Regional Disparities in Chinese Outward FDI Average Monetary Project Values

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1. Introduction

This project seeks to discover the underlying factors behind regional differences in the average monetary value of outward Chinese FDI projects. As defined by the Organisation for Economic Co-operation and Development (OECD), "Foreign direct investment (FDI) is a category of cross-border investment in which an investor resident in one economy establishes a lasting interest in and a significant degree of influence over an enterprise resident in another economy." Between 2000 and 2021, the Middle East received an average of 403.199 million dollars per Chinese FDI project. This was the highest average value recorded by a country, and this project seeks to determine why the next region, the Americas, received an average of 394.0268 million dollars per Chinese FDI project. Neither of these regions has the highest count of projects during this period, implying there must be underlying reasons for why these regions are recipients of, on average, much higher project values. To try and explain the variation, this project initially analyzes project-level variables such as project sector, intent, financial flow type, implementation status, and relation to China's COVID-19 response plan. In its second portion, the project analyzes economic indicator variables such as unemployment rates, GDP per capita, GDP, and FDI per capita to see whether they have an association with average outward Chinese FDI project values. In its third portion, the project observes the added associations of recipient country credit ratings and the annual percentage of Chinese exports to the recipients. Lastly, this project conducts OLS regression and machine learning model analysis to determine the degree to which these variables are associated with outward Chinese FDI project values.

1.1 Literature Review

Although research into the topic remains sparse, the current literature contributes these differences in outward Chinese FDI to recipient country characteristics such as market sizes, GDP growth levels, institution health, wealth of natural resources, and number of Chinese exports to a recipient country. Thus, focusing on country-level attributes as the main determinants of outward Chinese FDI project values, while my research focuses on project-level characteristics. Specifically, Kolstad and Wiig (2012) use an econometric analysis of the recipient country to determine what attracted Chinese FDI projects during the 2003-2006 period. They find that Chinese FDI is more prevalent in OECD recipient countries with large markets, and in non-OECD countries that have both large quantities of natural resources and poor institutions. Similarly, Zhang and Daly (2011) create pooled ordinary least squares (POLS) regressions for projects between 2003-2009 to identify outward Chinese FDI drivers as recipient country bilateral and multilateral trade levels, market size, GDP growth, market openness, and resource endowment. They also found that a stable inflation rate is important in attracting Chinese FDI values. Focusing on 49 One Belt One Road (OBOR) countries as recipients from 2003-2015, Liu et al. (2017) use System-GMM (SGMM) and regressions to identify exchange rate levels, market potential, market openness, and infrastructure facilities as the main determinants of Chinese FDI. However, they also find that the determinants of non-OBOR country FDI are different.

Focusing on Chinese FDI projects in Asia between 2003-2016, Kamal et al. (2019) used Random effect (RE), Fixed effect (FE) and SGMM methodologies to find that Chinese FDI is driven by market size, where GDP is a strong predictor of FDI across all Asian countries. However, they also find regional variation in FDI attraction. Specifically, in East and Southeast Asia, the availability of mineral resources is a significant driver of Chinese FDI (particularly in middle-income countries). Also focusing on Asian countries, Kang and Liu (2016) use a conditional logistic regression model to find that political risk and economic freedom are key factors in explaining Chinese FDI projects. Specifically, more projects take place in Asian countries that are politically stable and have experienced economic liberalization. Meanwhile, focusing on 22 African countries from 2008-2014, Shan et al. (2018) use regression analysis to find that contrary to common belief, the prevalence of natural resources in an area was not a significant driver of Chinese outward FDI. This is a particularly interesting finding as it contrasts that of Kamal et al., demonstrating the importance of regional variation in drivers of Chinese FDI. Nonetheless, they echo the results of Kamal et al. and Zhang and Daly, finding that market size is an incredibly significant factor in attracting Chinese FDI. They explain such behaviour by associating larger markets with higher potential returns on investment. Furthermore, they find that institutional factors such as political stability and regulatory quality both have negative impacts on Chinese FDI, although the effect of GDP on FDI is much greater. Cheung and Qian (2009) support these findings using regression analysis, reaffirming that FDI in developed and developing countries is driven by different factors, using an older dataset of FDI projects from 1991-2005. They support the findings of Shan et al., reaffirming that Chinese FDI is not primarily attracted to countries rich in natural resources in Africa. Most importantly, they find that Chinese exports to developing countries have a significant positive relationship with outward Chinese FDI, implying that FDI may serve to facilitate trade. Lastly, focusing on European data from 2004-2013, Lv and Spigarelli (2016) used an FE logit model and found that Chinese FDI projects are more often conducted in EU countries with a reduced rule of law and that market size is not necessarily a strong attraction factor — a finding that differs from much of the other literature, but it could be just a characteristic of Europe.

My work adds to the literature as it seeks to understand the regional differences in project values, instead of just the number of projects conducted in a region. Similarly, by finding project-level explanations for the regional differences instead of country-level characteristics, my research again differs from the literature. My findings show that from 2000 to 2021, the Middle East on average, received the greatest Chinese FDI project monetary value, however, as graphs were built, it was observed that the Middle East did not consistently receive the greatest average project value each year, yet held this title between 2007 and 2019. Similarly, it was observed that COVID-related projects did not contribute in the majority to a region's total project share but did make up a sizeable amount, demonstrating that it may be a useful measure for explaining differences in country average project value during the COVID years. For instance, in 2021, just under 30% of Chinese FDI projects in Asia were COVID-related. Consistent with the literature, I find in section 2.2. that regions with higher GDP levels attract, on average, higher value outward Chinese FDI. My findings in 2.3.3 also show a positive relationship between the recipient country's income level and average outward Chinese FDI. Unfortunately, the economic indicators of GDP per capita and unemployment were not observed to have a strong relation with average outward Chinese FDI project values, with the latter indicator reflecting a relatively weak relation. Adjusting FDI by population to create an FDI per capita measure also failed to address the disparities in average FDI project values across regions, demonstrating that population is not a major indicator of FDI project values.

In section 3.4.3, I find that credit ratings, and therefore institutional health, is a factor driving outward Chinese FDI project values and therefore the difference in project value by region, as the direction of the influence depends on the regions. For Asia and the Middle East, a higher country credit rating is associated with a higher average project value. In Africa, the Americas, and Europe, a higher country credit rating is associated with lower average project values. In section 3.5.2, I find that Chinese exports to an FDI recipient are positively related to average FDI project values. Lastly, in the Regression and Machine Learning sections, by running OLS regressions and machine learning models, I find that contrary to my hypotheses from Project 2, project-level characteristics are far better at explaining the variation in FDI project values, with attributes clustered among regions and explaining the regional disparities in values. Specifically, flow type, whether a project was COVID-related, and the project sector. Meanwhile, the strongest country-level explanation for the regional disparities in outward Chinese FDI project values is recipient GDP and income group.

2. The Data

This project initially analyzes outward Chinese Foreign Direct Investment (FDI) project-level data collected and published by AidData on November 6, 2023. The dataset captures 20,985 Chinese outward FDI projects across 165 recipient countries, over 22 commitment years (2000-2021), and project implementation status for over 24 years (2000-2023). Each observation in the dataset is a Chinese outward FDI project, with 125 variables outlining project-level and country-level data. This dataset was later merged with country-level economic indicators (e.g., inflation, unemployment, and GDP per capita) and population data from The World Bank over the same 22-year period. Economic indicators can be used to assess the health of a country's economy, which can in turn be used as a potential explainer for the disparity in average Chinese FDI projects across regions. For instance, it could be that regions with higher levels of unemployment, and therefore weaker economies, receive FDI projects with higher values.

Similarly, by controlling FDI for population, more accurate comparisons between regions of varying sizes can be made as it standardizes the FDI amount by the population of the country. For instance, a country with a larger population may have a higher average FDI level, but a lower FDI per capita when compared with a smaller country that has a smaller average FDI level.

Then, it was merged with web-scraped Moody's credit rating data from Wikipedia to analyze the effect of institution health on average outward Chinese FDI. Bonds considered investment grade have a credit rating of Baa3 or higher, while bonds rated Ba1 and below are speculative grade/"junk" bonds. Unfortunately, a limitation of this data is that it only has the latest credit rating of the country, but it still allows for a basic comparison with whether there is an association with the latest batch of credit ratings (since we average out FDI values over time, essentially removing the time dependence). This is an important data source as credit ratings indicate a country's institutional well-being/strength — a key driver of outward Chinese FDI according to the research from Kolstad and Wiig (2012) and Shan et al. (2018). For instance, it could be that regions and countries with lower credit ratings, and therefore poorer institutional health, receive higher project values of outward Chinese FDI, because China can then exert a greater influence on the country. Since this data only contained the most recent credit ratings, it was not included in the regression and machine learning analysis portion.

Lastly, the dataset was merged with World Integrated Trade Solution (WITS) country-level Chinese export data, and recipient distance from China from the website DistanceFromTo. The former dataset outlines the percentage of annual total Chinese exports devoted to a country from 2000-2021. After merging with these datasets, I analyze whether recipient country trade relations with China are a potential explainer for the disparity in average Chinese FDI projects across regions. For instance, regions with higher levels of Chinese imports may receive FDI projects with higher values so that regions are incentivized to continue purchasing Chinese goods and services. More importantly, as was mentioned in the introduction, Zhang and Daly (2011) identify recipient countries' bilateral and multilateral trade levels as key drivers of outward Chinese FDI. Thus, by adding export data, I investigate whether my findings corroborate those of the literature review, particularly, the findings of Cheung and Qian (2009). Recipient distance from China was added as the Gravity Model of Trade assumes that China would trade more with countries that are closer to it. Similarly, since FDI is with the intent of establishing influence within another country, it could be that China prefers countries further away so that it can have influence abroad, or China may prefer to extend its influence closer to home to protect its borders. After merging and data cleaning, the final observation count is 8,200.

3. Summary Statistics

3.1 Regional Descriptive Statistics

Table 1. groups project amounts by the recipient region. Interestingly, roughly 43% of projects during the 21-year period take place in Africa, followed by 31% in Asia, and 13% in the Americas. However, the region with the highest average project value is the Middle East, which recorded 403.199 million dollars in Chinese FDI. The Middle East is an interesting region as it also has a much larger minimum project value in comparison with the other regions, almost 10 thousand dollars greater than the next region. This minimum project was from 2019 in Iraq, where the Chinese Embassy provided Iftar meals to al-Adhamiyah neighbourhood at the Abu Hanifa mosque. These numbers demonstrate the varying distribution of project values across regions, prompting me to focus on investigating what motivates China to overall invest more in some regions and less in others.

Table 1. FDI Project Region Descriptive Statistics.

