An institutional approach to attention allocation and venture resource mobilization and acquisition

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Abstract

One or two sentences providing a **basic introduction** to the field, comprehensible to a scientist in any discipline.

Keywords: attention, resources, institutional capital, accelerators

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Introduction

Early stage entrepreneurs are faced with a range of resource choices to seek, and must decide what should garner their attention. The literature on entrepreneurial resources argues the resources entrepreneurs possess shape their resource acquisition and once they raise one resource others follow. Thus, one might theorize that founders should focus their attention on the resource they can leverage based on their existing resource endowment. However, resource acquisition depends on both entrepreneurs' resource endowment and the institutional-level capital. Both are indispensable antecedents that affect the mobilization and acquisition of additional capital.

The value of a resource varies with its institutional context (Holburn & Zelner, 2010). On the one hand, strong institutions can increase the value of a resource by streamlining access to complementary external resources (Khanna & Rivkin, 2001; North & others, 1990). For example, in countries with strong financing infrastructure, acquiring financing can streamline accessing other resources and thus it would make sense to focus on raising capital at venture's earliest stages. On the other hand, resources such as legitimation or social capital can substitute for the weak institutions and capital infrastructure, thereby increasing in value when institutions are weak (Khanna & Palepu, 1997; Kock & Guillén, 2001). Therefore, the broader environment can enhance or inhibit the optimal use of the endowed resource capital. I posit that an examination of both the venture and its broader institutional environment would give us more insights about where founders attention should be allocated. Specifically, I hypothesize that the institutional-level capital positively moderates the relationship between a founder's attention and its subsequent resource mobilization and acquisition. For example, attention to human capital is more positively related to a higher number of employees in contexts in which it has higher intuitional-level human capital. This similarly applies to social capital, and financial capital as the types of resources sought by entrepreneurs. Thus, in this paper I seek to examine the following research question: How does the alignment of the institutional context and the allocation of entrepreneurial attention toward specific resources influence the venture's resource mobilization and acquisition?

Hypotheses Development

At the heart of the intersection between resource acquisition and the institutional context is entrepreneurial attention, that is, founders' attention allocation to resources. Bounded by their limited attentional capacities, entrepreneurs cannot attend to all the resources; rather, they focus on some resources but must ignore others. Where they focus their attention determines the propensity of mobilizing and acquiring resources. A venture could miss the chance to exploit an opportunity of resources acquisition if that opportunity never appears on the entrepreneur's radar screens because they are too focused on an alternative resource. For example, a voluntary work with potential partners who are well connected to other investors might be missed because the founder is too focused on raising capital by honing their business plan over and over and even paying accounting boutique firms to develop that business plan for them.

Thus, selective attention plays a crucial role in both individual and organizational behavior because it bounds individual rationality and determines the menu of available actions (Simon, 1947). The debate over which resource should garner the entrepreneur's attention concludes that the founding team resource endowment is the key factor that influences resource acquisition. For instance, scholars argue that founding teams with a more ties to potential investors are more likely to gain funding (Shane & Stuart, 2002). Furthermore, if we focus on the findings of the stream of research examining the performance implications of acquiring financial capital (e.g.; (Hochberg, Ljungqvist, & Lu, 2007)) we would expect that early-stage financing should be most likely to garner founders' attention. However, the role of the institutional context has been ignored and neglected in this debate.

I argue that selective attention allocation depends on both entrepreneur's resource endowment and institutional capital.

Therefore, I state the following hypotheses about the relationship between the congruence level of the entrepreneurs' attention to resources and the institutional level capital, and the venture's resource mobilization, acquisition, and performance.

Hypothesis 1 *The higher the level of congruency of venture's attention to a resource and its institutional level capital, the higher the odds of mobilization that resource*

Hypothesis 2 *The higher the level of congruency of venture's attention to a resource and its institutional level capital, the higher the level of the accumulated resource*

Hypothesis 3 *The higher the level of congruency of venture's attention to a resource and its institutional level capital, the higher the venture performance*

Analysis

Measures

Data

Methods

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study.

