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Letter From the Editor

Dear Reader,

This edition of the Capitol Economics Journal is the culmination of a year's worth of work from the editors, authors, and myself. Our work was not limited to simply selecting and editing the articles presented here. The team honed their research, writing, and econometrics skills, raising the quality of our publication and strengthening the cohesion of our editorial board. Over the course of the year, the Journal underwent a transformation from merely an economics journal into an integrated research, editing, and publication group: the Capitol Economics Review.

The theme of this volume is inequality. Inequality in all forms remains a grave issue in our society. Whether through Robin Gloss's usage of unpaid work metrics to examine the discrepancies behind the gender pay gap or David Leo's examination of the link between income inequality and Japan's quantitative easing program, the articles contained in this publication offer detailed insight into these issues and provide a platform for future scholarship.

I would like to say a wholehearted "Thank you!" to the wonderful CER editing team: Jacob, Bassam, Esha, Severin, Jerry, and Kali, and extend a warm congratulations to all of our published authors. I would also like to give special thanks to my right-hand man, masterful organizer, and absolutely reliable Managing Editor, Andrew Khanin. None of this would have been possible without your help.

The launch of the Capitol Economics Review is just the beginning of a legacy that will last long past 2022. Thank you all for being part of this journey with us.

Best Regards,

Elijah Karshner
Editor-in-Chief
Capitol Economics Review

The Effect of Climate Change on the Pricing and Transactional Volume of Real Estate

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Abstract

As climate change continues to escalate, rising sea levels and intensification of weather events are being observed worldwide. Vulnerable communities are experiencing increased frequency and magnitude of flooding, and those situated on ocean fronts are at risk of permanent coastal inundation. This study examines the effect of climate change on the real estate industry—in particular, its impact on the pricing and transactional volume of residential properties. Data were collected from 34 Oregon counties over a five-year period from 2014-2018. Two random-effects models were constructed that regressed average precipitation, extreme maximum precipitation, and elevation against median price and median days on market. It was found that as extreme maximum precipitation increases, the transactional volume of coastal counties is more negatively impacted than those located in non-coastal regions. Furthermore, as elevation increases, coastal counties observe a larger decline in median days on market as compared to their non-coastal counterparts. JEL Codes: Q51, Q54, Q58, R30, R31

1 Introduction

In the state of Oregon, coastal and riverine flooding has occurred frequently throughout history. Due to the open nature of this stretch of seaboard, Oregon shores are left vulnerable to severe storms, coastal flooding, and erosion (Mote et al., 1999). The Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation are responsible for this climate variability that has been historically observed within the Pacific Northwest (PNW); this causes changes to be detected in patterns of coastal flooding, riverine flooding, and average precipitation on a roughly five-year basis (Mote et al., 1999). Unfortunately, with the onset of climate change, this "typical" climate variability within the PNW has been disrupted and is expected to increasingly diverge from recorded trends. This will result in coastal inundation—which is distinct from coastal flooding in that it is the result of permanent sea level rise—and a higher frequency of riverine flooding (Mote et al., 1999). With a large volume of residential and commercial development concentrated in high-flood-risk regions, the effect of climate change on Oregon and the rest of the PNW deserves immediate attention.

The effect of sea level rise (SLR) and increased flooding on the price and risk valuation of real estate is a pressing issue. In the states of California, Oregon, and Washington, 1,300 square miles of land are only three feet above the existing high tide line, and on this land area 1,047 miles of road, 32 schools, 7 power plants, and 569 EPA-listed waste dumps and sewage plants are situated (Strauss et al., 2014). With the projected range of SLR for 2100 being inclusive of three feet, this land area will likely be subjected to coastal inundation (Strauss et al., 2014).

