

# Replication-Project.Rmd

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## Introduction

For my final project, I replicated the analysis performed by Abhit Bhandari in his paper “Political Determinants of Economic Exchange: Evidence from a Business Experiment in Senegal.” In his experiment, Bhandari aimed to evaluate whether political connections and formal contracts impact the exchange of goods in Dakar, Senegal. To do this, he created his own business in Dakar that sold phone credits.

*All data and code in this paper can be found at the following link: <https://doi.org/10.7910/DVN/UIFXGX>*

## Senegal as a Place of Business

According to Bhandari, Senegal has weak legal institutions and consistently ranks poorly in work indexes for ease of doing business and enforcement of legal contracts. Furthermore, contractual enforcement becomes more complicated when the involved parties possess political connections. Per Bhandari, possessing political connections in Senegal affords one preferential treatment, including situations such as contractual enforcement. In essence, if a person breaks a legal contract, they are less likely to be held accountable if they hold political connections.

## Bhandari’s Hypotheses

Given this background information, Bhandari poses the following three hypotheses: The first hypothesis is that sellers who possess political connections will deter buyers from purchasing their goods. The second hypothesis is that formal legal contracts between sellers and buyers will increase the probability that a buyer purchases goods from the seller. The third hypothesis is that buyers have a higher probability of purchasing goods if they hold political connections and the seller in question does not hold political connections; conversely, buyers have a lower probability of purchasing goods if the seller possess political connections and the buyer does not.

Below, I have replicated Table 1 of Bhandari’s paper, which shows his theoretical predictions.

Table 1: Theoretical Predictions Under Asymmetric Political Connections

	Buyer is politically connected	
	No	Yes
Seller is not politically connected	Intermediate probability of purchase	High probability of purchase
Seller is politically connected	Low probability of purchase	Intermediate probability of purchase

## Bhandari’s Experiment Setup

Bhandari registered an official business in Senegal that offered phone credits. Since part of his hypothesis involved sellers’ signaling their political connections to buyers, he arranged for his nine hired employees to intern at a municipal council in Senegal. Afterwards, his employees began official employment.

Pertaining to treatment groups, Bhandari utilized a “factorial design” that involved three “treatment arms” which sought to assess how political connections and legal contracts would impact the exchange of goods between buyers and sellers.

The first treatment arm involved sellers revealing their political connections via bringing up their prior internship experience while talking to buyers (Note: according to Bhandari, it is customary for Senegal citizens to engage in long introductions when partaking in household business transactions).

The second treatment arm involved sellers’ requiring a formal contract signed between the seller and buyer for the transaction. This contract pertained to the transaction details, payment types, and product delivery information.

The third treatment arm involved sellers’ providing an optional formal contract to the buyer. In this scenario, buyers could chose to receive the same contract described above in exchange for a small fee.

A factorial experiment involves analyzing each level of independent factors in every combination possible with levels of other independent factors (Source: Penn State college of Health and Human Development). For example, in Bhandari’s experiment, factorial design gives us six different treatment groups (including the control group). This is because we have three types of contract availability (no contract, mandatory contract, and an optional contract). Additionally, for each of these treatments, the sellers either signaled or did not signal their connections. Hence,  $3 \times 2 = 6$  different permutations.

Below, I replicated Bhandari’s Table 2, which illustrates the six different treatment groups in his experiment.

Table 2: Treatment Groups

	Contract Availability		
	No contract	Contract (required)	Contract (optional)
Signaled connections	Pure control	Optional contract	Connection + required contract
Did not signal connections	Required contract	Connection	Connection + optional contract

## Block Randomization

For his experiment, Bhandari utilized block randomization in order to reduce sampling bias, as sampling bias may skewed the experiment’s results. He conducted the experiment across three housing communes. Each of the three communes had exposure to all six treatment types. In essence, Bhandari’s employees went to various homes in each commune, and in each home visit, they were randomly assigned a certain treatment to provide. To ensure treated individuals’ responses were independent and identically distributed (IID), Bhandari instructed sellers to visit houses that were a certain distance away from each other (in that way, neighbors wouldn’t gossip with each other about the new phone credit business) as well as only sell products to one person in each household (so that household members wouldn’t confer and influence each others’ responses).

## Data Collection

Data was collected in two waves. The first wave was the selling stage (i.e., sellers selling phone credits to prospective buyers). The second wave was post- transaction, when buyers were surveyed about topics such as their perceptions of sellers’ competency, trustworthiness, etc.

