

# HA2\_2.1

Ishwara Hegde, Jonathan Neiman and Aleksei Samkov

10/15/2020

## Summary

The paper explores the impact of providing microcredit to rural areas in Morocco. The existing literature on microcredit at the time found that microcredit has a positive impact on self-employment activities but no impact on consumption or overall income. This paper contributes to the literature in three ways. First, the program in question is the only microcredit organization in the area. Second, the paper uses a unique sampling strategy that provides sufficient power to estimate impacts on borrowers as well representative households. Third, it provides a strategy to test for externalities on non borrowers.

The authors find that overall the impact of microcredit on the population is fairly limited. Even in the case with no other access to credit, take-up is low. Further, the gains in self-employment investments, sales and profits are offset by declines in employment income.

## Dataset

Some useful points about the dataset:

- Create the Output folder in the same directory in which you extracted the file from AEA
- Run the Master do file
- Use output\_total, profit\_total and ids from the `endline_mini... dta` file.
- From baseline: \* `m1` -> no. of people in the HH \* `nadults_resid` -> number of mem that are adults \* `a7_11` -> age of the head of the HH \* `d2_6==1` -> family doing animal husbandry \* `d2_6!=1` -> family doing non agricultural activities \* `i1==0` no and `i1!=0` is yes -> Outside loan due for the past 12 months \* `a_31==2` -> Spouse responded to the survey \* `a_31!= 1 or 2` -> another HH member (not head / spouse) responded to survey \* `paire` -> 81 village-pair FE
- Run the `exporting_csv.do` to export the data

## Bootstrapping

```
#setting parameters
n<- nrow(data)
N<-nrow(data)
n1 <- sum(data[, (treatment)])
n0 <- n-n1

#Simple means estimator by OLS
ols_out<-tidy(lm(output_total~treatment,data=data))
ols_profit<-tidy(lm(profit_total~treatment,data=data))

#Simple means manually
tau_simple_out<-mean(data[treatment==1, (output_total)])-
```

```

      mean(data[treatment==0,(output_total)])

tau_simple_profit<-mean(data[treatment==1, (profit_total)])-
      mean(data[treatment==0,(profit_total)])

blocks<-data[, .(.N), by = .(paire)]
B<-100
tau_matrix2<-data.table(tau_bs_out=rep(0,B),tau_bs_profit=rep(0,B),
      b=seq(1:B))

for (i in 1:B){
  block_values2<-data.table(out=rep(-9999,5427),profit=rep(-9999,5427),
      treat=rep(-9999,5427),paire=rep(-9999,5427))
  paire_bs<-c(sample(1:81,81,replace = TRUE))
  start_val<-1
  for (j in paire_bs){
    n_block<-as.integer(blocks[paire==j,.N])
    block_values2[start_val:(start_val+n_block-1),]<-
      data[paire==j,. (output_total,profit_total,treatment,paire)]
    start_val<-start_val+n_block

  }
  summ_tab2<-
  block_values2[out!=-9999,.(mean_output=mean(out),mean_profit=mean(profit)),
    by=. (treat)]
  tau_matrix2[i,1:2]<-summ_tab2[treat==1,2:3]-summ_tab2[treat==0,2:3]
}

#Standard errors

bs_se<-tau_matrix2[,.(out_sd=sd(tau_bs_out),profit_sd=sd(tau_bs_profit))]
bs_se

##      out_sd profit_sd
## 1: 4723.288  1689.131

ols_out

## # A tibble: 2 x 5
##   term      estimate std.error statistic  p.value
##   <chr>      <dbl>    <dbl>    <dbl>    <dbl>
## 1 (Intercept) 33361.    2738.    12.2    1.38e-33
## 2 treatment   256.     3921.    0.0652  9.48e- 1

ols_profit

## # A tibble: 2 x 5
##   term      estimate std.error statistic  p.value
##   <chr>      <dbl>    <dbl>    <dbl>    <dbl>
## 1 (Intercept) 10128.    1181.     8.57    1.41e-17
## 2 treatment  -645.     1692.    -0.381  7.03e- 1

```

We notice that in both cases the simple estimator has a larger bootstrap variance than just standard OLS.