The Social Vulnerability Index has been developed to help measure a community's ability to respond to hazards; in the states of California, Oregon, and Washington, 18,000 people living within a three feet elevation of the current high tide line are indicated as having a high level of social vulnerability (Strauss et al., 2014). The financial burden placed on coastal communities endangered by climate change is further demonstrated by flood insurance costs. Because the Federal Emergency Management Agency (FEMA) has failed to update National Flood Insurance Program premium rates, they are set at noncompetitive, low prices that only encourage the development of high-flood-risk regions, and despite these relatively cheap premiums, an increasing number of low- and middle-income families have been unable to afford flood insurance (Netusil et al., 2021). Furthermore, 15% of the American population living within designated 100-year floodplains are impoverished, and "roughly 44% of Americans do not have $400 of liquid funds for emergency" (Peri et al., 2017, as cited in Netusil et al., 2021; Board of Governors of the Federal Reserve System, 2017, as cited in Netusil et al., 2021, p. 17). If populations within floodplains are unable to afford flood insurance, then recovery from flooding events is extremely unlikely.

To examine the effect of climate change on the real estate industry, this study will conduct an empirical analysis comparing the price and transactional volume of residential property in Oregon against climate-change-related and geographic factors such as average precipitation, extreme maximum precipitation, average elevation level and coastal proximity. Within this study, the term climate-change-related factors refers to average precipitation and extreme maximum precipitation—as these variables encompass flood-risk and are expected to increase as climate change progresses. The majority of literature exploring the relationship between climate change and residential real estate pricing involves study of the coastal communities of Florida. However, this research will provide insight into this relationship within the state of Oregon and the Pacific Northwest region. Furthermore, FEMA has failed to inform Americans of the actual climate-change risks associated with purchasing properties in coastal areas; in addition to the National Flood Insurance Program's low, uncompetitive premiums, FEMA's outdated floodplain maps create a "false binary" between those vulnerable to flooding and those who are not (Netusil et al., 2021, p. 19). The purpose of this research is to better inform homebuyers of the effect of climate-change-related factors such as SLR and flooding on the real estate industry. As a substantial number of institutions are choosing to ignore the climate changes that are taking place today within the United States, more literature should be produced for the consumption of everyday Americans who are most involved in housing transactions.

2 Literature Review

Several studies have been conducted that delve into the effects of climate change on sea level rise and flooding patterns within and around the state of Oregon. Strauss and authors (2014) report that vulnerability to sea level rise decreases moving northward along the Pacific coast; by 2100, an increase of 1.7-4.9 feet is expected on San Diego shores, while a 0.8-3.9 feet increase is anticipated in the Olympic Peninsula region—placing projections for Oregon SLR somewhat in the middle. The study also explores the effect of climate change on existing patterns of flooding. As of the study's publication in 2014, the annual probability for a flood to exceed the high tide line in Los Angeles by 2.3 feet was 1%; however, a mere six inch increase in sea level would have increased this event's annual likelihood to 100% (Strauss et al.).

Mote and authors (1999) provide an analysis of climate-change-related SLR and flooding based on the Pacific Decadal Oscillation. The Pacific Northwest experiences periods of fluctuation in the average temperature, precipitation, snow depth, streamflow, and frequency of forest fires. These periods of variability can be explained by the different combinations of the El Niño Southern Oscillation and PDO phases: when a cool PDO phase accompanies La Niña or when a warm phase accompanies El Niño, higher probability of flooding is observed in the Pacific Northwest (Mote et al., 1999). El Niño is primarily responsible for coastal flooding as it temporarily increases average sea levels by about 5-10 cm, and on the other hand, La Niña is connected to fluvial flooding—which occurs as a result of wet winters that increase the stream-flow of rivers and overload bodies of water (Mote et al., 1999). The authors explain that climate change could result in new SLR and flooding patterns resemblant of PDO-caused climate variability but more severe in magnitude (Mote et al., 1999). However, another possibility is that the PDO cycle is completely overridden. For example, the PDO phases cause fluctuations between -4% and 2% of the average precipitation, but climate change could cause a permanent 5% increase of the PNW's average precipitation from the years 1999 to 2050—allowing for no periods of relief with lower flood-risk (Mote et al., 1999).

As flooding caused by both sea level rise and the increasing frequency and intensity of storms manifests in the Pacific Northwest, the housing industry will become increasingly affected. Clayton and authors (2021) discuss the effect of temporary weather events on the pricing of residential property. The general consensus is that hurricanes and flooding events do not affect the long-run pricing of residential properties. Fisher and Rutledge (2021, as cited in Clayton et al., 2021) found that the housing market typically experiences price reductions three years following major hurricanes, but prices ultimately rebound to original levels. Another literature that studied the effect of hurricanes on the pricing of residential property produced similar results: major hurricanes from 1996 to 2012 caused a 3.8% discount on real estate prices following the storm that became unobservable 60 days post-hurricane (Below et al., 2017, as cited in Clayton et al., 2021).