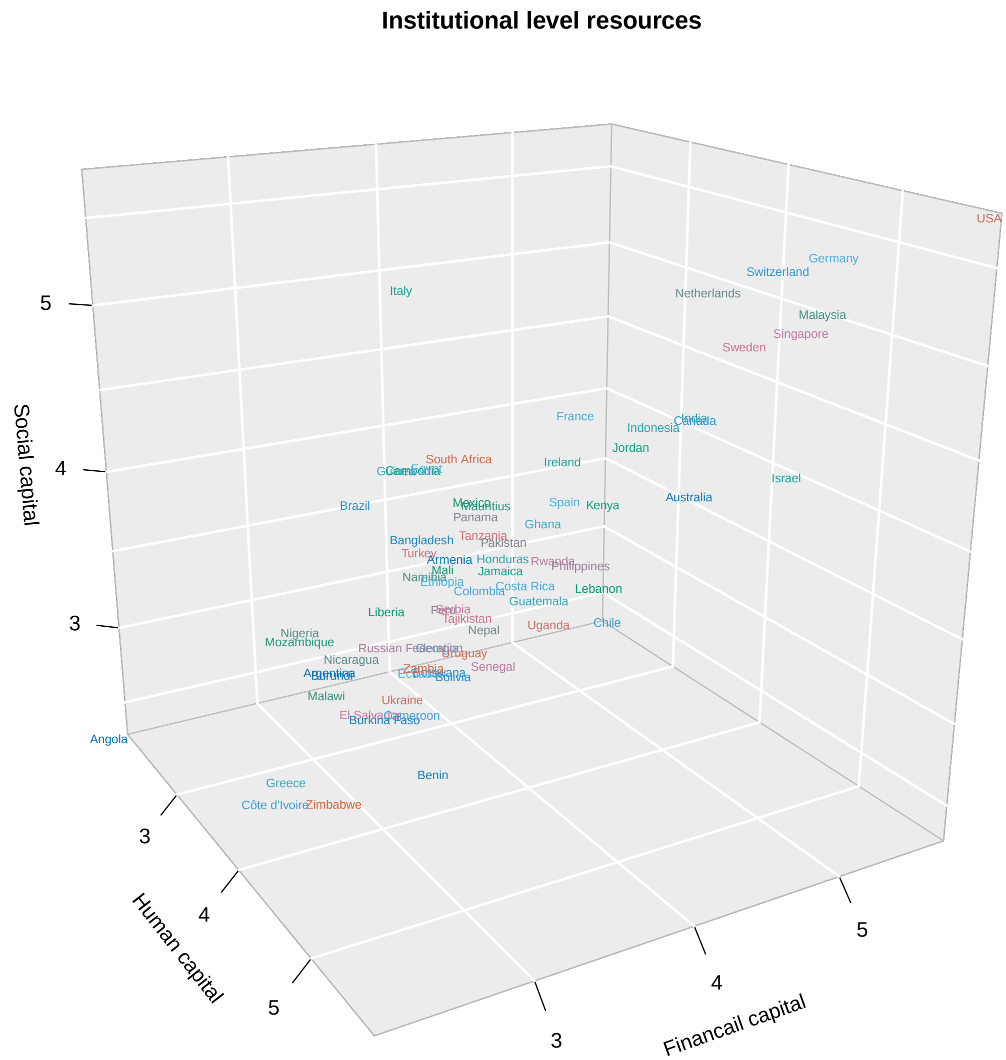
Data analysis

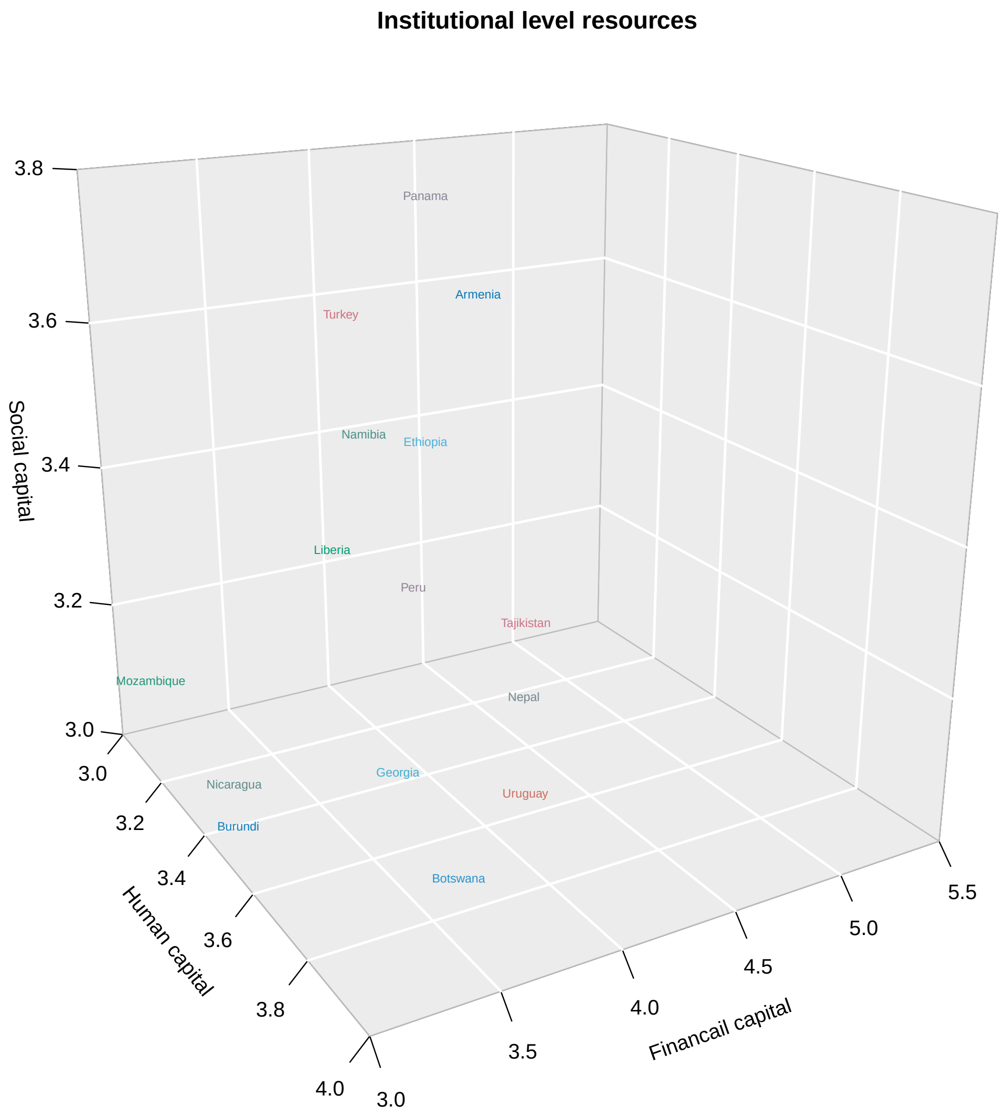
I used R (Version 4.0.2; R Core Team, 2020b) and the R-packages *caret* (Version 6.0.86; Kuhn, 2020), *dplyr* (Version 1.0.0; Wickham et al., 2020), *EFAutilities* (Version 2.0.0; Zhang, Jiang, Hattori, & Trichtinger, 2019), *forcats* (Version 0.5.0; Wickham, 2020), *foreign* (Version 0.8.80; R Core Team, 2020a), *ggplot2* (Version 3.3.2; Wickham, 2016), *haven* (Version 2.3.1; Wickham & Miller, 2020), *janitor* (Version 2.0.1; Firke, 2020), *knitr* (Version