Regions	Count	Mean	SD	Minimum	25^{th} percentile	50^{th} percentile	75^{th} percentile	Maximum
Africa	5120.0	129.108	775.931	14.52	0.845	9.505	54.889	32.033
America	1527.0	394.027	2829.789	21.78	0.487	6.845	59.040	89.963
Asia	3681.0	205.115	1030.266	43.24	1.144	16.682	104.455	33.668
Europe	536.0	277.280	1091.222	670.10	1.826	15.807	165.663	16.921
Middle East	376.0	403.020	2060.943	11235.65	1.523	8.906	62.051	29.892
Oceania	769.0	30.288	179.142	25.69	0.184	1.800	11.168	4.033

Note: All but count and min columns in millions, max in billions

3.2. Project-level Descriptive Statistics

Table 2. shows the descriptive statistics for project characteristics such as status, intent, flow type, monetary value, and COVID-relation. Looking at status, completed projects and those that are still in the Commitment phase have the smallest average project value. This points to the fact that more expensive projects either take longer to complete or have stalled in implementation. Thus, alluding to the fact that China may be inflating its FDI value by not following through on higher monetary value projects. Suspended projects have the greatest average project value, closely followed by Pledged and Cancelled projects. This is an important finding as it may suggest that project status is a sizable factor in determining the average project value in a region if regions have varying completion or cancellation project rates. Regions with greater cancellation rates may have higher average project values, but this needs to be further investigated as the number of suspended, pledged, and called projects is not that large in comparison.

From intent, it is observed that an overarching amount of projects are Development-related (73%). However, projects that are Mixed have the greatest average and median project values, which are close in range, demonstrating that the distribution of the Mixed category is fairly normal in shape. Unsurprisingly, Representational projects have the smallest average project value as well as other value statistics, demonstrating that regions that are dominated by Representational Chinese FDI projects may explain a smaller regional average project value, compared to regions dominated by Mixed projects, for instance. Focusing on flow type, more than half (54%) of projects are Grants, closely followed by Loans (42%). However, the latter and Vague projects have the greatest average project value, although they also have the largest standard deviations, demonstrating that values vary greatly in that category. While the smallest and greatest project values were discussed in section 3.1, it is interesting to note that the smallest was a grant, while the greatest was a loan. Loans and Debt forgiveness also had the highest median values. It would also be worthwhile in later stages to group flow types by region to see whether other trends emerge and how much flow type may contribute to explaining the variation in average project value across regions.

Table 2. FDI Project Descriptive Statistics.

Variables	Count	Mean	SD	Minimum	25th percentile	50th percentile	75th percentile	Maximum
Status								
Cancelled	75.0	555.449	1490.905	0.011	27.668	98.061	342.412	10.567
Completion	7565.0	115.147	722.123	0.000	0.205	3.475	37.566	21.422
Implementation	1504.0	383.543	2570.573	0.005	16.766	65.628	225.857	89.963
Pipeline: Commitment	2078.0	103.553	574.138	0.001	4.731	13.025	39.364	14.402
Pipeline: Pledge	755.0	791.010	2865.678	0.002	11.928	84.171	445.726	33.668
Suspended	32.0	1225.135	2772.383	3.261	149.167	411.292	1014.640	14.484
Intent								
Commercial	882.0	234.907	624.784	0.017	20.547	50.556	176.053	10.152
Development	8800.0	86.525	823.917	0.000	0.310	3.758	19.026	33.668
Mixed	2232.0	614.869	2572.766	0.003	46.740	136.387	414.842	89.963
Representational	95.0	2.069	6.123	0.001	0.025	0.101	1.167	0.049
Flow Type								
Debt forgiveness	158.0	123.225	784.490	0.139	10.080	23.477	55.849	9.331
Free-standing technical assistance	76.0	2.778	5.790	0.003	0.232	1.123	2.519	0.036
Grant	6489.0	9.494	79.089	0.000	0.123	1.331	7.200	5.904
Loan	5075.0	436.507	1997.110	0.011	27.303	83.517	272.262	89.963
Scholarships/training in the donor country	112.0	0.706	1.656	0.002	0.014	0.034	0.495	0.010
Vague TBD	99.0	450.039	2630.406	0.025	7.881	22.777	96.221	25.812
Monetary Value	12009	194.953	1340.767	14.50	0.807	9.839	66.217	89.963
COVID	12009	0.095	0.293	0.000	0.000	0.000	0.000	1.000

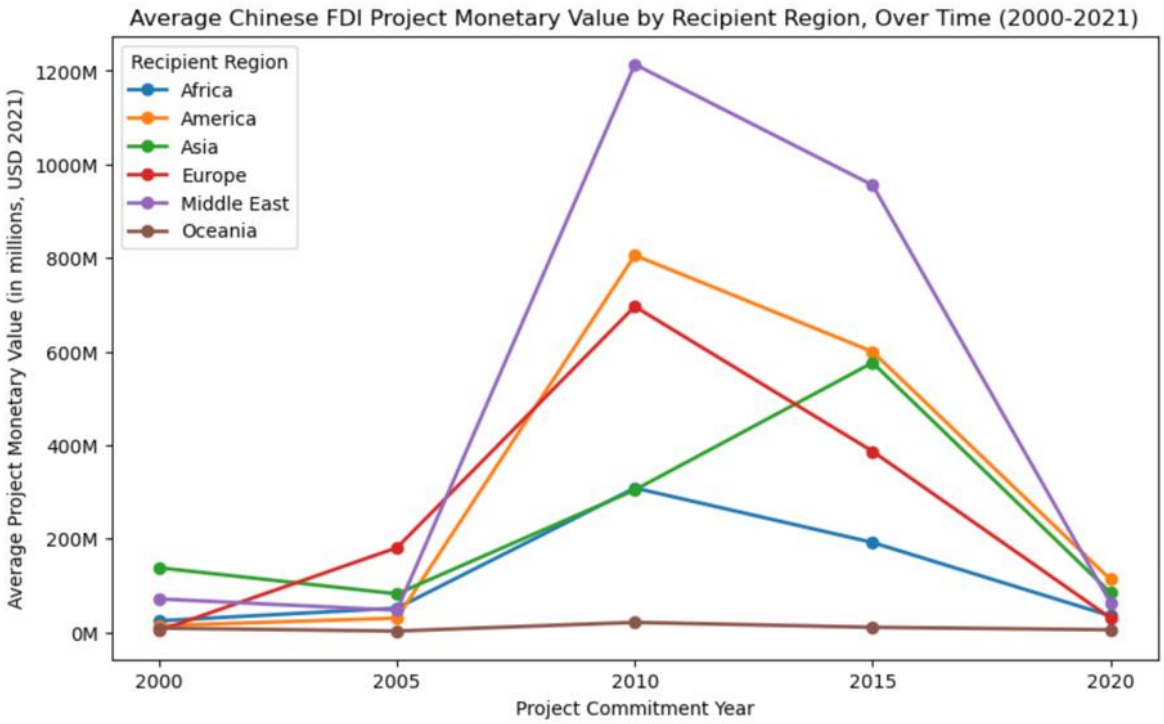
Note: All but COVID row, count and min columns in millions, max in billions

Moreover, table 2. shows statistics for the dummy variable COVID and the monetary value variable detailing each project's financial commitment. Interestingly, the overall mean project value is very high, 194.95 million dollars. However, the standard deviation is incredibly large, demonstrating significant variation in project value. The highest project value overall is a commitment from 2007 of 89.96 billion dollars to the China-Venezuela Joint Fund in a loan syndicate. Meanwhile, the lowest project value overall is a commitment from 2020; the Chinese Embassy donated 14.5 USD worth of hospital materials to Tanzania Vijibweni Hospital. Since COVID is a dummy for whether the project was a part of China's COVID-19 response plan, the mean represents the percentage of FDI projects that were COVID-related between 2000 and 2021 — in this case, on average, 9.5% of projects. This seems like a sizable percentage considering the 21-year period, however, it must be noted that data cleaning resulted in a large number of projects being dropped since they did not have a corresponding monetary value, which was my Y-variable. This is an important finding as it could be that an increase in COVID-related projects drove higher FDI values in countries which received such COVID-related aid, granted COVID-related projects had comparatively higher or lower values, on average. Thus, acting as a potential explainer for the disparities in FDI values across regions (i.e., regions with higher COVID mortality rates received higher COVID-related levels of FDI, which were in turn more expensive).

4. Visualizations

4.1 Average Chinese FDI Project Monetary Value by Recipient Region Over Time (2000-2021)

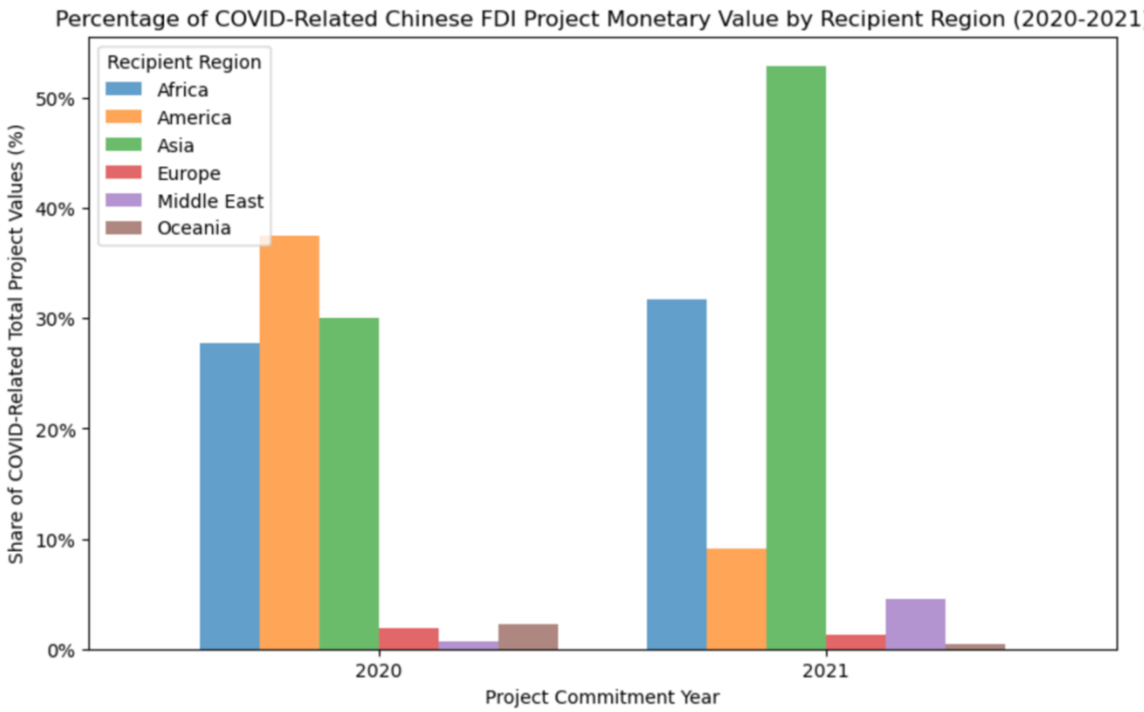
This plot provides valuable insights into which region received the highest Chinese FDI average project value per year. We know from the summary statistics table that between 2000-2021, on average, the Middle East received the highest project values. From this graph, it is evident that that trend is not evident in each year. Rather, between roughly 2007 and 2019 the Middle East received on average, the highest project values. The region also experienced a very huge burst, unlike other regions, making a huge jump between its 2005 and 2010 levels. Moreover, this implies that further research is necessitated on the inflection points and periods leading up to and following this trend. Specifically, to determine what changed between 2000 and 2007 to make project values in the Middle East increase so steeply, on average. Some of the overall significant drop in average project monetary value after 2015 can likely be attributed to COVID-19, with China possibly choosing to spend less on FDI to fund its COVID recovery efforts. However, that explanation can only account for post-2019 data and does not explain the decrease between 2015 and 2019. Interestingly, Oceania has had a small variation in its average project value, unlike the other regions which significantly fluctuated every five years on the graph. The years 2010 and 2015 may also require further analysis, as all regions collectively rose and fell during those periods except for Asia, which rose in 2015 while other regions fell from their previous levels. Thus, Asia requires



further investigation, particularly during that interval to understand why it did not follow the same pattern as other regions.