However, Clayton and authors (2021) report that a high, maintained frequency of severe weather events has the capacity to permanently affect real estate prices—which could suggest correlation between climate change and real estate prices due to the expected increase in storm frequency. Ortega and Taspinar (2018, as cited in Clayton et al., 2021) similarly explain that the increasing frequency of weather events may lead to "belief updating" (p. 6). The authors note that 2013 was a landmark year for the widespread adoption of climate change awareness in the American population—which may have potentially altered the relationship between climate-change-exacerbated weather events such as hurricanes and flooding and the pricing of residential real estate. For example, the occurrence of Hurricane Sandy created pricing trends in-consistent with the previously-discussed literature. Ortega and Taspinar (2018, as cited in Clayton et al., 2021) concluded that properties damaged by Sandy experienced price discounts of 17%-22% and properties that were unscathed experienced reductions of around 8% following the storm. In accordance with past observations, the long-term prices of the damaged properties rebounded to usual levels; however, the prices of unflooded properties never fully recovered. This abnormal trend can be explained by the following: after the occurrence of Sandy, government-sponsored floodplain maps were redrawn to now include these unscathed properties, and this action led to "belief updating" in regards to flood-risk that resulted in a permanent decrease in price (Ortega & Taspinar, 2018, as cited in Clayton et al., 2021).

Literature also suggests that the level of belief in homeowners in regards to climate change has the capacity to affect residential real estate prices. Two distinct studies utilized the Yale Climate Opinion Maps to explore the relationship between the level of climate change belief and the prices of residential real estate exposed to SLR. Bernstein and authors (2018) concluded that "areas in the 90th percentile of climate change worry. . . sell at an 8.5% discount," while Baldauf and colleagues (2020) contributed with similar findings: "homes located in climate change 'denier' neighborhoods sell for about 7% more than homes in 'believer' neighborhoods" (p. 4; p. 1291). According to Keys and Mulder (2020), these beliefs are more salient in homeowners than lenders. In this study, the authors found that the number of home transactions in coastal Florida declined starting in the year of 2013, and despite this decrease in demand from home-buyers, only "small changes in the rate of loan denial, securitization, or refinancing volume with respect to SLR exposure" were observed (Keys & Mulder, 2020, p. 4). Because of federal initiatives such as the National Flood Insurance Program that "actively mis-price climate risk," lenders' risk valuation processes in relation to climate change and real estate acquisition differ when compared against that of home-buyers (Keys & Mulder, 2020, p. 27).

Beliefs about climate change also hold important implications in regards to supply and demand within the housing market. Clayton and authors (2021) argue that these shifts within the real estate industry have effects beyond price-setting: "private asset transaction markets adjust not only by price but jointly via changes in both price and liquidity" (p. 11). When climate-change risk becomes apparent to potential home-buyers, the number of home-buyers within that local market may decrease in comparison to the existing number of sellers—decreases in transactional volume may also occur if homeowners are unwilling to sell at a reduced price that is inclusive of climate-risk (Clayton et. al, 2021). In Keys and Mulder's (2020) study, similar evidence was found within the coastal Florida residential market; the authors concluded that climate-driven changes in the volume of housing transactions may be observed before changes in price: "16,500 fewer home transactions took place from 2013-2018" and "starting in 2016, prices in more-SLR exposed tracts began to relatively decline" (p. 3).

3 Hypothesis and Test

This study will examine the effect of climate-change and geographic factors on the real estate industry in Oregon counties for years 2014-2018. The average median price and the average median days on market for single-family homes will be regressed against county-level average elevation, average precipitation and the extreme maximum precipitation value. An indicator will also be used to distinguish between coastal and land-locked Oregon counties. The hypothesis is as follows: counties exposed to climate-change factors that contribute to SLR or flooding will observe a higher median days on market value as compared to less-vulnerable counties—however, prices will not be reflective of climate risk.