1.29; Xie, 2015), *lattice* (Version 0.20.41; Sarkar, 2008), *lme4* (Version 1.1.23; Bates, Mächler, Bolker, & Walker, 2015), *lmerTest* (Version 3.1.2; Kuznetsova, Brockhoff, & Christensen, 2017), *lubridate* (Version 1.7.9; Grolemund & Wickham, 2011), *Matrix* (Version 1.2.18; Bates & Maechler, 2019), *papaja* (Version 0.1.0.9997; Aust & Barth, 2020), *plm* (Version 2.2.3; Croissant & Millo, 2008; Millo, 2017), *plot3D* (Version 1.3; Soetaert, 2019), *preprocessCore* (Version 1.50.0; Bolstad, 2020), *psych* (Version 1.9.12.31; Revelle, 2019), *purrr* (Version 0.3.4; Henry & Wickham, 2020), *readr* (Version 1.3.1; Wickham, Hester, & Francois, 2018), *readxl* (Version 1.3.1; Wickham & Bryan, 2019), *reshape2* (Version 1.4.4; Wickham, 2007), *rio* (Version 0.5.16; Chan, Chan, Leeper, & Becker, 2018), *sjPlot* (Version 2.8.4; Lüdecke, 2020), *stringr* (Version 1.4.0; Wickham, 2019), *tibble* (Version 3.0.3; Müller & Wickham, 2020), *tidyr* (Version 1.1.0; Wickham & Henry, 2020), *tidyverse* (Version 1.3.0; Wickham, Averick, et al., 2019), and *XLConnect* (Version 1.0.1; Mirai Solutions GmbH, 2020) for all our analyses.

#CGI data

#Plotting all countries along the 3 dimensions


Institutional level resources
Social capital
Human capital
Financail capital
3
4
5
3
4
5
3
4
5
USA
Germany
Switzerland
Netherlands
Malaysia
Singapore
Sweden
Italy
France
Indonesia
Canada
Jordan
South Africa
Ireland
Israel
Brazil
Mexico
Mauritius
Spain
Kenya
Australia
Panama
Ghana
Tanzania
Pakistan
Bangladesh
Turkey
Armenia
Honduras
Rwanda
Philippines
Mali
Jamaica
Namibia
Ethiopia
Colombia
Costa Rica
Lebanon
Guatemala
Liberia
Tajikistan
Uganda
Chile
Nigeria
Mozambique
Nepal
Uruguay
Nicaragua
Senegal
Zambia
Bolivia
Malawi
Ukraine
Burkina Faso
Cameroon
Angola
Benin
Greece
Côte d'Ivoire
Zimbabwe



