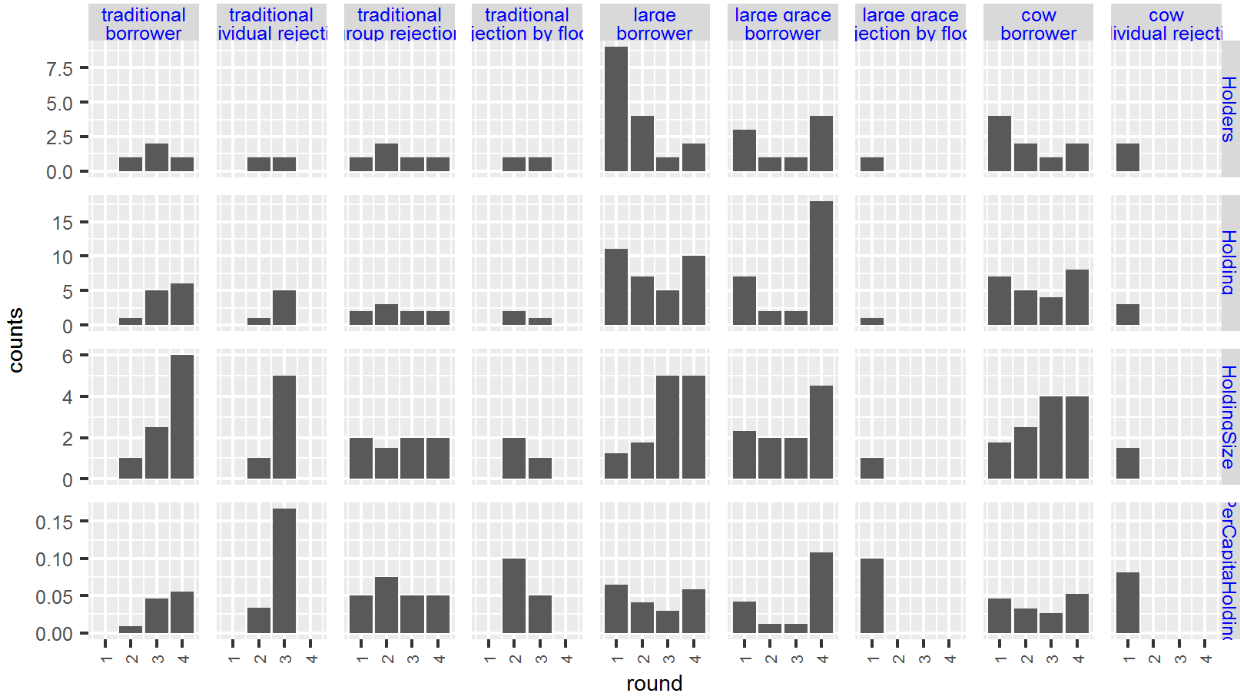
FIGURE 21: CATTLE HOLDING BY ARM AND BORROWER STATUS



Source: Survey data.

Note: Numbers of loan recipients are 109, 171, 167, 153, numbers of reported livestock holding are 109, 171, 167, 153 for traditional, large, large grace, cow arms, respectively. Red horizontal lines indicate number of loan recipients.

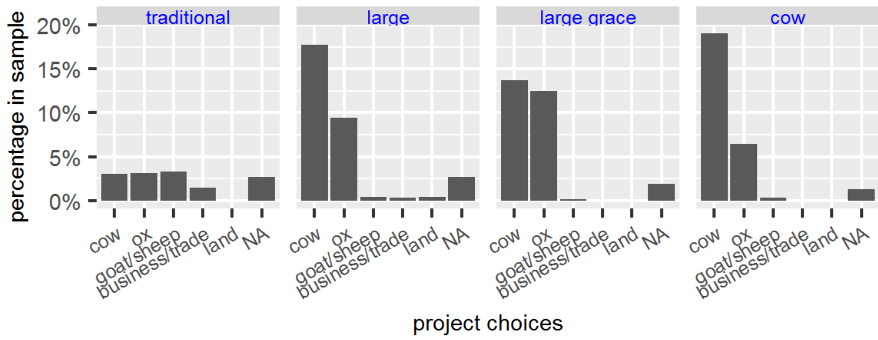
Figure 22: Goat holding by arm and borrower status



Source: Survey data.