4 Data and Empirical Model

4.1 Data

The primary dataset being used in this study is Redfin Housing Market Data (n.d.). From this dataset, the median sale price and the median days on market for single-family residential properties were extracted for years 2014 to 2018 on a county-level basis for the state of Oregon. The dataset did not include values for Lake and Lincoln counties, leaving observations to be collected from the 34 remaining counties over a five-year timeframe—which totals to be 170 observations. Both the median sale price and the median days on market of single-family residential properties were provided on a monthly basis, so the median values were averaged out to find the corresponding average annual values.

Data on climate-change-related factors was collected from the National Oceanic and Atmospheric Administration's (2016) Climate Data Online. This dataset contained statistics on annual county-level average elevation, average precipitation, and extreme maximum precipitation. The National Oceanic and Atmospheric Administration (NOAA) relies on a network of weather stations to collect this data; some counties are equipped with one station, while others contain several. That being said, in counties with multiple weather stations, the values recorded by each of the stations were averaged to produce a singular county-level datapoint. Measurements on precipitation included the annual average precipitation and the extreme maximum precipitation produced in one weather event during that one-year period. Lastly, using maps produced by the NOAA, an indicator variable was created to distinguish between coastal and land-locked counties in order to represent SLR risk.

Demographic control variables were extracted from the Bureau of Economic Affairs' (n.d.) Regional Data and the U.S. Census Bureau's (2010) County Population Totals. From the dataset entitled Regional Data, GDP, per capita income, and total employment were extracted for the five-year timeframe on a county-level basis. Population totals provided by the U.S. Census were also collected. For further variable descriptions and summary statistics see Tables 1 and 2.

Table 1: Variable Descriptions

Name	Description	Source
Price_{it}	Average annual median sale price of single-family residential homes (USD) in county i in year t	Redfin
Days_{it}	Average annual median days on market of single-family residential homes in county i in year t	Redfin
Prcp_{it}	Average annual precipitation (in.) in county i in year t	NOAA
Emxp_{it}	Extreme maximum precipitation (in.) produced in one weather event in county i in year t	NOAA
Elevation_{it}	Elevation (ft.) in county i in year t	NOAA
Coast_{i}	Indicator of whether or not county i is located on the Pacific coast	NOAA
Demographic controls		
Pop	Yearly total population of the county (2014-2018)	U.S. Census
Income	Yearly per capita income of the county (2014-2018)	BEA
Employ	Yearly total employment of the county (2014-2018)	BEA
Gdp	Yearly real GDP (thousands of chained 2012 USD) of the county (2014-2018)	BEA

Note: The data comes from the *BEA, NOAA, Redfin,* and *U.S. Census Bureau* and includes 34 Oregon counties from 2014-2018.

Table 2: Summary Statistics

	Observations	Mean	SD	Minimum	Maximum
Price_{it}	166	222136.3	87234.42	53142.86	449250
Days_{it}	166	163.2163	242.763	14.83333	2399
Prcp_{it}	166	44.49157	25.22121	5.42	119.1225
Emxp_{it}	166	2.045696	1.089533	0.5	5.845
Elevation_{it}	166	756.9666	530.7992	11.95	1799.55
Coast_{i}	166	0.1764706	0.3823463	0	1
Demographic controls					
Pop	170	118331	178224.7	1319	809072
Income	170	41983.86	6292.269	29107	61951
Employ	170	71193.05	127492.1	737	671068
Gdp	170	5846102	11800000	30230	62000000

Note: Author's calculation. The data comes from the *BEA, NOAA, Redfin,* and *U.S. Census Bureau* and includes 34 Oregon counties from 2014-2018.

4.2 Empirical Model

As explored by Keys and Mulder (2020), the effects of climate change on residential real estate are observed in the transactional volume before being observed in the price. That being said, separate regression models were constructed to evaluate the effect of climate-change and geographic factors on both of the dependent variables *price* and *days*. Data on housing prices and transactional volume are extracted from single-family residential homes to control for price variations that arise from housing-type. A Hausman test was conducted to determine whether or not the data would be most properly suited by a fixed- or random-effects model, and it was found that random effects would be most appropriate. Two regression models were formulated to compare *price* and *days* against climate-change and geographic factors that contribute towards SLR and flood vulnerability. In each of the models, random-effects is denoted by α, μ_{it}, and ϵ_{it}. County-level demographic controls *pop, income, employ,* and *gdp* were included to account for time-variant factors that affect the pricing and transactional volume of residential housing.