#Debiased Estimator

*# Prepare data*

```
data_db_model <- na.roughfix(data[,.(m1,nadulsts_resid,a7_11,d2_6,  
                                i1,a3_1,paire,output_total,profit_total)])
```

*# Cross fitting*

```
index_1 <- sample(1:n,floor(n/2))  
index_2 <- setdiff(1:n,index_1)  
index_11 <- index_1[data$treatment[index_1]==1]  
index_10 <- setdiff(index_1, index_11)  
index_21 <- index_2[data$treatment[index_2]==1]  
index_20 <- setdiff(index_2, index_21)
```

```
data_1 <- data_db_model[index_1,]  
data_2 <- data_db_model[index_2,]  
data_11 <- data_db_model[index_11,]  
data_10 <- data_db_model[index_10,]  
data_21 <- data_db_model[index_21,]  
data_20 <- data_db_model[index_20,]
```

*# Random forest*

*#The minus meanns that all columns except that one*

```
fit11_output <- randomForest(output_total ~ . - profit_total, data = data_11)  
fit21_output <- randomForest(output_total ~ . - profit_total, data = data_21)
```

```
fit10_output <- randomForest(output_total ~ . - profit_total, data = data_10)  
fit20_output <- randomForest(output_total ~ . - profit_total, data = data_20)
```

```
fit11_profit <- randomForest(profit_total ~ . - output_total, data = data_11)  
fit21_profit <- randomForest(profit_total ~ . - output_total, data = data_21)
```

```
fit10_profit <- randomForest(profit_total ~ . - output_total, data = data_10)  
fit20_profit <- randomForest(profit_total ~ . - output_total, data = data_20)
```

*# Output*

```
m21_output <- predict(fit11_output, data_2)  
m11_output <- predict(fit21_output, data_1)  
m1_output <- rep(0,n)  
m1_output[index_1] <- m11_output  
m1_output[index_2] <- m21_output
```

```
m20_output <- predict(fit11_output, data_2)  
m10_output <- predict(fit21_output, data_1)  
m0_output <- rep(0,n)  
m0_output[index_1] <- m10_output  
m0_output[index_2] <- m20_output
```

*# Profit*

```
m21_profit <- predict(fit11_profit, data_2)
```

```

m11_profit <- predict(fit21_profit, data_1)
m1_profit <- rep(0,n)
m1_profit[index_1] <- m11_profit
m1_profit[index_2] <- m21_profit

m20_profit <- predict(fit11_profit, data_2)
m10_profit <- predict(fit21_profit, data_1)
m0_profit <- rep(0,n)
m0_profit[index_1] <- m10_profit
m0_profit[index_2] <- m20_profit

# Construct \tau_db

W_1 <- data$treatment
W_0 <- 1-W_1
gamma_1_simple <- n/n1
gamma_0_simple <- n/n0

tau_db_output <- mean(m1_output-m0_output) +
  mean(W_1*(data$output_total-m1_output))*gamma_1_simple
- mean(W_0*(data$output_total-m0_output))*gamma_0_simple

## [1] -1390.422

tau_db_profit <- mean(m1_profit-m0_profit) +
  mean(W_1*(data$profit_total-m1_profit))*gamma_1_simple
- mean(W_0*(data$profit_total-m0_profit))*gamma_0_simple

## [1] -661.0388

```

## Debiased Standard Errors

```

B<-100
tau_matrix3<-data.table(tau_bs_out=rep(0,B),tau_bs_profit=rep(0,B),
  b=seq(1:B))

for (i in 1:B){
  block_values2<-data.table(out=rep(-9999,5427),profit=rep(-9999,5427),
    treat=rep(-9999,5427),paire=rep(-9999,5427),
    m1=rep(-9999,5427),nadults_resid=rep(-9999,5427),
    a7_11=rep(-9999,5427),d2_6=rep(-9999,5427),
    i1=rep(-9999,5427),a3_1=rep(-9999,5427))

  paire_bs<-c(sample(1:81,81,replace = TRUE))
  start_val<-1
  for (j in paire_bs){
    n_block<-as.integer(blocks[paire==j,.(N)])
    block_values2[start_val:(start_val+n_block-1),]<-
      data[paire==j,. (output_total,profit_total,treatment,paire,
        m1,nadults_resid,a7_11,d2_6,i1,a3_1)]
    start_val<-start_val+n_block
  }
}