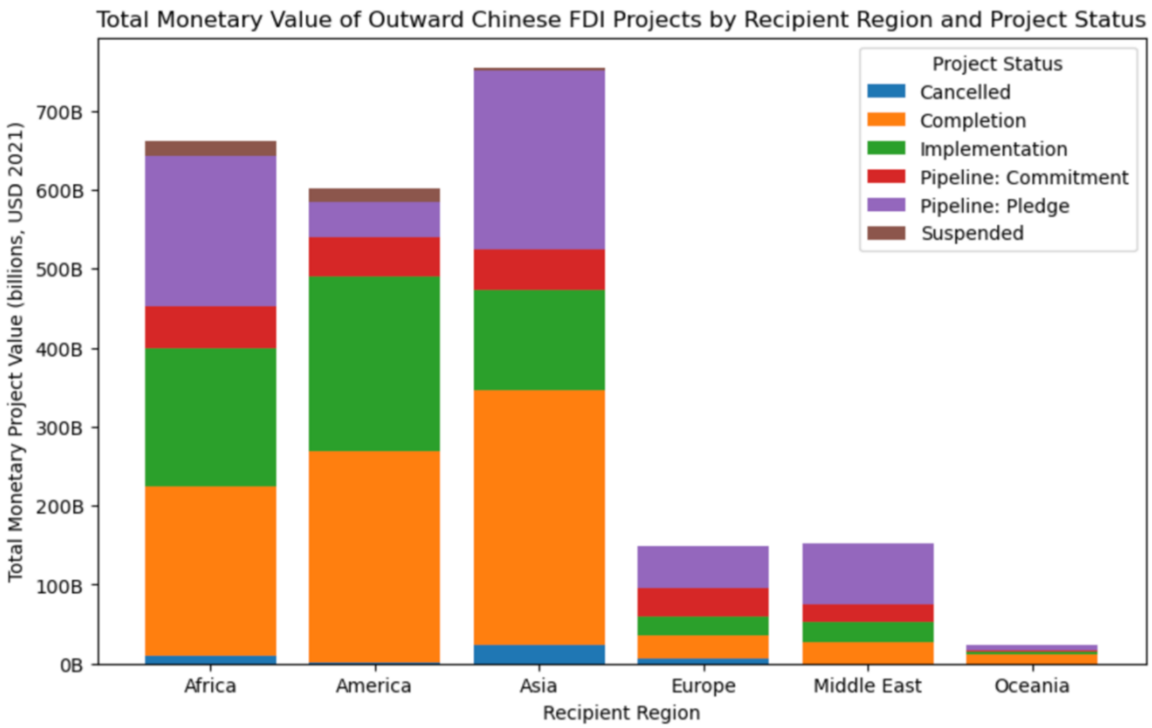
4.2 Percentage of COVID-Related Chinese FDI Project Monetary Value by Recipient Region

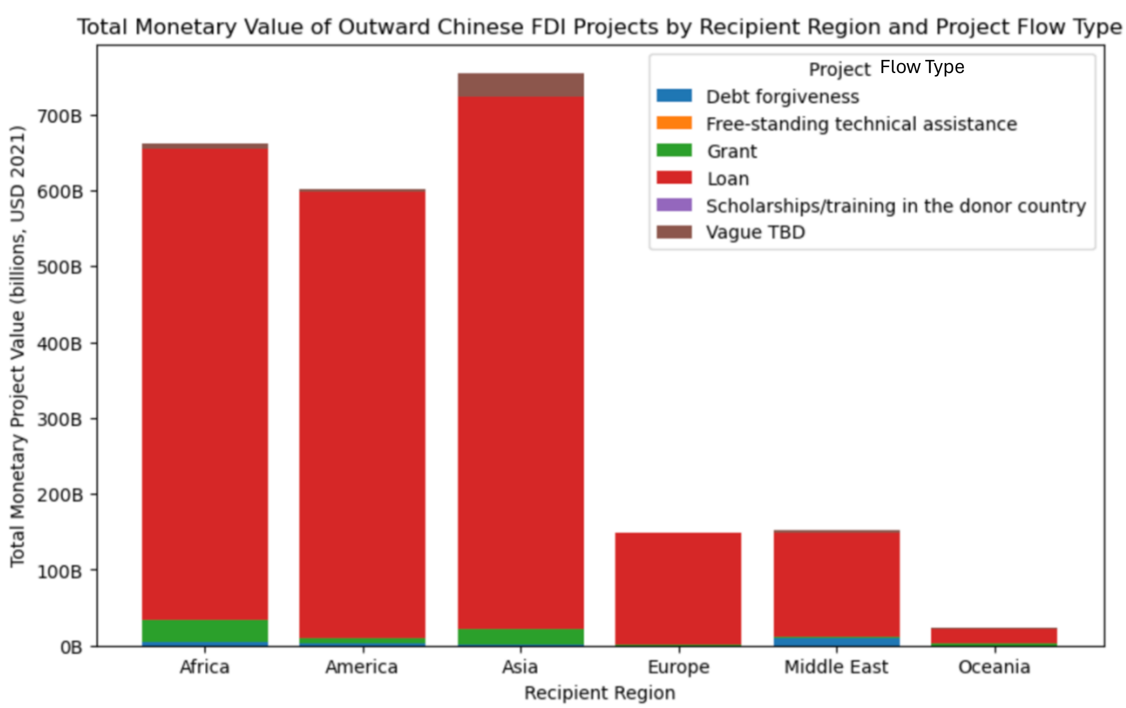
This plot visualizes what percentage of Chinese FDI in the COVID-19 years, defined as 2020 and 2021, was directed towards COVID-related goals for each region. Interestingly, in 2020, the Americas region had the greatest share of the FDI received as COVID-related, a little under 20%. Meanwhile, in 2021, Asia had under 30% of FDI directed to COVID-related projects, while the Americas dropped to almost 5%. This is an interesting trend considering that Asia was one of the first regions to be hit by COVID-19, considering the virus emerged from China. This graph may also help explain the insights found in the previous plot, as it is evident that a very small share of Chinese FDI received by the Middle East was COVID-related projects. However, considering that almost 50% of total Chinese FDI was allocated to COVID-related projects during the COVID years, it can be deduced that this is possibly why the Middle East received far less FDI per project, on average, after 2019.



4.3 Monetary Value of Chinese FDI Projects by Region and Key Project Attributes (2000-2021)

These plots visualize the total monetary project value a country has received as Chinese FDI between 2000 and 2021. This emphasized the interesting relationship between total and average project value, where the Middle East has a small total received number, yet the largest average project amount out of all the regions. The plot further dissects the project value data by visualizing first what portion of a region's project value is associated with cancelled, completed, and suspended projects, and secondly by visualizing the project flow types. Overall, the plot provides plausibility to the analysis from 3.6, where it was hypothesized that China may be inflating average project FDI value in regions by not following through on higher monetary value projects. For instance, the majority value of Middle Eastern projects has consisted of projects that have not yet been completed and are only pledged, cancelled, or in the implementation process. Meanwhile, the American, Asian, and African countries have a large portion of their project value as completed projects, yet their average project values are much smaller than those of the Middle East.

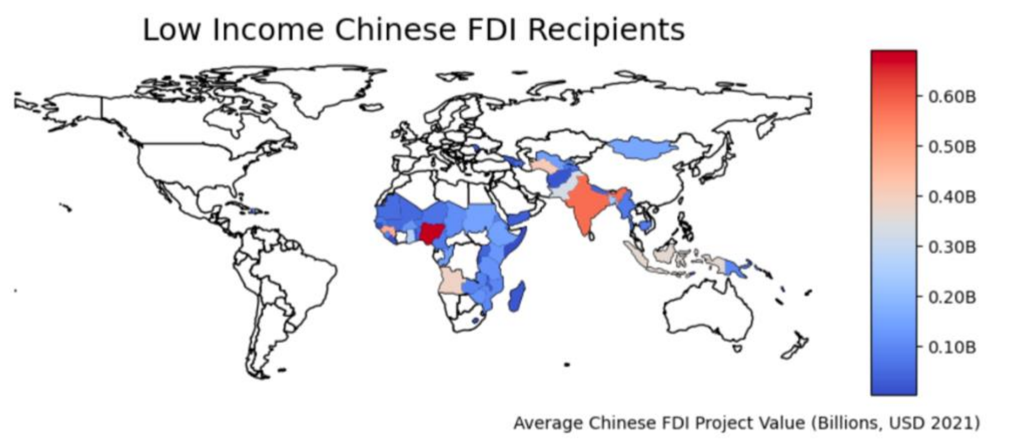

Total Monetary Value of Outward Chinese FDI Projects by Recipient Region and Project Status
Project Status
Cancelled
Completion
Implementation
Pipeline: Commitment
Pipeline: Pledge
Suspended
Total Monetary Project Value (billions, USD 2021)
0B
100B
200B
300B
400B
500B
600B
700B
Africa
America
Asia
Europe
Middle East
Oceania
Recipient Region