## Measuring Primary Outcomes

Bhandari aimed to measure two outcomes: the buyers' willingness to purchase the product, as well as the amount of risk buyers were willing to take on in the transaction.

In order to capture the salient data, Bhandari's business offered three different phone credit packages. The first package cost 700 West African CFA francs and offered almost instant delivery of a small amount of phone credits. The second package was cheaper, offered more phone credits, but was subject to a 3-day delivery delay after purchase (for which buyers were told was due to administrative processing). The third package was the most expensive option and also would be delivered after 3 days; however it also offered the greatest amount of phone credits per currency unit of all the packages available.

Below I have replicated Table 3 of Bhandari's paper, which showcases the full inventory of phone credit packages that his business offered as well as the associated risks of each package.

Table 3: Phone Credit Purchase Options

Purchase level	Cost (CFA)	Credits received (CFA)	When phone credit arrived	Type of risk
Declined deal	-	-	-	-
No delay	700	1,000	Several minutes	Risk of substandard quality
Delay (\$)	500	1,500	In 3 days	Risk of substandard quality and nondelivery
Delay (\$\$\$)	1,000	3,000	In 3 days	Risk of substandard quality and nondelivery

## Bhandari's Findings

Bhandari ultimately found that employees who signaled connections caused buyers to be less likely to purchase a service. This is likely due to buyers being hesitant that sellers with political connections are less likely to be held accountable if they breach a contract. Additionally, the presence of a formal sales contract induced buyers to be more willing to purchase a service; however, this effect was larger for buyers with political connections. This result may be due to politically connected buyers feeling more secure that they have the legal system's support, compared to individuals who do not have such connections.

## Additional Model Replications

I replicated 15 of Bhandari's models, which made up 3 tables total. *Note: In this paper, Bhandari uses exclusively OLS linear regressions.*

Below, I have replicated Table 4, which Bhandari utilizes to prove the validity of the experiment set-up (i.e., that sellers' signalling political connections actually led buyers to believe the seller possessed political connections).

In creating this model, I regressed the `thinks_seller_is_connected` outcome variable on several covariates: The covariate we're most interested in is `pool_T1`, which is a binary indicator for whether the seller signaled political connections. In essence, we want to see, when the seller talks about their prior work experience with the municipal government, does that cause the buyer to believe the seller holds political connections? Bhandari is trying to prove this is the case because it is only then he can measure how political connections can influence the exchange of goods. After all, if buyers don't think sellers have political connections even if the sellers signal it, then this experiment would be ineffective at capturing political connections' effects on the exchange of goods.

All other covariates consisted fixed effects from block randomization and enumerators as well as controls.

List of additional covariates: `-enum`, which indicated which enumerator surveyed the buyer after the transaction period (range: 1-9) `-block.id`, which randomization block the survey respondent resides in (range:

1-243) **-descriptives.age**, which refers to the survey respondent’s age **-gender**, which refers to the survey respondent’s gender **-educ\_level**, which refers to the survey respondent’s highest level of completed education (range: 1-5) **-employed**, binary indicator on whether the survey respondent is employed **-student**, binary indicator on whether the survey respondent is a student **-coethnicreligion**, binary indicator on whether the survey respondent and the seller shared the same ethnicity and/or religion

In replicating this model, I also included the interaction between **pool\_T1** and **coethnicreligion**, which served to examine if sharing the same religion or ethnic affects how a buyer perceives a sellers’ signaling of political connections.

From just reading the methodology in Bhandari’s paper alone, I was able to capture somewhat similar coefficients in my model. However, I ultimately had to glance at Bhandari’s code to see what I was missing, which ended up being the factorization of **enum**, **blockid**, **educ\_level**. Factorization of these three variables was definitely important since otherwise, they would be erroneously treated as numeric variables (which did end up skewing my regression outputs). Additionally, I did not include the interaction between **pool\_T1** and **coethnicreligion** in my initial model.

However, in my initial model, I did include the **religion** and the **ethnicity** of the survey respondent, since I would consider them to be a part of the fixed effects. I assume Bhandari did not include them because he thought **coethnicreligion** would sufficiently cover that domain.