The first regression model is:

$$\begin{gathered} \ln price_{it} = \beta_0 + \beta_1 prcp_{it} + \beta_2 emxp_{it} + \beta_3 elevation_{it} + \\ \beta_4 coast_i + \beta_5 prcp_{it} X elevation_{it} + \beta_6 prcp_{it} X coast_i + \beta_7 emxp_{it} X elevation_{it} + \\ \beta_8 emxp_{it} X coast_i + \beta_9 elevation_{it} X coast_t + \beta_{10} pop_{it} + \beta_{11} income_{it} + \\ \beta_{12} employ_{it} + \beta_{13} gdp_{it} + \alpha + \mu_{it} + \epsilon_{it} \end{gathered} \tag{1}$$

and regresses the natural log of price against climate-related and geographic factors. Average precipitation level and extreme maximum precipitation reflect a county's risk for rainfall-induced flooding. Furthermore, the regressors *elevation* and *coast* account for geographic characteristics that increase the likelihood of flooding events. Lower elevation levels may increase a region's likelihood of flooding following a weather event, so the interaction variables *prcpXelevation* and *emxpXelevation* are used to represent the effect of elevation on both *prcp*'s and *exmp*'s relationships with the dependent variable. In addition to elevation levels, coastal proximity may also be determinant of a region's flood-risk—both temporary flooding and permanent coastal inundation. The interaction variables *prcpXcoast, emxpXcoast*, and *elevationXcoast* differentiate between coastal and non-coastal counties and thus allow for the effect of average precipitation, extreme maximum precipitation, and elevation levels on *lnprice* to be compared across the two types of counties. Lastly, the second regression model employs *days* as the dependent variable in order to examine the effect of climate- and geographic-related factors on the transactional volume of residential real estate. Regression (2) contains the same independent regressors as Regression (1) and is written as follows:

$$\begin{gathered} days_{it} = \beta_0 + \beta_1 prcp_{it} + \beta_2 emxp_{it} + \beta_3 elevation_{it} + \\ \beta_4 coast_i + \beta_5 prcp_{it} X elevation_{it} + \beta_6 prcp_{it} X coast_i + \beta_7 emxp_{it} X elevation_{it} + \\ \beta_8 emxp_{it} X coast_i + \beta_9 elevation_{it} X coast_t + \beta_{10} pop_{it} + \beta_{11} income_{it} + \\ \beta_{12} employ_{it} + \beta_{13} gdp_{it} + \alpha + \mu_{it} + \epsilon_{it} \end{gathered} \tag{2}$$

5 Results

Table Three summarizes the results from Regressions (1) and (2). The table reports regression results of housing prices and days on market against climate- and geographic-related factors. The sample includes 163 observations from 34 Oregon counties, 2014-2018. Random effects and demographic controls are used in Regressions (1) and (2).

Table 3: Housing Prices and Days on Market

	(1)	(2)
Prcp	0.001159	-5.537099
	(.0044804)	(4.0544837)
PrcpXelevation	.00000133	.0081624***
	(.00000524)	(.0047131)
PrcpXcoast	.0033521	-5.49811
	(.0053728)	(4.909206)
Emxp	.0917453	53.60785
	(.0932952)	(84.66897)
EmxpXelevation	-.0000808	-0.1275043
	(.0001103)	(.1005513)
EmxpXcoast	-.114375	158.0931***
	(.0976805)	(90.47747)
Elevation	-0.0000404	-.0236078
	(.0001875)	(.1362022)
ElevationXcoast	.0005202	-1.455857***
	(.0006519)	(.4438027)
Coast	-.1951413	505.7801***
	(.3831095)	(299.8371)
Constant	10.54334***	343.3049
	(.3203686)	(233.9471)
R-squared	0.5529	0.3083

Note: Standard errors in parentheses: ***p<0.001, **p<0.05, *p<0.1.