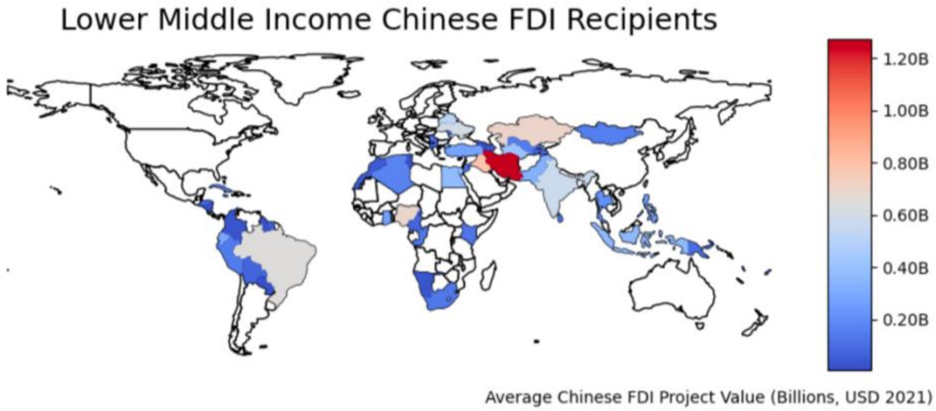

Total Monetary Value of Outward Chinese FDI Projects by Recipient Region and Project Flow Type
Project Flow Type
Debt forgiveness
Free-standing technical assistance
Grant
Loan
Scholarships/training in the donor country
Vague TBD
Total Monetary Project Value (billions, USD 2021)
0B
100B
200B
300B
400B
500B
600B
700B
Africa
America
Asia
Europe
Middle East
Oceania
Recipient Region

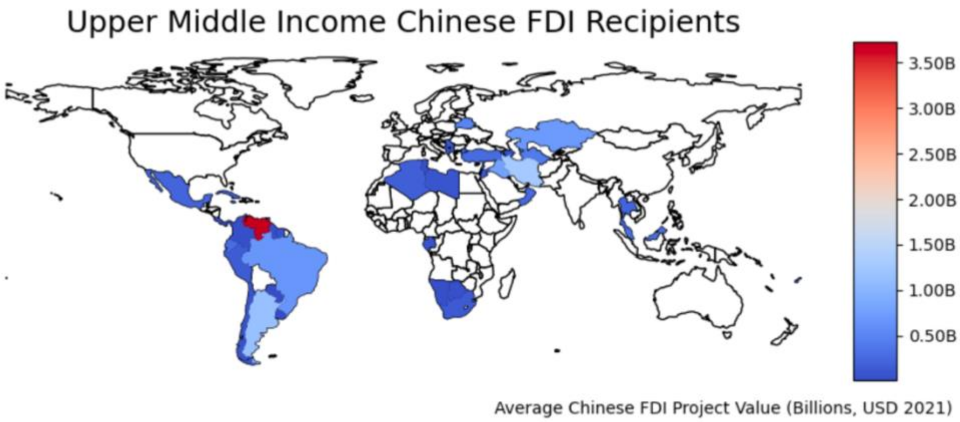
The most interesting finding from these plots, however, is that an overwhelming majority of project values consist of loans — also demonstrating that countries are heavily indebted to China. Focusing on regional differences, Asia, Europe, and the Middle East stand out the most. While other regions seem to have grants as their second greatest project flow type, Asia's is undetermined flows, the Middle East's is debt forgiveness, while Europe seems to be wholly dominated by loans. Considering that the Middle East has the greatest average project value, the importance of flow type in determining average project FDI levels necessitates further investigation. From the project flow type summary statistics, it was determined that vague flow type projects had the greatest average project values, signifying that it could skew upwards a region's average project value if there are many such projects. Following loans, debt forgiveness had the greatest average project value, demonstrating again, that many projects with this flow type in a region could skew upwards a region's average project value.

4.4 World Maps of Average Chinese FDI Project Values by OECD Income Group (2000-2021)

Using the OECD income group classifications, these maps provide valuable insights into how a recipient country's income level is associated with its average outward Chinese FDI project value. There is a positive relationship observed between the two, with low-income countries associated with lower average Chinese FDI project values, while upper-middle-income countries were associated with higher average Chinese FDI project values.



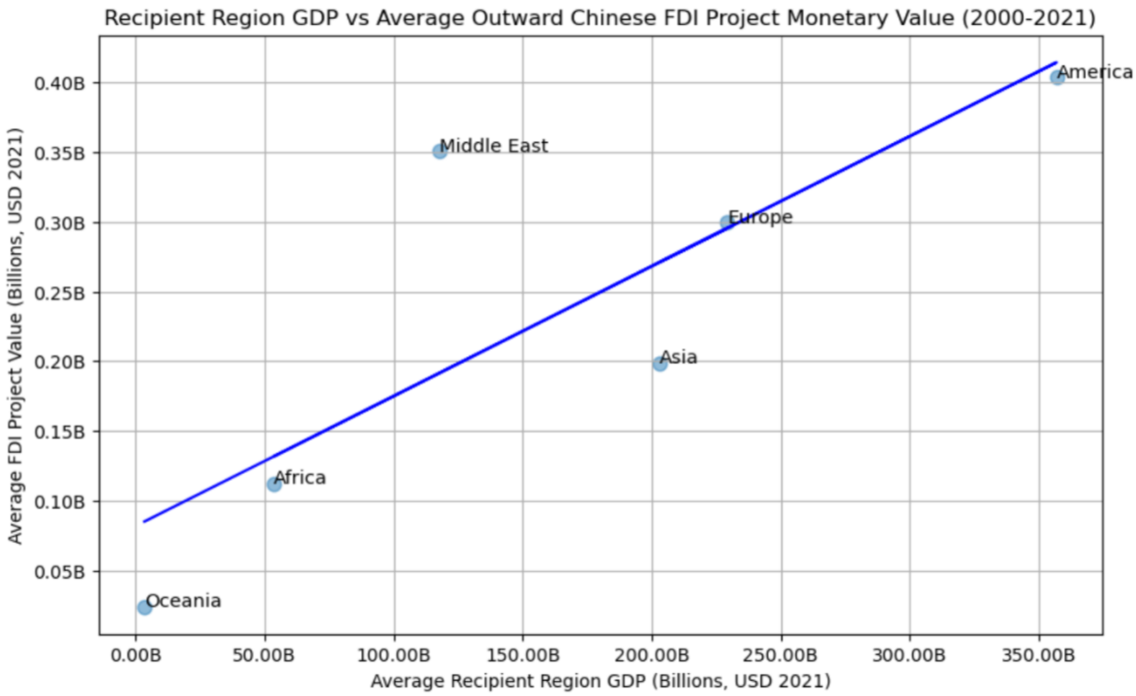




Similarly, the variation in project values seems to increase as income levels increase. Visually excluding outliers, the upper-middle-income map seems to have a range of between 1.5-0.5 billion USD range, lower-middle-income countries have a range of 0.7-0.1 billion USD, and low-income countries have a range of 0.5-0.1 billion USD. These findings are consistent with the results found in the literature, where market size and GDP growth are important determinants of outward Chinese FDI. Interestingly, the upper-middle-income map only seems to have one outlier; Venezuela. Thus, reaffirming that factors such as GDP, market size, and now income level, contribute to explaining the regional variation in average outward Chinese FDI project values, as it seems that Chinese FDI is more attracted to high levels of such attributes.

4.5 GDP vs Outward Chinese FDI Project Value by Region (2000-2021)

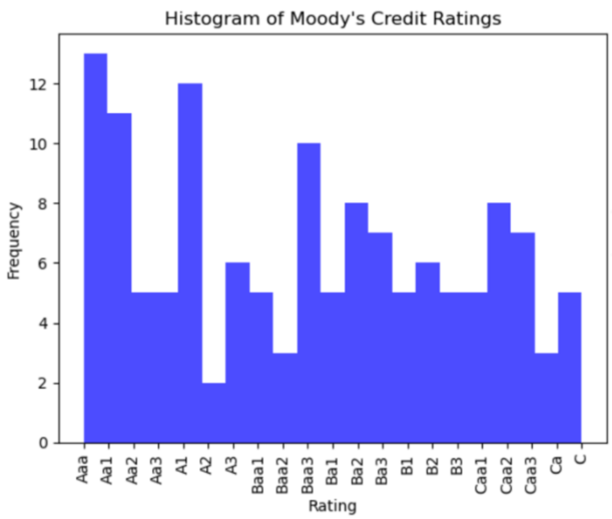
This plot provides valuable insights into GDP, a potential explainer for the regional differences in average outward Chinese FDI monetary project values.

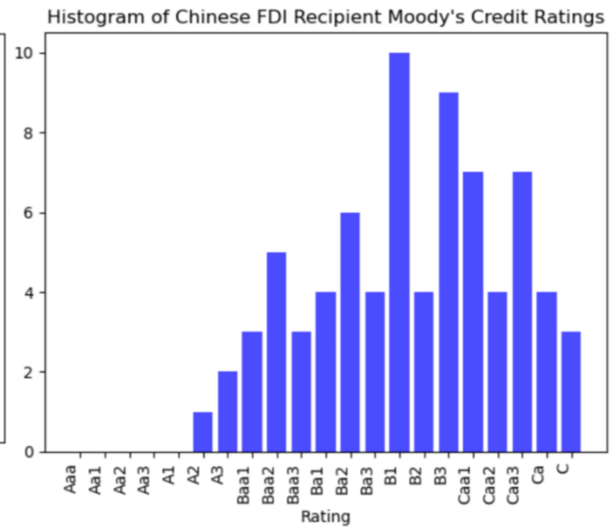


Although this graph changes the ranking of average FDI project value, this is solely due to the data collection process, as the lack of availability of GDP data for some years and regions resulted in dropped observations. Similarly, some regions had FDI allocated to the region as a whole, rather than to a specific country within the region. Considering the accuracy of the original dataset, it is better to use the values from there when comparing average FDI project value by region. However, this plot still provides valuable insights by demonstrating a positive relationship between recipient region GDP and FDI project value. Thus, remaining consistent with the findings in the literature that outward Chinese FDI is attracted to higher GDP levels, and therefore larger markets. This is an important contribution as it is one of the strongest explanations at the moment for answering my research question, although regressions in later projects will help assess the magnitude of this association to determine whether it is a statistically and economically significant determinant of outward Chinese FDI levels.

4.6 Distribution of Moody's Credit Ratings

These histograms contrast the overall world distribution of credit ratings across countries with the credit ratings of those receiving outward Chinese FDI.