Table 4: Buyer Belief of Seller Connections Driven by Connection Signal

	<i>Dependent variable:</i>
	Buyer believes seller has political connections
Connection signaled	0.188*** (0.023)
Control group outcome mean	0.169
Control group outcome std. dev	0.362
Outcome range	0, 1
Fixed effects	Yes
Controls	Yes
Observations	1,458
<i>Note:</i>	
*p<0.1; **p<0.05; ***p<0.01	

As you can see from this table, buyers who were treated to the seller’s signaling of political connections were 18.8% more likely to believe the seller possessed political connections compared to buyers who did not receive the treatment.

I next replicated Table 5 of Bhandari’s paper, which analyzed how the three treatments (signaling political connections, requiring a contract, offering an optional contract) affected whether buyers purchased phone credits as well as the level of risk buyers were willing to engage in for their purchase.

This table contains four different models. The first model (1) regresses the **purchased** variable (if a buyer purchased anything) over several covariates, including signaling political connection, requiring a contract, offering an optional contract, interaction terms between signaling political connections and the contracts, as well as various fixed effects and constants (same as those used for Table 4).

This first model uses “unpooled” data, which means that the optional contract is separate from not offering a contract at all. However, Bhandari states that the optional contract treatment arm is “conceptually similar” to not offering a contract at all. Hence, in Model 2, the regression is identical to Model 1, except the optional contract variables has been “pooled” with the control group (not offering a contract at all). Hence, we do not see a model output for the optional contract and its interaction with political connection signal for Model 2.

Models 3 and 4 follow the same philosophy, except this time, the outcome variable is if the buyer ended up purchasing a phone credit service that entailed a delay (i.e, a higher-risk purchase). Model 3 is a linear regression with the **optional contract** variable unpooled, whereas Model 4 has **optional contract** pooled with the control group.

Table 5: Average Treatment Effects

	<i>Dependent variable:</i>			
	Purchased at all Unpooled	Pooled	Purchased with Delay Unpooled	Pooled
	(1)	(2)	(3)	(4)
Political connection signaled	-0.053 (0.042)	-0.044 (0.031)	0.001 (0.036)	-0.013 (0.027)
Required contract	0.047 (0.043)	0.048 (0.037)	0.104*** (0.037)	0.075** (0.032)
Optional contract	-0.003 (0.043)		0.059 (0.037)	
Political connection signal x required contract	0.045 (0.055)	0.035 (0.048)	-0.003 (0.048)	0.011 (0.041)
Political connection signal x optional contract	0.019 (0.055)		-0.029 (0.047)	
Control group outcome mean	0.315	0.31	0.145	0.163
Control group outcome std. dev	0.466	0.463	0.353	0.37
Fixed effects	Yes			
Controls	Yes			
Observations	1,458	1,458	1,458	1,458

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

We see in the unpooled model (1) that, when a political connection is signaled, then buyers are on average 5.3 less likely to purchase a phone credit service. In the pooled model (3), when a political connection is signaled, buyers are on average 4.4 less likely to purchase a phone credit service.

Additionally, in the unpooled model (3), we see that when the seller requires a formal contract for the transaction, buyers are 10.4% more likely to purchase a phone credit package that entails a delay. Similarly, in the pooled model, we see that when the seller requires a formal contract for the transaction, buyers are 7.5% more likely to purchase a phone credit package that entails a delay.

Overall, Table 5's results suggest that sellers' signalling political connections has a negative influence on buyers' willingness to make a purchase. In contrast, when the seller requires a formal contract, buyers are more willing to buy more high-risk product options.

The final replication I conducted was Table 6 of Bhandari's paper, which includes 10 models total. These models measure quality criteria of both sellers and buyers.

Models 1 and 2 estimate buyers' perception of sellers' competence based on the same pooled covariates mentioned in Table 5. The only difference between Model 1 and Model 2 is that Model 2 also contains an interaction term between the **political connection signal** and **formal contract** variables.