#Attention to capital - venture data

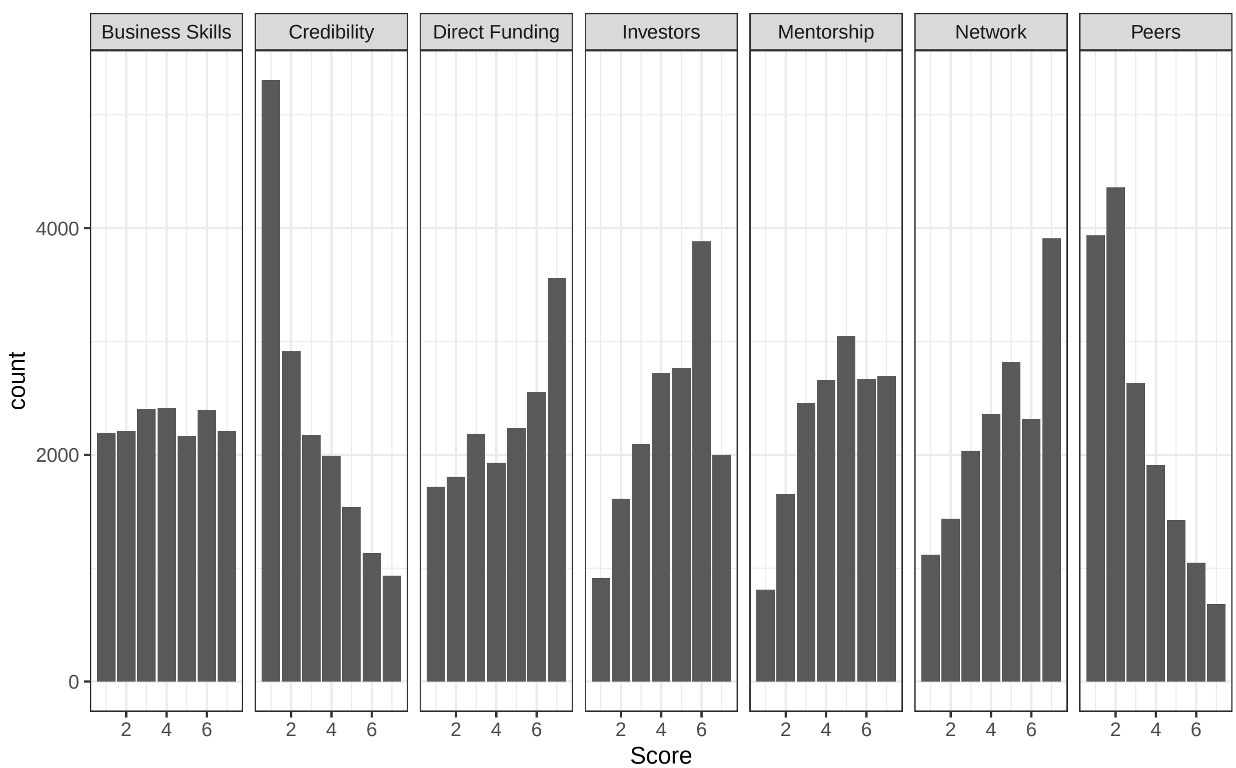
##Control variables

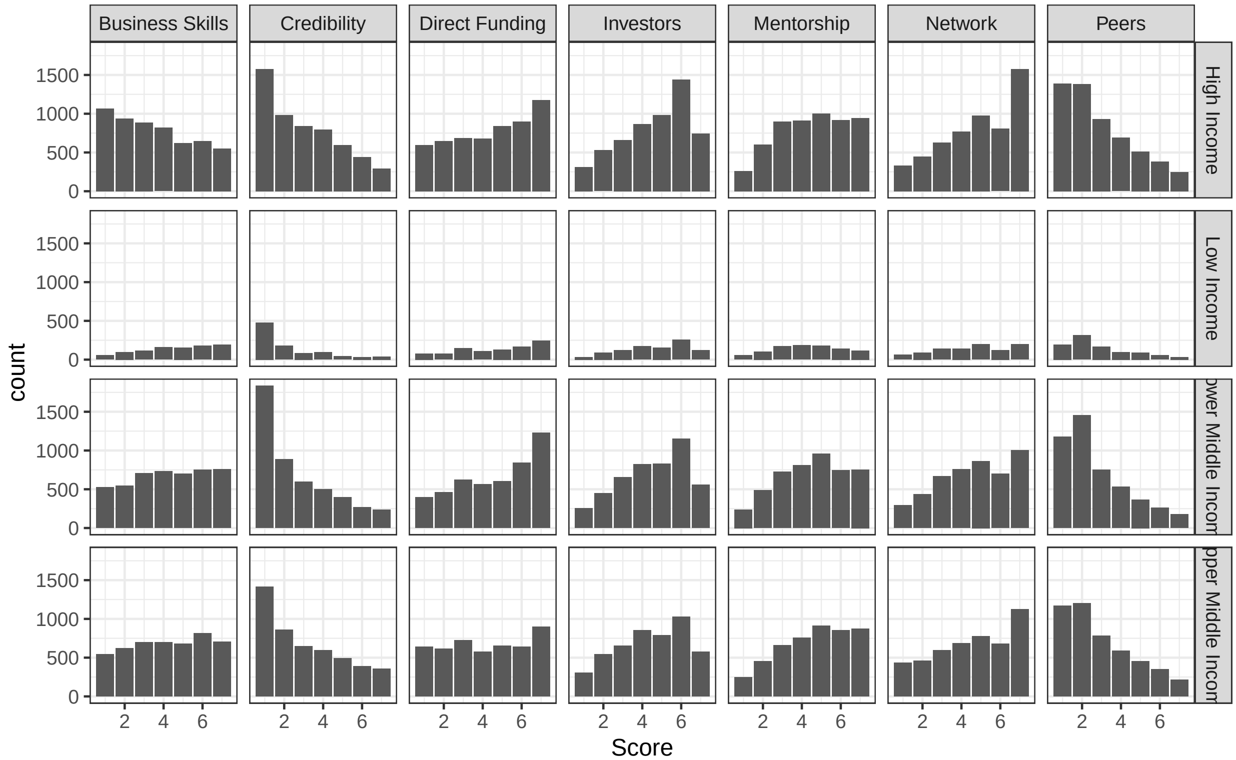
##Constrcuting human capital index (control variable) ###Graduate percentage, Prior C-level Executive Percentage, Average Team Tenure , Team Prior Founding