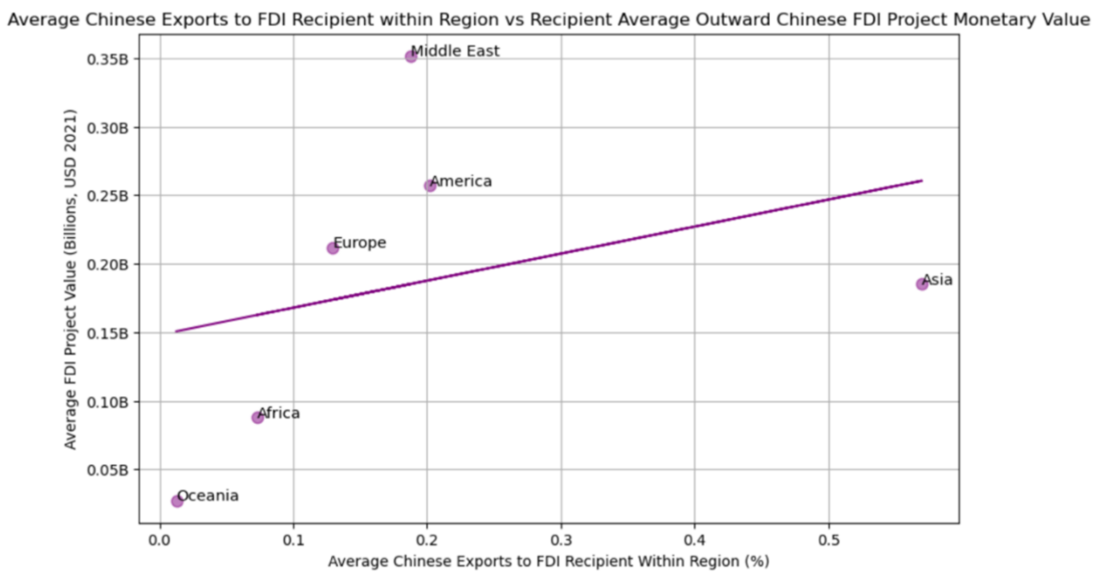


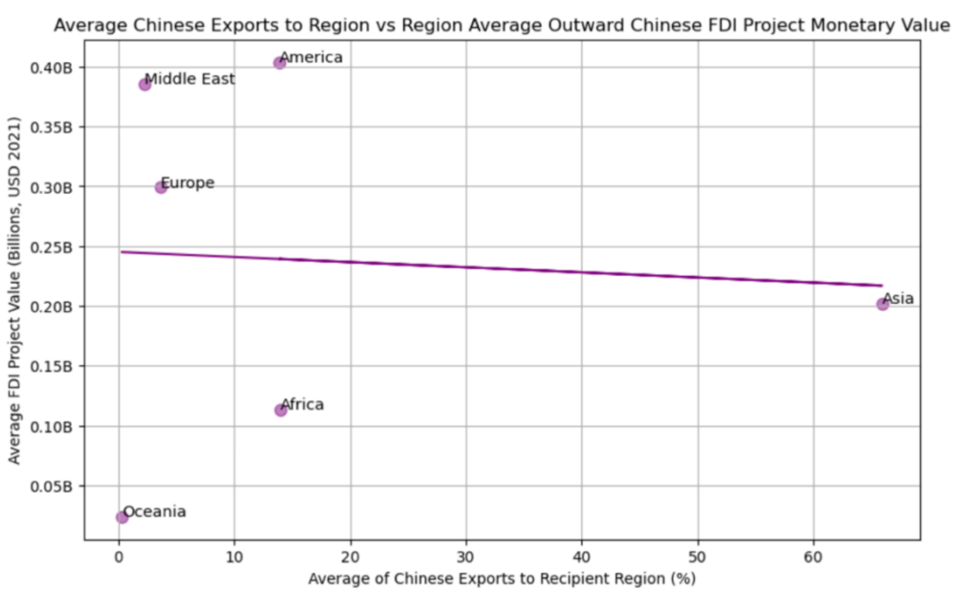
Namely, it demonstrates that Chinese FDI is much more common in countries with lower credit ratings, with the highest FDI receiving country credit rating as A2, which is Chile. The credit ratings with the most recipient countries are B1, B3, Caa1, and Caa3, respectively. Thus, it can be hypothesized that regional differences in Chinese FDI project values occurs because some regions have more countries with lower credit ratings, and therefore receive higher monetary values of FDI. However, from this histogram alone, it is difficult to conclude whether that hypothesis is correct (i.e., it is unclear whether such low rating countries are also those receiving the highest average project FDI amounts) — but it guides my research towards answering that question, with the plots in the next section addressing that hypothesis.

4.7 Chinese Exports to Recipient Region vs Outward Chinese FDI (2000-2021)

These plots provide valuable insights into Chinese exports, a potential explainer for the regional differences in average outward Chinese FDI monetary project values. The first plot demonstrates a strong positive relationship between the average Chinese exports to a recipient country within a region and a country's FDI project value within that region, as was also indicated by Cheung and Qian (2009).

Meanwhile, the second plot looks at the average percentage of Chinese exports to a region and the average FDI project value received by that region - now demonstrating a negative relationship due to Asia. Without Asia, there would be a positive relationship between the two variables. Interestingly, Asia as an outer is the case for both plots. This is an important contribution as it acts as another potential explanatory factor of disparities in FDI project values across regions — regions with lower exports from China receive lower average FDI project values (like Oceania), while regions with higher exports from China receive higher average FDI project values (like the Middle East or Americas). This also prompts further research into the topic as to why this relationship does not necessarily hold for Asia.





5. OLS Regression Results

5.1 Country-level regressions

Six regressions focusing on country-level specifications were created, in which each includes recipient regions dummies as it allows me to control for the regional effects considering that my research question focuses on regional disparities. (1) Income Model; seeks to establish the magnitude by which income impacts FDI. Much of the literature highlighted the importance of GDP, or recipient market size, as the premier driving factor behind outward Chinese FDI. Similarly, much of my preliminary work supported this theory, with my main message plot and several maps demonstrating the positive relationship between regional average outward Chinese FDI project values and average regional GDP. When I sorted countries by their income group, it yielded a positive relationship observed between the two — making it a possible driver of regional disparities in FDI. Through a regression, I can establish its magnitude, and by including GDP as well, the model lets me assess overall how a recipient country's endowments may impact its average outward Chinese FDI project values. The two variables are also similar, so the regression allows me to control for the two. (2) GDPxRegion Interaction Model; Considering the importance of GDP and market size in the literature, this regression seeks to see how GDP within a region impacts outward Chinese FDI through the usage of interaction variables. The purpose of this is that some regions may have GDP negatively associated with outward Chinese FDI project values, while others may have positive associations. (3) Economic Health Model; Unlike the previous regressions, this model focuses on the economic health and stability of a country and how it may impact outward Chinese FDI project values. GDP and unemployment rates are frequently cited economic indicators of a country's health. Thus, I can use these variables as a proxy to determine how a recipient's economic health impacts its average FDI project value. Specifically, lower GDP and higher unemployment rates would be associated with countries that have poorer economic health and may be relatively unstable. (4) Trade Relationship; the literature emphasized the importance of a recipient country's trade relationship with China in attracting higher FDI values. Particularly, finding that Chinese exports to developing countries have a significant positive relationship with outward Chinese FDI, implying that FDI may serve to facilitate trade. Thus, by including the percentage of exports from China to a recipient country in this model, I will be able to test whether my data will support the findings of the research. Recipient distance from China has also been included, as the Gravity Model of Trade assumes that China would trade more with countries that are closer to it. Similarly, since FDI is with the intent of establishing influence within another country, it could be that China prefers countries further away so that it can have influence abroad, or China may prefer to extend its influence closer to home to protect its borders. (5) Comprehensive Economic Model; this model builds on regression 3 by also including income group and GDP per capita. Together, these variables provide a holistic view of the state of the economy, allowing me to observe how several economic indicators may have a combined influence on outward Chinese FDI project values. (6) Strongest Explanatory Variable Model; this model contains the variables which have stood out thus far as the most viable explanatory variables, each demonstrating a relationship with a region's average outward Chinese FDI project value. Thus, having a multiple regression model that incorporates each of the variables allows me to analyze which variable truly has the greatest impact on driving Chinese FDI project values, and therefore why there are regional differences in these average values. Similarly, it will allow me to determine the magnitude to which each variable has an impact. From my previous research I've determined possible explanations, but the regression allows me to determine whether it's significant.

Table 1. OLS Country-Level Drivers of Chinese Outward FDI Project Monetary Values.

	(1)	(2)	(3)	(4)	(5)	(6)
ln (GDP)	0.382***	0.281***	0.285***		0.358***	0.358***
	(0.024)	(0.036)	(0.022)		(0.025)	(0.047)
Distance		Yes		Yes		
GDPpc					Yes	
Unemployment rate			Yes		Yes	Yes
Income group						-0.3254
Lower-middle	-0.597***				-0.606***	-0.534***
	(0.099)				(0.104)	(0.103)
Upper-middle	-1.172***				-1.415***	-1.044***
	(0.116)				(0.170)	(0.128)
ln (exports)				0.261***		
				(0.022)		
Region						
Americas	-0.067	-3.062*	-0.663***	-0.641***	-0.219	-0.129
	(0.139)	(1.656)	(0.126)	(0.222)	(0.144)	(0.142)
Asia	0.274***	2.736**	0.109	0.210	0.199**	0.202**
	(0.089)	(1.309)	(0.091)	(0.220)	(0.093)	(0.100)
Europe	1.334***	-8.807***	0.932***	1.034***	1.302***	1.352***
	(0.181)	(2.456)	(0.175)	(0.198)	(0.181)	(0.182)
Middle East	1.222***	-19.118***	1.053***	0.919***	1.265***	1.251***
	(0.227)	(4.597)	(0.227)	(0.258)	(0.227)	(0.228)
Oceania	-0.294	5.925**	-0.984***	-0.922***	-0.456**	-0.420
	(0.181)	(2.678)	(0.175)	(0.174)	(0.189)	(0.189)
GDPxRegion						
GDP*Americas		0.093				
		(0.067)				
GDP * Asia		2.736**				
		(1.309)				
GDP * Europe		0.384***				
		(0.099)				
GDP * Middle East		0.798***				
		(0.184)				
		-0.314**				
GDP * Oceania		(0.124)				
Constant	6.556***	8.624***	8.945***	16.054***	7.169***	7.280***
	(0.571)	(0.922)	(0.527)	(0.302)	(0.595)	(1.238)
F Statistic	63.462***	38.088***	63.244***	53.773***	52.495***	51.350***
Adjusted R-Squared	0.057	0.051	0.050	0.043	0.059	0.058

Note: FDI project values were logarithmically transformed. N=8200, *p<0.1, **p<0.05, ***p<0.01

5.2 Project-level regressions

Three regressions focusing on project-level specifications were created, in which each includes recipient regions dummies as it allows me to control for the regional effects considering that my research question focuses on regional disparities. (1) COVID-Related Project Model; The primary purpose of this regression is to capture the importance of COVID-related projects in regional disparities in average outward Chinese FDI project values. Variables such as GDP and income group have been included as lower-income/lower-GDP regions were disproportionately affected by COVID. As was detailed in th visualizations, COVID-related projects made up a sizeable amount of projects in several regions in 2020 and 2021, demonstrating that it may be a useful measure for explaining regional differences in outward Chinese FDI project values during the COVID years. Thus, I added a dummy variable for COVID-related projects in this regression model, where COVID=0 means that the project was not COVID-related, while COVID=1 means that the project was COVID-related. (2) Project Purpose Model; this model focuses on the purpose of the FDI projects, grouped by the project sector and intent. This categorization allows me to observe whether the purpose of a project impacts FDI project values, and therefore can explain the regional disparities in average project values. For instance, it could be that health projects are particularly expensive due to expensive equipment. Thus, regions that receive higher levels of health projects may therefore have higher regional averages in project values. (3) Comprehensive Project Model; each of the variables included except for the recipient region is focused on the characteristics of the FDI projects. The purpose of this is that it allows me to see how the project-level characteristics could be driving regional differences in outward average Chinese FDI project values. Specifically, as I hypothesized in the summary stats section, it could be that some regions have higher average project values and also that more projects have been completed, indicating that China may give higher project values to projects that they don't intend to complete, or may take longer to complete. And if several of those projects are clustered within a region, it could very well explain the regional variation. Thus, instead of focusing on the country-level characteristics unique to a region, this model focuses on project characteristics, as it could be that a class of projects is unique to a region, and that is why there are regional differences in average outward Chinese FDI project values.