The interaction term difference is identical for Models 3 & 4, Models 5 & 6, Models 7 & 8, and Models 9 & 10. Models 3 & 4 estimate sellers' perceived trustworthiness to buyers. Models 5 & 6 estimate sellers' perceptions of the number of questions the buyer asked during the transaction. Models 7 & 8 estimate

Table 6: Quality Measures from Buyers and Sellers

	<i>Dependent variable:</i>									
	Seller's competence		Seller's Trustworthiness		Buyer's # of questions		Buyer's politeness		Buyer's suspicion	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Political connection signaled	-0.023 (0.032)	-0.035 (0.038)	-0.004 (0.050)	-0.026 (0.059)	0.038 (0.028)	0.064* (0.033)	0.050 (0.043)	0.040 (0.050)	0.063 (0.069)	0.076 (0.081)
Formal contract	0.044 (0.034)	0.026 (0.045)	0.073 (0.052)	0.040 (0.070)	0.033 (0.030)	0.072* (0.039)	-0.046 (0.045)	-0.061 (0.060)	0.006 (0.072)	0.027 (0.096)
Political connection signal x formal contract		0.035 (0.058)		0.066 (0.091)		-0.077 (0.051)		0.029 (0.078)		-0.040 (0.126)
Control group outcome mean	3.603	3.603	2.485	2.485	0.952	0.952	3.476	3.476	0.884	0.884
Fixed effects	Yes									
Controls	Yes									
Observations	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458	1,458

Note:

\* p&lt;0.1; \*\* p&lt;0.05; \*\*\* p&lt;0.01

buyers' politeness as perceived by the sellers. Models 9 & 10 estimate buyers' level of suspiciousness to the transaction deal, as perceived by the sellers.

Looking at the model outputs, we see that sellers were viewed by buyers as less competent and trustworthy when they signaled political connections. This may be due to the fact that buyers believe politically connected sellers will not be held accountable if they cheat customers. Furthermore, buyers may also believe that sellers gained employment via connections rather than merit. In contrast, sellers were viewed by buyers as more competent and trustworthy when they offered formal contracts. This could be due to mandatory business contracts serving a role of signaling that the seller is serious about their business (after all, people may think a lazy seller or cheater wouldn't go through such a hassle).

On the buyer side, we see that buyers were on average more likely to ask questions during the transaction when sellers' signaled having political connections compared to instances where sellers did not signal having political connections. This makes sense as buyers may feel more uncomfortable dealing with a politically connected seller, which would cause them to conduct more in-depth examination of the service the buyers are considering purchasing. Furthermore, buyers were on average more likely to ask questions during the transaction when sellers' required formal contract compared to instances where sellers did not require formal contracts. Buyers were also more likely to be suspicious of the deal with sellers signaled their political connections (for similar reasons discussed above).

Although I was able to replicate every part of this paper when exploring the data, for the scope of this replication, I decided to exclude several descriptive figures and two figures that examined how buyers' connections influenced the exchange of goods. This was because Bhandari's paper is quite lengthy, so I felt it would be best to focus my efforts on replicating one core part of it, which pertained to how sellers' behavior (e.g., signaling political connections and offering formal contracts) affect buyers' willingness to purchase goods and engage in various levels of risk in their transactions.

## Limitations of the Original Analysis + Proposed Extension

One thing I noticed was that Bhandari used mean imputation to impute missing values. But this is not a good method to impute missing values because it reduces the standard errors, which creates problems for hypothesis tests and confidence interval calculations (Wicklin SAS).

To avoid such problems, for my project's extension, I decided to use multiple imputation to fill in missing data (via MICE). First, I undid all of Bhandari's mean imputations for the variables (see Figure A).

I then used `mice` to fill the NA values via multi-imputation. I then ran the same model done on Table 5 on the mice dataset and compared it to Bhandari's original results. Below, Table 5a refers to the original table in the paper, and Table 5b refers to the table with MICE models.

Figure A: Proportion of NA Values in Original Data

	Proportion of NA Values
educ_level	0.0294925
descriptives.age	0.0267490
student	0.0246914
employed	0.0246914
coethnicreligion	0.0246914
thinks_seller_is_connected	0.0514403

Table 5a: Average Treatment Effects

	<i>Dependent variable:</i>			
	Purchased at all Unpooled	Pooled	Purchased with Delay Unpooled	Pooled
	(1)	(2)	(3)	(4)
Political connection signaled	−0.053 (0.042)	−0.044 (0.031)	0.001 (0.036)	−0.013 (0.027)
Required contract	0.047 (0.043)	0.048 (0.037)	0.104*** (0.037)	0.075** (0.032)
Optional contract	−0.003 (0.043)		0.059 (0.037)	
Political connection signal x required contract	0.045 (0.055)	0.035 (0.048)	−0.003 (0.048)	0.011 (0.041)
Political connection signal x optional contract	0.019 (0.055)		−0.029 (0.047)	
Observations	1,458	1,458	1,458	1,458
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01				