##Gender decomposition variable

#Reverse code attention variable

#Distribution of attention





##Outcomes

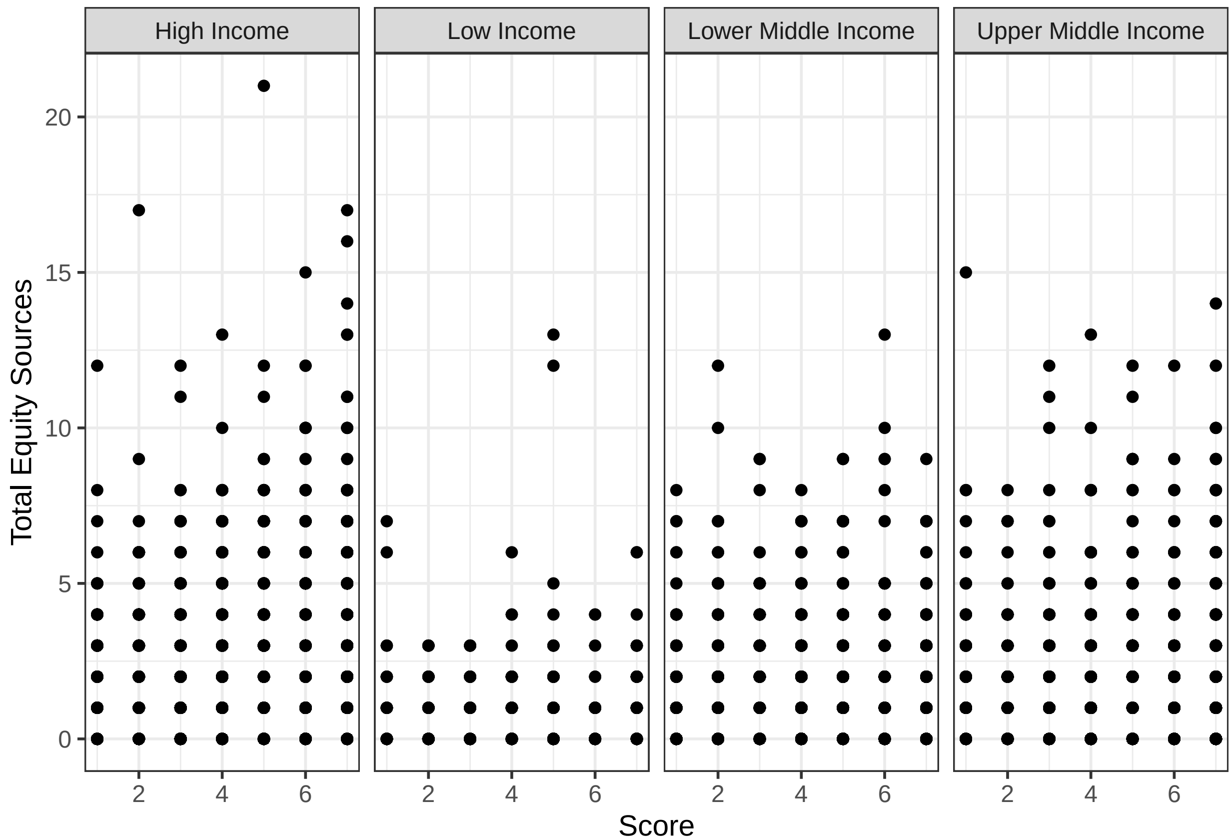
#Revenues

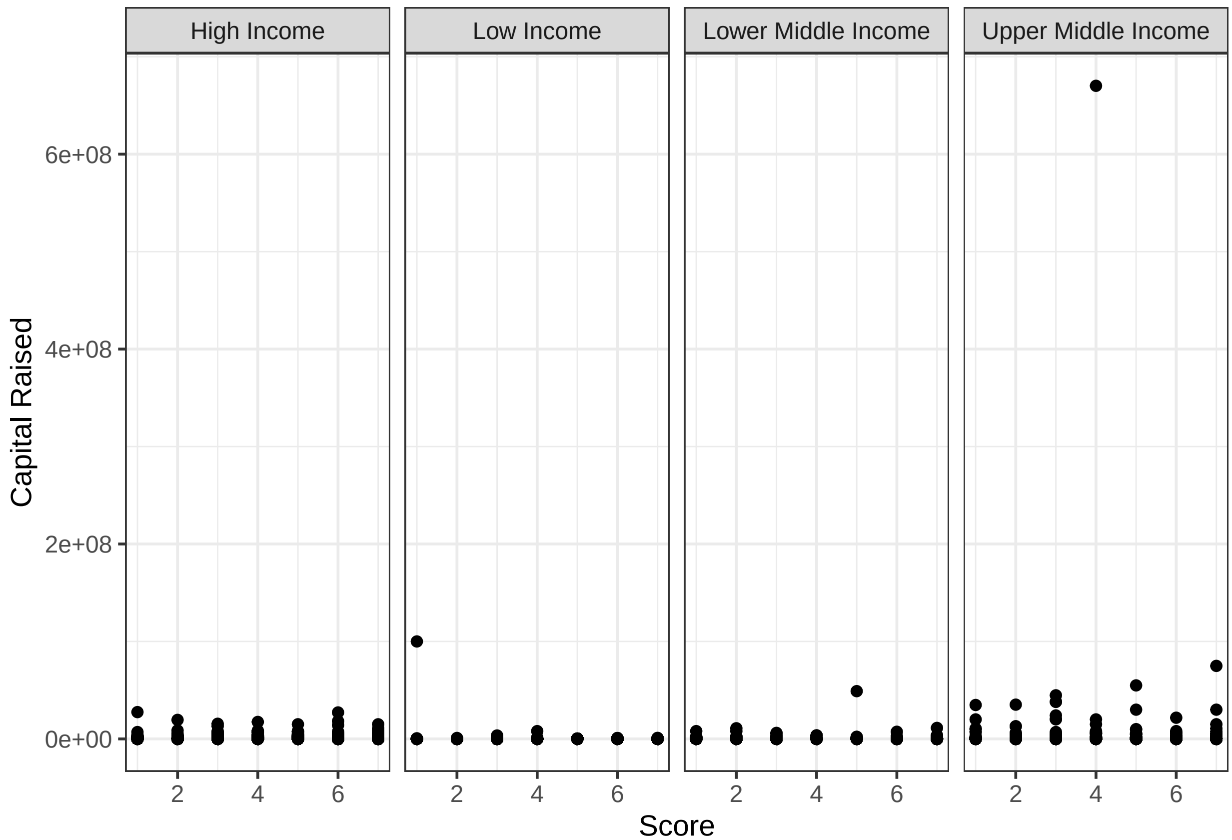
#Human capital acquisition

#Social capital acquisition

#Fiancial Capital acquisiton total

#Predictor and outcome plots


High Income
Low Income
Lower Middle Income
Upper Middle Income
Total Equity Sources
0
5
10
15
20
2
4
6
Score



#Join all 3 datasets

Results

#Mixed model analysis - Human capital

	b	SE	z
Intercept	-1.46	0.08	-19.18
Attention to Human capital(AHC)	0.11	0.07	1.54

	b	SE	z
Intercept	-0.85	0.53	-1.61
AHC	0.92	0.45	2.05
Ease of finding skilled employees	-0.14	0.12	-1.14
AHCxEase of finding skilled employees	-0.17	0.10	-1.79

	b	SE	*t*
Intercept	762.25	502.25	1.52
Attention to Human capital	2,955.97	2,238.11	1.32

	b	SE	*t*
Intercept	-1,955.91	3,599.05	-0.54
AHC	-10,174.65	16,704.03	-0.61
Ease of finding skilled employees	641.03	813.08	0.79
AHCxEase of finding skilled employees	3,118.93	3,842.90	0.81

#Mixed model analysis - Financial capital

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula:
## participated ~ accel_ben_rank_direct_funding + (accel_ben_rank_direct_funding |
##     country)
##    Data: gali_joined
##
##      AIC      BIC   logLik deviance df.resid
##  14773.7  14812.1  -7381.8  14763.7    15976
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.0388 -0.4890 -0.4207 -0.3515  3.0479
##
## Random effects:
##  Groups  Name                          Variance Std.Dev. Corr
```

```
##  country (Intercept)                   0.300861 0.54851
##          accel_ben_rank_direct_funding 0.007982 0.08934  -1.00
## Number of obs: 15981, groups:  country, 82
##
## Fixed effects:
##                               Estimate Std. Error z value Pr(>|z|)
## (Intercept)                   -1.45326    0.07722 -18.821  < 2e-16 ***
## accel_ben_rank_direct_funding -0.19333    0.06321  -3.059  0.00222 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr)
## accl_bn_r__ -0.171
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula:
## participated ~ accel_ben_rank_direct_funding * EOSQ425 + (accel_ben_rank_direct_fundi
##     country)
##    Data: gali_joined
##
##      AIC      BIC   logLik deviance df.resid
##  14562.1  14615.8  -7274.1  14548.1    15720
##
```