Table 5. OLS Project-Level Drivers of Chinese Outward FDI Project Monetary Values.

	(1)	(2)	(3)
OECD Income Group	Yes		
Intent		Yes	
Ln (GDP)	Yes		
COVID	-4.331*** (0.106)		-1.431*** (0.111)
Flow Type			
Free-standing technical assistance			-3.221*** (0.534)
Grant			-2.681*** (0.442)
Loan			0.341 (0.438)
Scholarships/training in the donor country			-4.948*** (0.507)
Vague TBD			-0.592 (0.510)
Region			
America	0.002 (0.127)	-0.544*** (0.089)	-0.413*** (0.081)
Asia	0.293*** (0.082)	-0.022 (0.062)	0.208*** (0.056)
Europe	0.962*** (0.165)	0.207* (0.123)	0.295*** (0.112)
Middle East	1.007*** (0.207)	0.671*** (0.161)	0.687*** (0.145)
Oceania	-0.296* (0.165)	-0.933*** (0.120)	-0.446*** (0.109)
Sector			
Education		-3.659*** (0.228)	-1.213*** (0.409)
Emergency Response		-3.747*** (0.225)	-1.319*** (0.408)
Health		-4.298*** (0.209)	-0.991** (0.406)
Other Commodity Assistance		-3.467*** (0.678)	-1.495** (0.706)
Other Multisector		0.039 (0.242)	1.172*** (0.413)
Population Policies/Reproductive Health		-4.905*** (0.850)	-2.412*** (0.843)
Unallocated/Unspecified		-0.649*** (0.219)	0.455 (0.403)
Status			
Completion			-0.983*** (0.302)
Implementation			-0.146 (0.306)
Pipeline: Commitment			-0.597* (0.308)
Pipeline: Pledge			0.274 (0.314)
Suspended			1.118** (0.568)
Constant	5.961*** (0.521)	18.186*** (0.228)	17.851*** (0.362)
F Statistic	63.462***	38.088***	63.244***
Adjusted R-Squared	0.057	0.051	0.050

Note: FDI project values were logarithmically transformed. N=8200, *p<0.1, **p<0.05, ***p<0.01

5.2 Interpreting the regressions

My regression results are incredibly important, as they've demonstrated that project-level characteristics have far better predictive power to explain the regional disparities in FDI project values, as is illustrated by the significantly higher R-squared values of regressions containing project-level characteristics. For country-level regressions, the models with the highest R-squared are the Comprehensive Economic model and the Explanatory Variable model, each around 6%, demonstrating that economic indicators still do play a role in determining outward Chinese FDI project values. After adding more controls, many variables change their degree of statistical significance. Importantly, in each of my models containing GDP, it remains a statistically significant coefficient at the 1% level. From the Comprehensive Economic model, a 10% change in GDP is associated with, on average, a 3.58% change in FDI project value - demonstrating that GDP has a meagre impact on FDI project value. Exports also seem to not be statistically significant after controlling for recipient GDP, recipient income group, and recipient credit rating (i.e., moving from the Trade Relationship model to the Explanatory Variable model). This is important as the literature emphasized a relationship between trade openness with China and their received FDI project values. From my regressions, it seems as if perhaps the contribution by exports in the Trade Relationship model was due to confounding variables, so controlling for the other economic indicators diminished/absorbed the impact that was previously attributed to exports. Thus, I cannot necessarily corroborate all the views found in the literature, but it could be due to a difference in periods, as the literature used data that was at least 10 years older than mine — it could be that determinants of outward Chinese FDI project values have also changed over time, something which I had not previously considered.

A key finding from my regression results is that all the regional coefficients are statistically significant, but are fairly large in the country-level regressions despite varying control variables. The purpose of including these variables was to control for regional differences that my other variables may not be able to pick up on, such as regional-specific infrastructure and policies, and see the degree to which regional characteristics influence outward Chinese FDI project values. The Middle East and Europe consistently have the highest coefficients, demonstrating that regional qualities have the greatest impact on the project values in those regions. This points out that there may be other regional-specific variables which should've been included in my model, such as natural resource yield. Interestingly, this was not a concern in the project-level regressions, where all the regional coefficients dropped.

The GDPxRegion Interaction Model from the country-level regressions was also key, as it demonstrated that GDP has different effects on project values in different regions. Specifically, for European, Asian, and Middle Eastern countries, there is a strong positive relationship between GDP and FDI project values, when compared to Africa which is the base category. For the other regions, the relationship is weaker or unclear. The greatest impact of GDP is seen in the Middle East, where a 10% change in GDP is associated with, on average, a 7.98% change in FDI project value. Compared to the 3.58% change predicted by the Comprehensive Economic model, it demonstrates that GDP could be the best explanatory variable for regional differences in average FDI project value, contributing greatly to answering my research question. Lastly as was mentioned, project-level characteristics have the greatest predictive power in explaining variation in outward Chinese FDI project values. Project flow types in particular have the greatest coefficients, meaning that they impact the predicted project values the most. Specifically, the coefficients range from a 0-50% change in FDI project value. Out of the sectors, education, emergency response, population policies, general budget support, other multisector, and other commodity assistance have the highest coefficients, in the 10-30% range. This is a large contribution and reaffirms my hypothesis from Project 1 that some sectors may require higher project values, and if a country receives several such projects, then its average project value will rise.

My preferred specification is the Comprehensive Project Model since it's the regression with the highest R-squared (0.607) and Adjusted R-squared (0.605). This means that the variables chosen within this model explain 60.7% of the variability in outward Chinese FDI project monetary values. The R-squared is important to me as it signals whether my model and its variables do a good job of explaining FDI project values — which is my research question and therefore my main focus. Similarly, this result was very unexpected, for I thought that country-level data would have far greater predictive power associated with FDI project values.

6. Machine Learning Results

6.1 Comprehensive Project Model Regression Tree

Interestingly, the tree has identified that whether a project was a loan, completed, in the commitment phase, a vague flow type, in the pledged phase, or an unspecified sector are all key factors influencing outward Chinese FDI project monetary value. Importantly, this demonstrates that project status and flow type are key explanatory variables in explaining variations in outward Chinese FDI project monetary values. To interpret the values, they must be exponentiated since my dependent variable is logged. Projects that were not loans are predicted to be on average, about 799,706 USD. Then, if projects weren't completed, they are predicted to be on average, about 5,178,365 USD, while completed projects were predicted to be on average, about 432,786 USD. This finding is consistent with the hypothesis in Project 1 that it could be that China gives large project amounts to projects that they drag out the completion for or may take longer to complete. For completed projects, they are then divided into the categories of COVID-related or not, where COVID-related projects are predicted to be on average, 124,616 USD, while non-COVID-related projects are predicted to be on average, 646,934 USD. For incomplete projects, they are split into whether they were a vague flow type (i.e., uncategorized), with vague flow type projects predicted to be on average, 46,781,575 USD, while non-vague flow type projects are predicted to be on average, 4,662,209 USD.

For projects that were loans, the value is predicted to be on average, significantly higher, at about 86,443,363 USD. Projects were then split into whether they have only been committed to (i.e., no progress on the project), with committed projects being predicted as on average, 39,114,351 USD, while non-committal projects are predicted as on average, 105,582,162 USD. This finding goes against my initial thoughts in Project 1, where it was assumed that since China has only decreased its total FDI amounts in recent years, China may commit to high-value projects but then fail to follow through with its plans. For non-committal projects, they are then split into whether their status is in the pledge phase, with non-pledge projects predicted to be on average, 96,688,013 USD - the second highest project value predicted by the tree - while pledge projects are predicted to be on average, 203,667,638 USD – the highest project value predicted in the entire tree. For projects in the commitment phase, they are split into whether the project sector is unspecified, with specified sector projects predicted to be on average, 16,419,824 USD, while unspecified sector projects are predicted to be on average, 52,116,908 USD.

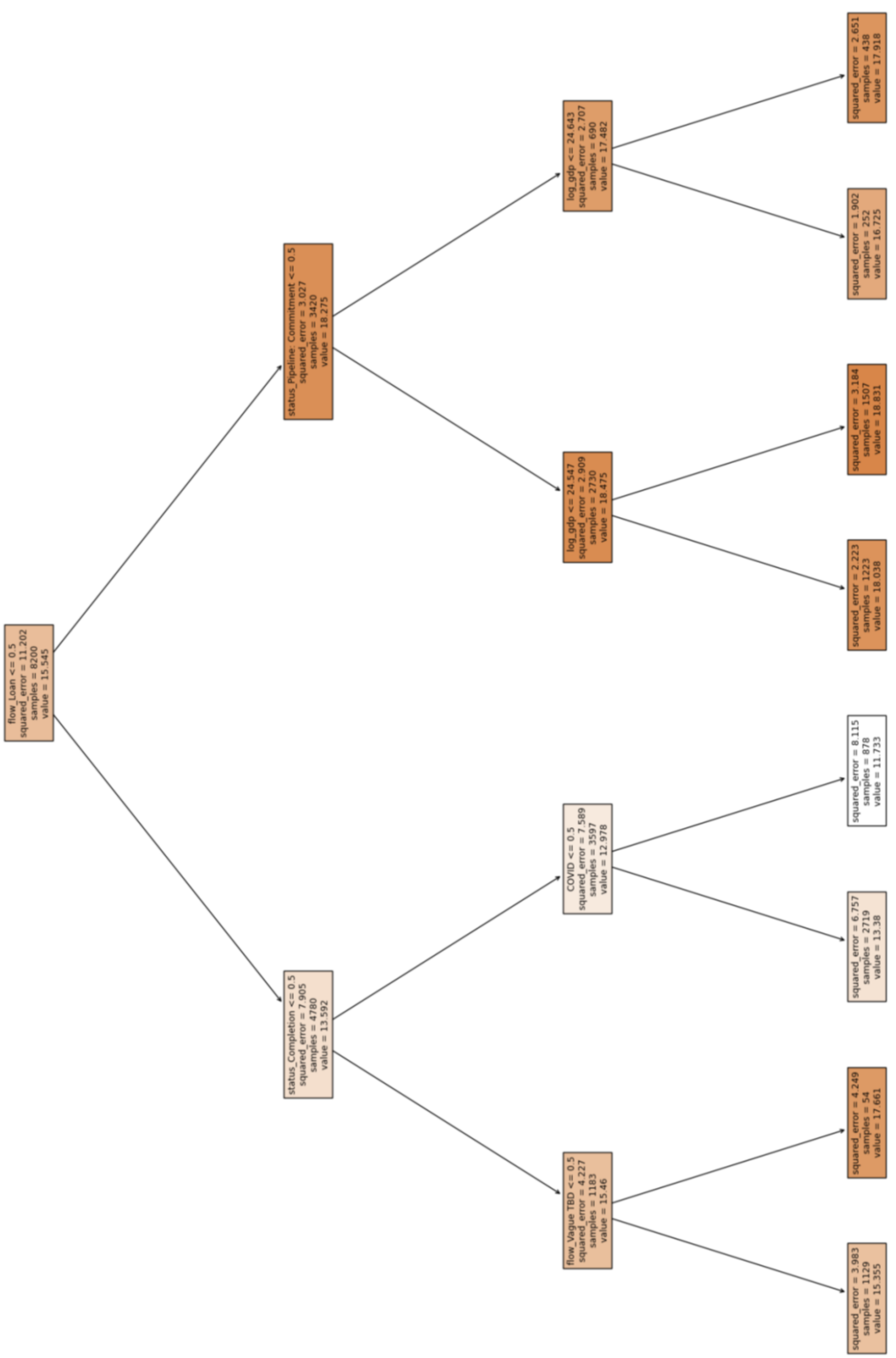
The average multiplicative error of the model is about 9.029, meaning that on average, the model prediction is off by roughly nine times the actual value (i.e., values could be nine times greater or nine times lower). This is a huge error and indicates that the model has a lot of room for improvement. However, this is to be expected considering there's still a lot of mystery about what influences FDI values, and there is a huge range of project values in the dataset (from double digits to the millions). To improve the error, I could try and add more variables which I believe are relevant, such as country-level data, or further adjust the model parameters.