5.1 Average Precipitation

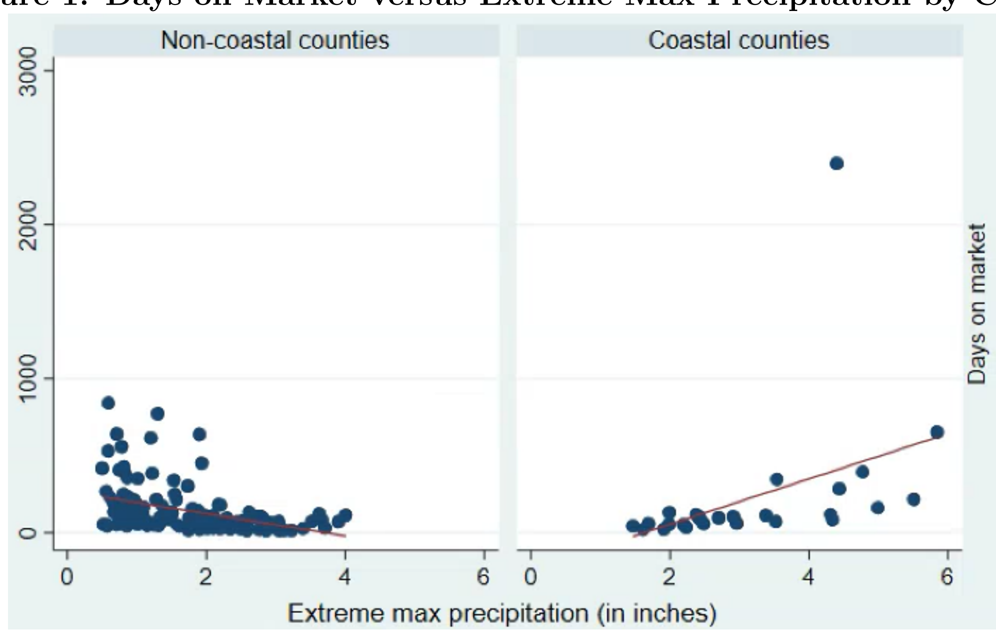
Regression (1) can be interpreted as follows: a one inch increase in a county's average annual precipitation level is predicted to increase the average annual median price of residential housing by 0.12%. If homebuyers were to account for the increased flood-risk accompanied by higher levels of precipitation, then a negative coefficient on *prcp* would have been expected. In terms of transactional volume, a one inch increase in *prcp* would result in the average days on market decreasing by 5.54 days. Therefore, residential real estate would experience an increase in transactional volume. Both of these results proved to be statistically insignificant, demonstrating that an increase in the volume of precipitation has little effect on the pricing or transactional volume of residential property.

In Regression (1), the interaction variables *prcpXelevation* and *prcpXcoast* produce statistically-insignificant coefficients of 0.00000133 and 0.003351, signifying a negligible effect of elevation levels and coastal proximity on the relationship between *prcp* and *lnprice*. However, when the interaction variables are instead regressed against average days on market, the coefficient on *prcpXelevation* proves to be statistically significant. With a value of 0.0082, it can be interpreted that as elevation increases, the effect of precipitation levels on the average days on market becomes more positive—leading to a decline in transactional volume. This proves contradictory: higher elevation levels would serve as a natural protection from flooding, meaning that as elevation increases, the negative effect of precipitation on transactional volume should lessen. Although the coefficient on *prcpXelevation* proved statistically significant, 0.0082 is a relatively small value and suggests that the effect of elevation on the relationship between precipitation levels and transactional volume is unlikely to be observed—unless across counties with drastic differences in elevation.

5.2 Extreme Maximum Precipitation

As extreme maximum precipitation increases by one inch, the average price increases by 9.17% and the average days on market increases by 53.61 days. Because an increase in *emxp* would be caused by the development of more severe weather events, it would be expected that *emxp* would have a negative effect on prices and a positive effect on days on market. Although the results obtained from Regression (1) prove contradictory, the results derived from Regression (2) prove more in line with this interpretation. However, neither finding can be considered statistically-significant.