Note: Numbers of loan recipients are 116, 180, 180, 190, numbers of reported livestock holding are 109, 171, 167, 153 for traditional, large, large grace, cow arms, respectively. No member reports goat holding among individual rejecters in large, large grace arms.

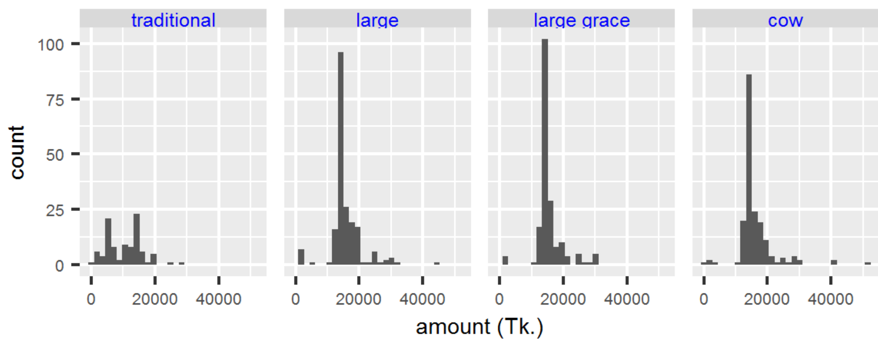
Figure 23: Project choices



Source: Survey data.

Note: Ratios of reported project choices using the lending to total number of projects in InitialSample. NAs include nonresponse to the question and dropped out individuals.

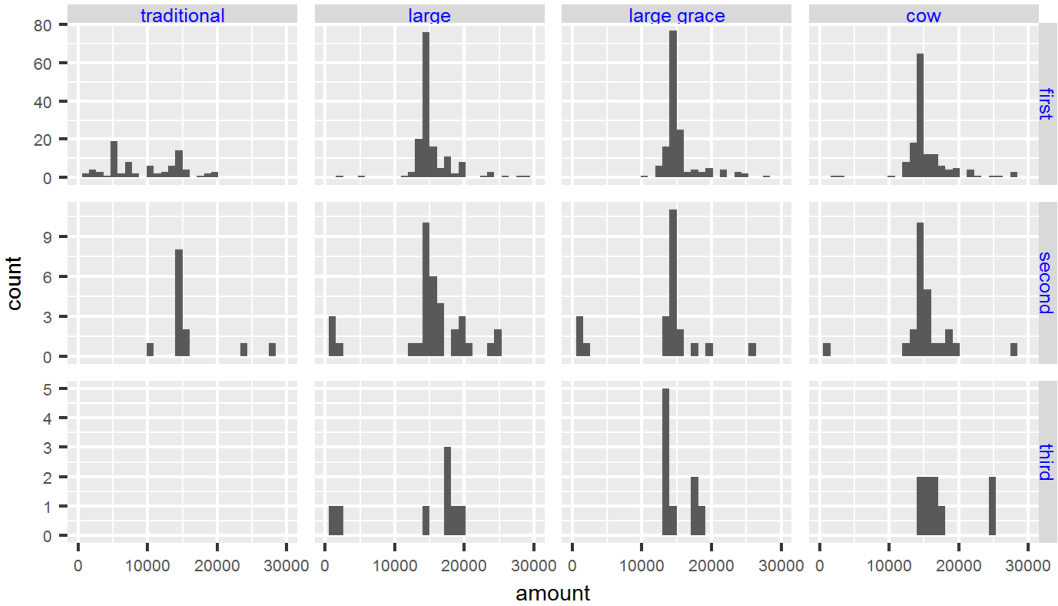
Figure 24: Largest fixed investment amount



Source: Survey data.

Note: Reported largest one-off investment amounts of the lending.

FIGURE 25: FIXED INVESTMENT SEQUENCE AND AMOUNTS



Source: Survey data.

Note: Reported largest one-off investment amounts of the lending. Top figure is the first investments reported by year, bottom figure is later investments reported by the sequence of investment projects.

References

Wooldridge, Jeffrey M., *Econometric Analysis of Cross Section and Panel Data*, MIT Press, 2010.