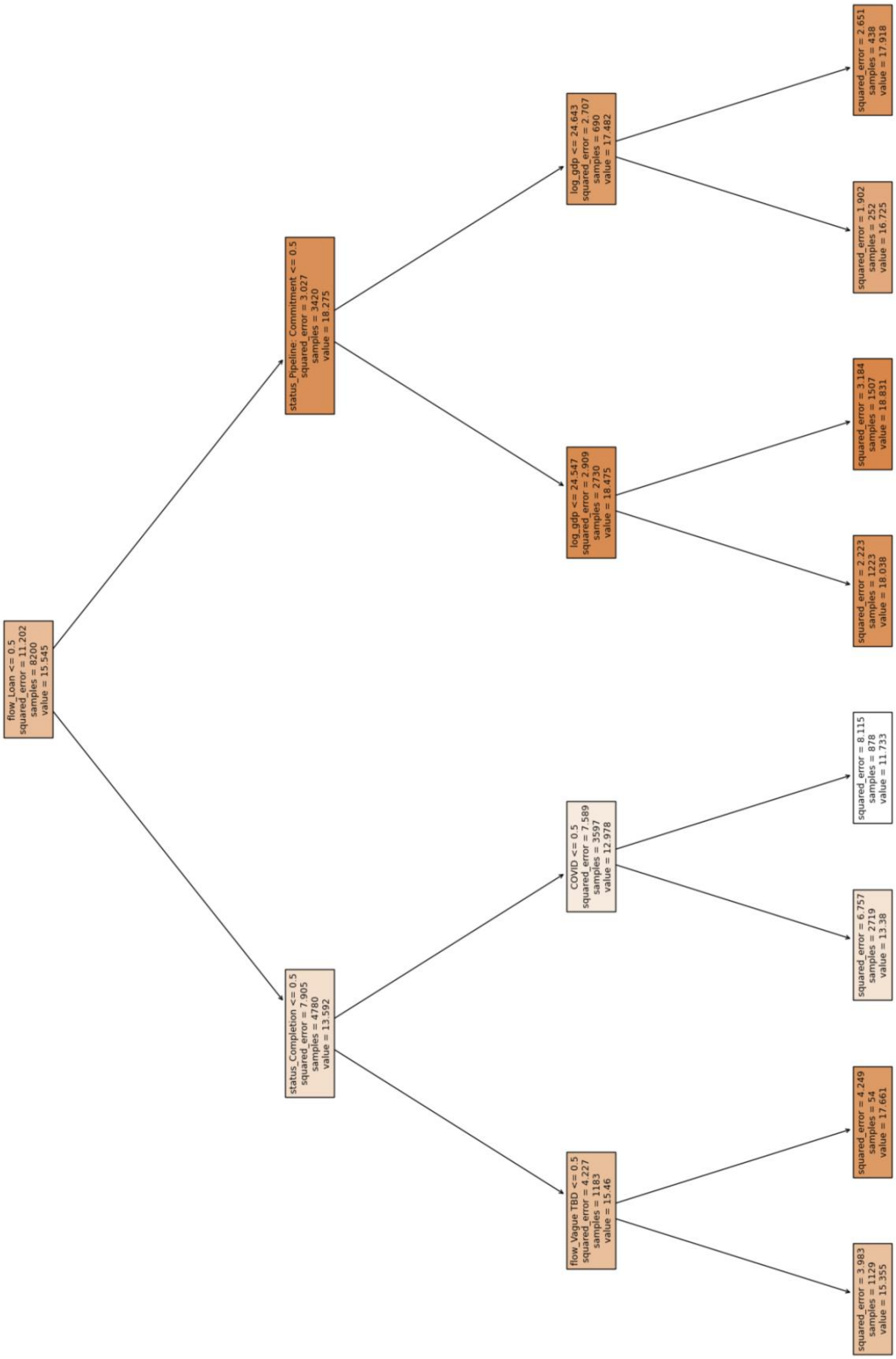
Interestingly, most of the node variables identified by the regression tree are not statistically significant in the OLS model, such as flow_loan, status_pipeline: pledge, flow_vague TBD, and sector_UNALLOCATED/UNSPECIFIED. Meanwhile, in the OLS model, both COVID and status_completion were statistically significant at the 1% level, while status_pipeline: commitment was statistically significant at the 10% level. Without the regression tree, I likely wouldn't think that the node variables mentioned were important in determining Chinese outward FDI project values due to their lack of statistical significance in the OLS model, so the regression tree gave me extra information about what variables have the best ability to explain the variation in average outward FDI project values. The reason for this discrepancy may be due to the OLS regression treating the data as a homogeneous group while the regression tree identifies subgroups for which these variables are important determinants of FDI project values. Thus, it may be that the regression tree is uncovering heterogeneity in effects that my OLS model averages out, giving me information that the OLS wouldn't. Similarly, OLS is more sensitive to outliers and linearity while the regression tree limits these problems through the partitioning process and can work with nonlinear relationships.

The subgroups that the regression tree provides me with are also key information which the OLS model lacks. Considering the huge range of project values, purposes, and recipient locations, it is understandable that project values would not all be influenced by the same characteristics. Through the regression tree, you learn about what impacts the project FDI value in specific subsets, which allows me to better pinpoint why there is regional differences in FDI project values – it could be that there is a clustering effect of that one specific characteristic which then affects all others. For instance, in the literature, Cheung and Qian (2009) found that developed and developing country FDI project values are driven by different factors. From my regression tree, I can conclude that the variability in the projects that were loans are best explained by variables different from the projects that were not – something which is not evident from the OLS regression.

6.2 Additional Variable Regression Tree

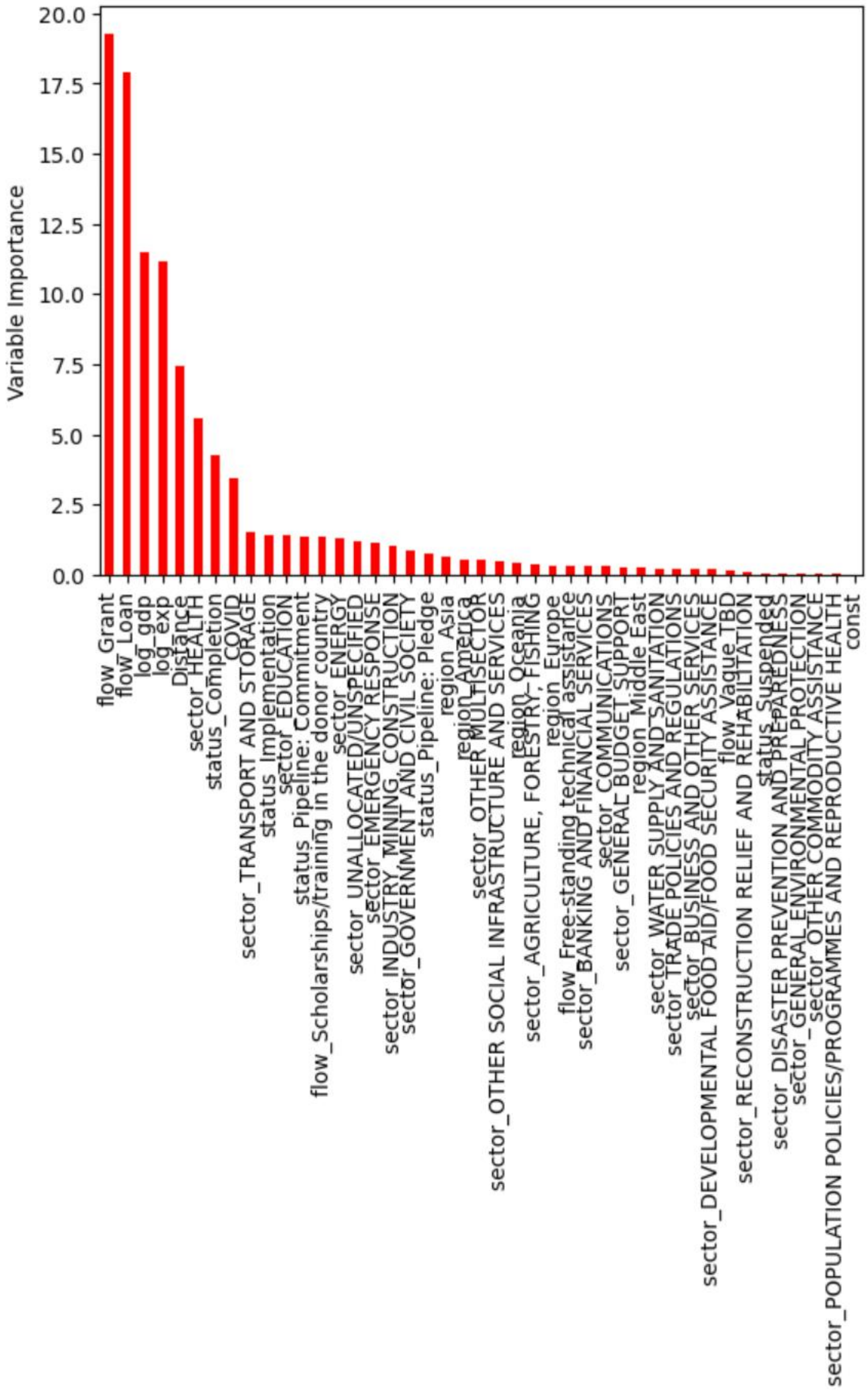
The next regression tree incorporates GDP, distance, and export percentage data to see whether to node variables will change after adding country-level characteristics. Interestingly, much of the tree remains the same. The only major changes are the interior nodes under status = commitment, which are now both GDP (with different thresholds), while the previous tree had status = pledge and sector = unspecified. This demonstrates that like the findings in the literature, GDP, and therefore market size, are important determinants of outward Chinese FDI project values. However, the importance of GDP is highlighted for projects that were loans, with project values that are slightly higher if not currently in the commitment phase. The MSE has also dropped very slightly, from 4.84 in the first tree using the comprehensive project specification, to now be 4.80. Nonetheless, this still implies that the error has been reduced and that incorporating country-level data does help explain disparities in outward Chinese FDI project values – although project-level characteristics may still be more important.