Figure 1: Days on Market versus Extreme Max Precipitation by Coast

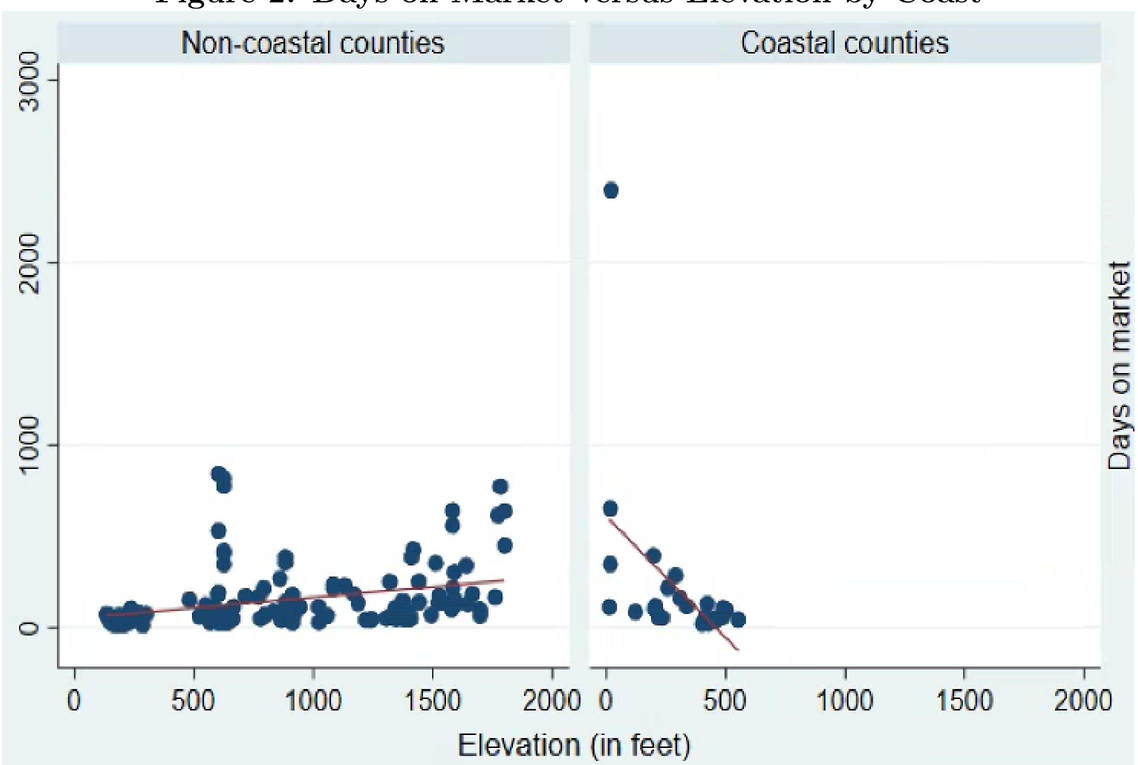


Notes. The sample includes 34 Oregon counties from 2014-2018. Data is derived from the *NOAA* and *Redfin*. The lines are lines of best fit.

In regards to the interaction variables, the coefficient on *emxpXelevation* takes on a negligible and statistically-insignificant value for both Regressions (1) and (2). When analyzing the interaction variable *emxpXcoast*, Regression (1) produces a coefficient of -.11. Because, this result proved to be statistically-insignificant, it can be assumed that the effect of extreme maximum precipitation on pricing does not vary between coastal and non-coastal counties. In terms of transactional volume, a statistically-significant coefficient on *emxpXcoast* was obtained: a one inch increase in *emxp* results in an increase of average days on market that is approximately 158 days larger in coastal versus non-coastal counties. Because coastal communities are more vulnerable to flooding when exposed to extreme precipitation levels, a larger decline in transactional volume can be observed in coastal counties. Figure One demonstrates the differing relationship between *days* and *emxp* experienced in non-coastal vs. coastal counties.

5.3 Elevation

Figure 2: Days on Market versus Elevation by Coast



Notes. The sample includes 34 Oregon counties from 2014-2018. Data is derived from the *NOAA* and *Redfin*. The lines are lines of best fit.