Table 5b: Average Treatment Effect (MICE)

	<i>Dependent variable:</i>			
	Purchased at all Unpooled	Pooled	Purchased with Delay Unpooled	Pooled
	(1)	(2)	(3)	(4)
Political connection signaled	−0.048 (0.043)	−0.040 (0.032)	0.006 (0.036)	−0.007 (0.027)
Required contract	0.036 (0.044)	0.039 (0.038)	0.093** (0.037)	0.066** (0.032)
Optional contract	−0.006 (0.045)		0.055 (0.037)	
Political connection signal x required contract	0.051 (0.058)	0.043 (0.050)	−0.002 (0.048)	0.011 (0.042)
Political connection signal x optional contract	0.015 (0.058)		−0.026 (0.048)	
Observations	7 1,458	1,458	1,458	1,458
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01				

Comparing Tables 5a and 5b, it seems that, overall, model outputs from the mean imputation and multi-imputation data agree on the effects of political signaling and formal contracts on the exchange of goods in countries with weak legal institutions such as Senegal. Both models show that sellers' signaling political connections on average decreased the likelihood of buyers making a purchase compared to instances where sellers' did not signal political connections..

Furthermore, both models showed that sellers' requiring a contract on average increased the likelihood of a buyer making a purchase (as well as the likelihood of a buyer making a riskier purchase) compared to when sellers did not mandate a formal contract.

While these two models overall tell the same narrative about the impact of political connections and contracts, it is important to note that the model coefficients between the mean imputation model and the multi-imputation model were noticeably different.

In particular, we should pay attention to the coefficient of the **required contract** variable for the unpooled, purchased with delay model. For Bhandari's model, this coefficient (-0.104) has a standard error of 0.037, meaning the coefficient is around 2.81 standard errors from zero. Meanwhile, the same variable in multi-imputation model has a coefficient value of 0.093 with a 0.037 standard error. That means this coefficient is around 2.51 standard errors from zero, which is a somewhat substantial change from Bhandari's original results.

More alarming is the **required contract** variable in the pool, purchased with delay model. With the mean imputation data, this variable has a coefficient of 0.075 and a 0.032 standard error, which means the coefficient is 2.34 standard errors away from zero. However, with the multi-imputation data, this same variable has a coefficient of 0.066 and a 0.032 standard error, which means the coefficient is only 2.06 standard errors away from zero.. A 2.06 standard deviation borders on a variable not being significant in conventional modeling terms (i.e., a  $\geq 1.96$  standard error is the cut-off for a p value of  $< 0.05$ ).

The difference in standard errors from zero for the same variable is important to note, because coefficient significance can play a large role in what factors we consider to be important in a variable relationship. Thus, the difference between the mice and mean models demonstrates how we need to be careful when choosing how to impute missing values.

## Conclusion

In this project, I walked the reader through Abhit Bhandari's experiment that explores how political connections and formal contracts impact the exchange of goods in countries with weak legal institutions such as Senegal. I accurately replicated 2 descriptive figures showcasing the experiment design as well as 3 additional tables that encompassed a cumulative 15 models.

The first table served to validate Bhandari's methodology of having sellers convince buyers that the seller held political connections, via the seller's mentioning prior work experience with a municipal council. The second table estimated the average treatment effect for experiment subjects that were subject to a certain permutation of treatments (including political connection signal, contract requirement, and optional contract offering) in regards to two different outcome variables (if the buyer purchased anything at all and if the buyer purchased a product that entailed a delay in its delivery). The third table estimated certain quality measures such as sellers' competence, sellers' trustworthiness, and buyers' inquisitiveness, and buyer politeness, among others.

Ultimately, I arrived at the same conclusions at Bhandari. Sellers' signaling political connections was associated with a negative impact on buyers' willingness to purchase goods from the seller. Additionally, the presence of mandatory formal contracts was associated with buyers being more willing to purchase higher-risk products.

Finally, I extended my models measuring the impact of political connections and formal contracts on buyers' willingness to purchase goods (and their willingness to purchase risky products) by running models on data with multi-imputation instead of Bhandari's mean imputation.



## Additional References and Resources

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*Link to my Github, where all code and files have been published: <https://github.com/sophie-z-li/senegal-business-experiment.git>*