flow_Loan <= 0.5
squared_error = 11.202
samples = 8200
value = 15.545
status_Pipeline: Commitment <= 0.5
squared_error = 3.027
samples = 3420
value = 18.275
status_Completion <= 0.5
squared_error = 7.905
samples = 4780
value = 13.592
log_gdp <= 24.643
squared_error = 2.707
samples = 690
value = 17.482
log_gdp <= 24.547
squared_error = 2.909
samples = 2730
value = 18.475
COVID <= 0.5
squared_error = 7.589
samples = 3597
value = 12.978
flow_Vague TBD <= 0.5
squared_error = 4.227
samples = 1183
value = 15.46
squared_error = 2.651
samples = 438
value = 17.918
squared_error = 1.902
samples = 252
value = 16.725
squared_error = 3.184
samples = 1507
value = 18.831
squared_error = 2.223
samples = 1223
value = 18.038
squared_error = 8.115
samples = 878
value = 11.733
squared_error = 6.757
samples = 2719
value = 13.38
squared_error = 4.249
samples = 54
value = 17.661
squared_error = 3.983
samples = 1129
value = 15.355


flow_Loan <= 0.5
squared_error = 11.202
samples = 8200
value = 15.545
status_Pipeline: Commitment <= 0.5
squared_error = 3.027
samples = 3420
value = 18.275
status_Completion <= 0.5
squared_error = 7.905
samples = 4780
value = 13.592
log_gdp <= 24.643
squared_error = 2.707
samples = 690
value = 17.482
log_gdp <= 24.547
squared_error = 2.909
samples = 2730
value = 18.475
COVID <= 0.5
squared_error = 7.589
samples = 3597
value = 12.978
flow_Vague TBD <= 0.5
squared_error = 4.227
samples = 1183
value = 15.46
squared_error = 2.651
samples = 438
value = 17.918
squared_error = 1.902
samples = 252
value = 16.725
squared_error = 3.184
samples = 1507
value = 18.831
squared_error = 2.223
samples = 1223
value = 18.038
squared_error = 8.115
samples = 878
value = 11.733
squared_error = 6.757
samples = 2719
value = 13.38
squared_error = 4.249
samples = 54
value = 17.661
squared_error = 3.983
samples = 1129
value = 15.355

6.2 Random Forest Model/Importance Matrix

This importance matrix indicates that project flow type (grants and loans), recipient country GDP, recipient Chinese export percentage, recipient distance from China, project sector (health), project status (completed), and project COVID-relation are in order, the most important variables in determining outward Chinese FDI project values. Thus, changes in these variables have a large effect on an average project's value. Although the following variables are still important, and demonstrate diminishing importance, there is a dramatic drop in significance following the COVID variable. There is also a notable drop in variable importance following flow type = loan, which is about 18, while log GDP is about 11. Thus, demonstrating just how important a project flow type is in determining a project's value. While the importance of GDP and export percentage were emphasized in the literature, the significance of project-level characteristics was not discussed, making this an important contribution to the field. In relation to my research question, this could reaffirm my hypothesis from Project 1, where projects with some characteristics are clustered within a region, which explains regional variation. However, why this clustering occurs within a region is a question necessitating further research.


Variable Importance
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
flow_Grant
flow_Loan
log_gdp
log_exp
Distance
sector_HEALTH
status_Completion
COVID
sector_TRANSPORT AND STORAGE
status_Implementation
sector_EDUCATION
status_Pipeline: Commitment
flow_Scholarships/training in the donor country
sector_ENERGY
sector_UNALLOCATED/UNSPECIFIED
sector_EMERGENCY RESPONSE
sector_INDUSTRY, MINING, CONSTRUCTION
sector_GOVERNMENT AND CIVIL SOCIETY
status_Pipeline: Pledge
region_Asia
region_America
sector_OTHER MULTISECTOR
sector_OTHER SOCIAL INFRASTRUCTURE AND SERVICES
region_Oceania
sector_AGRICULTURE, FORESTRY, FISHING
region_Europe
flow_Free-standing technical assistance
sector_BANKING AND FINANCIAL SERVICES
sector_COMMUNICATIONS
sector_GENERAL BUDGET SUPPORT
region_Middle East
sector_WATER SUPPLY AND SANITATION
sector_TRADE POLICIES AND REGULATIONS
sector_BUSINESS AND OTHER SERVICES
sector_DEVELOPMENTAL FOOD AID/FOOD SECURITY ASSISTANCE
flow_Vague TBD
sector_RECONSTRUCTION RELIEF AND REHABILITATION
status_Suspended
sector_DISASTER PREVENTION AND PREPAREDNESS
sector_GENERAL ENVIRONMENTAL PROTECTION
sector_OTHER COMMODITY ASSISTANCE
sector_POPULATION POLICIES/PROGRAMMES AND REPRODUCTIVE HEALTH
const

7. Conclusion

The analysis of Chinese FDI project monetary values across regions over 21 years demonstrates that there is a persistent variation among regions in average project values, with the explanatory variables chosen preliminarily addressing the research question of why disparities in average Chinese FDI project monetary value emerge across regions. This finding continues to hold despite controlling for population levels, although it results in changes in the rankings of which regions and countries received the average highest levels of outward Chinese FDI project values. While the Middle East consistently had, on average, the greatest project values during the period of 2007 to 2019, this lead did not hold over the entire dataset period, demonstrating that there were factors which must have contributed to this rise and fall. The comparison between total and average project values also underscores the importance of considering both metrics, revealing that the Middle East, despite a smaller total received value, boasts the largest average project amount. The observed decline in average project values post-2015, particularly during the COVID-19 years, is most likely explained by the COVID-19 pandemic. The shift in FDI towards COVID-related projects varied across regions, with the Americas having a substantial share in 2020, followed by Asia leading in 2021. The plots in section 2. provide a potential explanation for the decline in FDI per project in the Middle East after 2019, as the region received a relatively small proportion of COVID-related projects, while COVID-related projects made up a majority of Chinese FDI project values. The comparison of COVID-related and non-COVID-related projects, particularly in the summary statistics portion and later plot demonstrating the share of COVID-19 projects emphasizes that, contrary to expectations, the average value of non-COVID-related projects is higher across all regions. As a result, it can be interpreted that from the plot, countries that received more COVID-related support during the COVID years may as a result have lowered the regions' average project value. The distribution of project values within the COVID recovery plan, along with insights into project flow types and sectors, contributes to the research question, aiming to explain the variation in average Chinese FDI project values across regions. Overall, the analysis of total project values across the dataset period, project status categories, project sector categories, project intents, and flow types reveals relationships that contribute to understanding China's investment decisions across regions. Thus, helping to explain the variation observed.

Focusing on economic indicators, visually, there was a weak relationship observed between unemployment and average FDI values, while GDP had the greatest observed association. Specifically, there is a positive relationship between recipient GDP and average outward Chinese FDI values. This is an important finding as it echoes the results found in the literature, where researchers concluded that factors such as market size, GDP, and market openness acted as major determinants of outward Chinese FDI values. Similarly, by sorting countries into income groups as defined by the OECD (i.e., low-income, lower-middle-income, and upper-middle-income), there was an observed positive relationship between income level and average FDI project levels. The greater the country's income level, the greater the average FDI value. Interestingly, there is also less variation observed in values as the income level decreases. Web scraping Moody's credit rating data and WITS Chinese export data were also incredibly important, as their analysis demonstrated that the two factors are drivers of average FDI project monetary values. While both exhibit a positive relationship with project value regardless of the region, indicating that regions with lower endowments of the factors will have lower average FDI project values as well, the same does not hold within a region. Specifically, the association with credit ratings within a region depends on the region. For Asia and the Middle East, a higher country credit rating is associated with a higher average project value. In Africa, the Americas, and Europe, a higher country credit rating is associated with lower average project values. However, within regions, the positive association between Chinese export levels and average FDI project value continues to hold.

By running OLS regressions and machine learning models, I find that contrary to my initial hypotheses, project-level characteristics are far better at explaining the variation in FDI project values, with attributes clustered among regions and explaining the regional disparities in values. Specifically, flow type, whether a project was COVID-related, and the project sector. As was demonstrated in Project 1, different project characteristics dominate a region's total FDI amount received, so if specific characteristics are associated with higher project values, then that region will have skewed values as well.

This was seen in the Middle East, where loan projects dominated their FDI values, and had greater average project values. This was a new contribution as much of the research focused on country-level characteristics which influence FDI project values instead of project-level characteristics. Similarly, much of the research also focused on the number of projects undertaken in a region instead of the average value of these projects. As was demonstrated in Project 1, some regions receive a huge number of projects but do not necessarily receive the highest project values. Meanwhile, the strongest country-level explanation for the regional disparities in outward Chinese FDI project values is recipient GDP and income group. For European, Asian, and Middle Eastern countries, there is a strong positive relationship between GDP and FDI project values, when compared to Africa which is the base category — for the remaining regions, the relationship is weaker or unclear. This finding reaffirmed the findings in the literature which often cited GDP and therefore market size as one of the main attractors of outward Chinese FDI.

However, the large regional coefficients in the project-level regressions demonstrate that more research may be needed into regional characteristics that may impact FDI values. For instance, resource levels, as indicated by the current literature, should also aim to be included and analyzed in the project's next steps, as it could help explain the variation in FDI values across low-income countries. After adding such variables, it would be suggested to run similar regressions as those in my project but group them by time and region, as there also may be changes in determinants over time, as was suggested by some of the literature. My credit data was also limited by the time horizon, further research should include a country's credit rating over the entire horizon, and then run regressions.

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