```
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.0463 -0.4908 -0.4210 -0.3513  3.0165
##
## Random effects:
##  Groups  Name                           Variance Std.Dev. Corr
##  country (Intercept)                    0.287438 0.53613
##          accel_ben_rank_direct_funding 0.009936 0.09968  -1.00
## Number of obs: 15727, groups:  country, 73
##
## Fixed effects:
##                                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)                           -1.349694   0.434021  -3.110  0.00187 **
## accel_ben_rank_direct_funding         -0.210801   0.285396  -0.739  0.46013
## EOSQ425                               -0.021755   0.112408  -0.194  0.84654
## accel_ben_rank_direct_funding:EOSQ425  0.003382   0.065751   0.051  0.95898
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) ac____ EOSQ42
## accl_bn_r__ -0.246
## EOSQ425     -0.983  0.246
## a____:EOSQ4  0.280 -0.974 -0.289
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
```

```
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula:
## participated ~ accel_ben_rank_direct_funding * EOSQ089 + (accel_ben_rank_direct_fundi
##     country)
##    Data: gali_joined
##
##      AIC      BIC   logLik deviance df.resid
##  14561.6  14615.2  -7273.8  14547.6    15720
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.0482 -0.4904 -0.4209 -0.3510  3.0323
##
## Random effects:
##  Groups  Name                          Variance Std.Dev. Corr
##  country (Intercept)                   0.284084 0.53299
##          accel_ben_rank_direct_funding 0.009676 0.09837  -1.00
## Number of obs: 15727, groups:  country, 73
##
## Fixed effects:
##                                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)                            -1.21998    0.28033  -4.352 1.35e-05 ***
## accel_ben_rank_direct_funding          -0.24283    0.19650  -1.236    0.217
## EOSQ089                                -0.07084    0.09006  -0.787    0.432
## accel_ben_rank_direct_funding:EOSQ089  0.01463    0.05184   0.282    0.778
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) ac____ EOSQ08
## accl_bn_r__ -0.232
## EOSQ089     -0.960  0.230
## a____:EOSQ0  0.281 -0.944 -0.300
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: participated ~ accel_ben_rank_direct_funding * DOMCREDITGDP +
##     (accel_ben_rank_direct_funding | country)
##    Data: gali_joined
##
##      AIC      BIC   logLik deviance df.resid
##  14561.8  14615.5  -7273.9  14547.8    15720
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.0466 -0.4909 -0.4213 -0.3514  3.0629
##
## Random effects:
##  Groups  Name                          Variance Std.Dev. Corr
##  country (Intercept)                   0.289392 0.53795
##          accel_ben_rank_direct_funding 0.009926 0.09963  -1.00
```

```
## Number of obs: 15727, groups:  country, 73
##
## Fixed effects:
##                                              Estimate Std. Error z value
## (Intercept)                                -1.3735020  0.1256629 -10.930
## accel_ben_rank_direct_funding              -0.2051438  0.1031016  -1.990
## DOMCREDITGDP                               -0.0010317  0.0017273  -0.597
## accel_ben_rank_direct_funding:DOMCREDITGDP  0.0001439  0.0009667   0.149
##                                            Pr(>|z|)
## (Intercept)                                  <2e-16 ***
## accel_ben_rank_direct_funding                0.0466 *
## DOMCREDITGDP                                 0.5503
## accel_ben_rank_direct_funding:DOMCREDITGDP   0.8817
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) ac____ DOMCRE
## accl_bn_r__ -0.193
## DOMCREDITGD -0.778  0.159
## a____:DOMCR  0.233 -0.779 -0.313
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: capital_raised_tot ~ +(accel_ben_rank_direct_funding | country)
##    Data: gali_joined
##
```

```
##       AIC       BIC    logLik  deviance  df.resid
##  541645.1  541683.5 -270817.5  541635.1     15976
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
##  -0.316  -0.040  -0.029  -0.018 120.803
##
## Random effects:
##  Groups   Name                         Variance  Std.Dev. Corr
##  country  (Intercept)                  1.187e+11  344600
##           accel_ben_rank_direct_funding 2.332e+09   48286  1.00
##  Residual                              3.062e+13 5533830
## Number of obs: 15981, groups:  country, 82
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)   226024      79869    2.83
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: capital_raised_tot ~ accel_ben_rank_direct_funding * EOSQ425 +
##     (accel_ben_rank_direct_funding | country)
##    Data: gali_joined
##
##       AIC       BIC    logLik  deviance  df.resid
##  533280.8  533342.1 -266632.4  533264.8     15719
##
```