```

```

}
n<-nrow(block_values2[treat!=--9999])
n1 <- sum(block_values2[treat!=--9999,(treat)])
n0 <- n-n1
block_values2<-block_values2[treat!=--9999]

data_db_model <-
na.roughfix(block_values2[treat!=--9999,.(m1,nadulsts_resid,a7_11,d2_6,
      i1,a3_1,paire,out,profit)])

# Cross fitting
index_1 <- sample(1:n,floor(n/2))
index_2 <- setdiff(1:n,index_1)
index_11 <- index_1[block_values2$treat[index_1]==1]
index_10 <- setdiff(index_1, index_11)
index_21 <- index_2[block_values2$treat[index_2]==1]
index_20 <- setdiff(index_2, index_21)

data_1 <- data_db_model[index_1,]
data_2 <- data_db_model[index_2,]
data_11 <- data_db_model[index_11,]
data_10 <- data_db_model[index_10,]
data_21 <- data_db_model[index_21,]
data_20 <- data_db_model[index_20,]

# Random forest

#The minus meanns that all columns except that one
fit11_output <- randomForest(out ~ . - profit, data = data_11)
fit21_output <- randomForest(out ~ . - profit, data = data_21)

fit10_output <- randomForest(out ~ . - profit, data = data_10)
fit20_output <- randomForest(out ~ . - profit, data = data_20)

fit11_profit <- randomForest(profit ~ . - out, data = data_11)
fit21_profit <- randomForest(profit ~ . - out, data = data_21)

fit10_profit <- randomForest(profit ~ . - out, data = data_10)
fit20_profit <- randomForest(profit ~ . - out, data = data_20)

# Output
m21_output <- predict(fit11_output, data_2)
m11_output <- predict(fit21_output, data_1)
m1_output <- rep(0,n)
m1_output[index_1] <- m11_output
m1_output[index_2] <- m21_output

m20_output <- predict(fit11_output, data_2)
m10_output <- predict(fit21_output, data_1)
m0_output <- rep(0,n)
m0_output[index_1] <- m10_output

```

```

m0_output[index_2] <- m20_output

# Profit
m21_profit <- predict(fit11_profit, data_2)
m11_profit <- predict(fit21_profit, data_1)
m1_profit <- rep(0,n)
m1_profit[index_1] <- m11_profit
m1_profit[index_2] <- m21_profit

m20_profit <- predict(fit11_profit, data_2)
m10_profit <- predict(fit21_profit, data_1)
m0_profit <- rep(0,n)
m0_profit[index_1] <- m10_profit
m0_profit[index_2] <- m20_profit

W_1 <- block_values2$treat
W_0 <- 1-W_1
gamma_1_simple <- n/n1
gamma_0_simple <- n/n0

tau_db_output <- mean(m1_output-m0_output) +
  mean(W_1*(block_values2$out-m1_output))*gamma_1_simple
- mean(W_0*(block_values2$out-m0_output))*gamma_0_simple

tau_db_profit <- mean(m1_profit-m0_profit) +
  mean(W_1*(block_values2$profit-m1_profit))*gamma_1_simple
- mean(W_0*(block_values2$profit-m0_profit))*gamma_0_simple

tau_matrix3[i,1]<-tau_db_output
tau_matrix3[i,2]<-tau_db_profit
}

#Standard errors

bs_se2<-tau_matrix3[ ,.(out_sd=sd(tau_bs_out),profit_sd=sd(tau_bs_profit))]
bs_se2

##      out_sd profit_sd
## 1: 828.9038 342.3852

```

Now the standard deviations are much smaller. This makes sense since the de-biased estimators have lower conditional means and therefore lower variance than the simple difference in means. This follows from the Variance decomposition formula. ““