```
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
##  -0.311  -0.041  -0.028  -0.016 119.888
##
## Random effects:
##  Groups   Name                         Variance  Std.Dev. Corr
##  country  (Intercept)                  1.247e+11  353102
##           accel_ben_rank_direct_funding 2.606e+09   51053  1.00
##  Residual                              3.109e+13 5575911
## Number of obs: 15727, groups:  country, 73
##
## Fixed effects:
##                                       Estimate Std. Error t value
## (Intercept)                              -4885     444377  -0.011
## accel_ben_rank_direct_funding          -191024     590675  -0.323
## EOSQ425                                  59478     112868   0.527
## accel_ben_rank_direct_funding:EOSQ425    31388     134942   0.233
##
## Correlation of Fixed Effects:
##             (Intr) ac____ EOSQ42
## accl_bn_r__  0.106
## EOSQ425     -0.982 -0.103
## a____:EOSQ4 -0.111 -0.975  0.111
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: capital_raised_tot ~ accel_ben_rank_direct_funding * EOSQ089 +
```

```
##     (accel_ben_rank_direct_funding | country)
##    Data: gali_joined
##
##       AIC       BIC    logLik  deviance  df.resid
##  533280.7  533342.0 -266632.3  533264.7     15719
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
##  -0.310  -0.041  -0.028  -0.015 119.888
##
## Random effects:
##  Groups   Name                          Variance  Std.Dev. Corr
##  country  (Intercept)                   1.245e+11  352894
##           accel_ben_rank_direct_funding 2.412e+09   49109  1.00
##  Residual                               3.109e+13 5575889
## Number of obs: 15727, groups:  country, 73
##
## Fixed effects:
##                                         Estimate Std. Error t value
## (Intercept)                               66014     285162   0.231
## accel_ben_rank_direct_funding           -205433     401458  -0.512
## EOSQ089                                   51858      88843   0.584
## accel_ben_rank_direct_funding:EOSQ089     41162     104375   0.394
##
## Correlation of Fixed Effects:
##             (Intr) ac____ EOSQ08
## accl_bn_r__  0.083
```

```
## EOSQ089     -0.957 -0.080
## a____:EOSQ0 -0.094 -0.944  0.098
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: capital_raised_tot ~ accel_ben_rank_direct_funding * DOMCREDITGDP +
##     (accel_ben_rank_direct_funding | country)
##    Data: gali_joined
##
##       AIC       BIC    logLik  deviance  df.resid
##  533280.9  533342.2 -266632.4  533264.9     15719
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
##  -0.310  -0.041  -0.028  -0.016 119.887
##
## Random effects:
##  Groups   Name                          Variance  Std.Dev. Corr
##  country  (Intercept)                   1.245e+11  352820
##           accel_ben_rank_direct_funding 2.381e+09   48795  1.00
##  Residual                               3.109e+13 5575926
## Number of obs: 15727, groups:  country, 73
##
## Fixed effects:
##                                            Estimate Std. Error t value
## (Intercept)                                190993.0   128015.3   1.492
## accel_ben_rank_direct_funding             -121351.9   210078.0  -0.578
```

```
## DOMCREDITGDP                                 572.9     1620.3   0.354
## accel_ben_rank_direct_funding:DOMCREDITGDP   768.4     1952.7   0.393
##
## Correlation of Fixed Effects:
##             (Intr) ac____ DOMCRE
## accl_bn_r__  0.058
## DOMCREDITGD -0.761 -0.043
## a____:DOMCR -0.062 -0.776  0.085
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

#Mixed model analysis - Social capital

```
##                          Estimate  Std. Error   t value
## (Intercept)            0.20316446 0.012552069 16.185735
## accel_ben_rank_network 0.01831386 0.009581619  1.911353
```

```
##                                     Estimate Std. Error      t value
## (Intercept)                     3.133837e-01 0.06847055  4.576912615
## accel_ben_rank_network          1.746818e-02 0.05079577  0.343890367
## EOSQ109                        -2.763492e-02 0.01732516 -1.595074599
## accel_ben_rank_network:EOSQ109 -4.430267e-05 0.01131854 -0.003914168
```

```
##                          Estimate Std. Error   t value
## (Intercept)            0.57925930 0.04337800 13.353759
## accel_ben_rank_network 0.06485941 0.04797524  1.351935
```

```
##                                  Estimate Std. Error   t value
## (Intercept)                    -0.2751093 0.21194630 -1.298014
## accel_ben_rank_network         -0.6038282 0.24619417 -2.452650
```

```
## EOSQ109                           0.2185398 0.05339006  4.093266
## accel_ben_rank_network:EOSQ109  0.1708510 0.05804559  2.943393
```

Data and Methods

Our dataset, the Global Accelerator Learning Initiative (GALI), covers entrepreneurs who applied to scores of accelerators that began accepting applications between 2013 and 2020. Our data include information – collected during program applications – about ventures, founding teams, and pre-program performance. They also identify which applicants went on to participate in each program. Finally, these data include follow-up information collected from selected and rejected applicants in the years following each application window. The anonymized dataset containing both application and follow-up data can be accessed at GALI Data.

When entrepreneurs apply to a GALI-participating accelerator, they are asked to complete a standardized survey which asks basic questions about their venture's business model, financial performance, and founding team. Then, after one year, they are asked to complete a follow-up survey, whether or not they were accepted into the program to which they applied.

All financial statistics are in United States Dollars (USD).

Table 1: Ventures in sample, by country of operation and survey responses

Discussion

References

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