In regards to the pricing of residential real estate, a one foot increase in the average elevation level would lead to a small decrease in the average real estate price by 0.004%. Furthermore, the coefficient on the interaction variable *elevationXcoast* is 0.000502, meaning that coastal counties actually observe a slight increase in price as elevation increases. However, both of these coefficients demonstrated statistical insignificance, so there is a negligible relationship between elevation and residential housing prices and it does not differ between coastal and non-coastal counties. On the other hand, the coefficient on *elevationXcoast* is statistically significant when regressed against days on market. The results can be interpreted as follows: with a one foot increase in elevation, the average days on market decreases by 1.46 days more in coastal markets than in their non-coastal counterparts. These findings directly support the study's hypothesis; it is supposed that the natural protection provided by higher elevation levels increases the demand for and thus transactional volume of residential housing in high-flood-risk coastal communities. The difference in relationship between *days* and *elevation* across non-coastal and coastal counties can be observed in Figure Two.

6 Conclusion

As observed in Regression (1), the effect of climate- and geographic-related factors on the pricing of residential properties proved statistically-insignificant. However, there is a demonstrated statistical significance when comparing days on market against the interaction variables *emxpXcoast* and *elevationXcoast*. In coastal versus non-coastal counties, a stronger negative impact can be observed on transactional volume as extreme maximum precipitation increases. This can be explained by the added risk of coastal flooding and SLR that is accompanied by a county's location alongside the Pacific Ocean. Furthermore, as elevation increases, the average days on market experiences a more negative impact in coastal versus non-coastal counties. In coastal counties, a one foot increase in the average elevation level decreases the days on market by approximately a day and a half more than what is observed in non-coastal counties; higher-elevated coastal properties are likely in greater demand due to their natural protection from flooding and SLR. Because the magnitude of extreme weather events is anticipated to increase with climate change, the data can lead us to assume that the county-level transactional volume of residential homes in Oregon will decrease as extreme weather events intensify.

Although Regression (2) supports the hypothesis that counties exposed to climate-change factors contributing to SLR or flooding will observe a higher median days on market value as compared to less-vulnerable counties, there are several limitations to this study that affect its applicability to the real-world housing market. In particular, vulnerability to climate-change-related events such as SLR and flooding has great spatial variation. Because the data was collected on a county-level basis, it is difficult to account for these differences. Furthermore, the proportion of non-coastal to coastal counties in the state of Oregon is not equally distributed. That being said, the small number of coastal counties may have failed to provide an adequate sample size when breaking down the regressions by the coastal indicator. Lastly, there are climate-change factors beyond those explored in this study that are responsible for potential changes in the real estate market.

Despite the observed effect of climate- and geographic-related factors on the transactional volume of Oregon's residential real estate, price is largely unaffected. This could be the result of the "lag" observed between changes in prices and transactional volume as discussed by Keys and Mulder (2020). That being said, continuation of this study would allow for this to be further explored. An alternative explanation is that the pricing of Oregon's residential property may not properly reflect climate risk due to the absence of "belief-updating." Because Oregon and the Pacific Northwest experience frequent coastal and riverine flooding as a result of fluctuations in the PDO cycle, gradual increases in flooding frequency and magnitude as a result of climate change may be indistinguishable from the Pacific Northwest's historic climate variability. However, attributing this lack of price adjustment to Oregon's level of climate-change belief may be problematic, as the state's level of belief proves well above the national average; a survey conducted by *The Oregonian* found that "97% of Democrats, 86% of Independents, and 64% of Republicans" in Oregon believe in climate change, and this gap observed between Democrats and Republicans is 13 points lower than the average nationwide difference (Williams, 2020, para. 2-3).

That being said, it is hard to support the argument that Oregonians have not experienced "belief-updating" in regards to climate change. However, Oregonians may believe that the effects of climate change manifest in events beyond SLR and flooding—such as wildfires. Although flooding is a frequent occurrence in the Pacific Northwest, the prevalence of wildfires has "increased fourfold during the period 1987-2003 as compared to 1970-1986, while the total area burned increased six-fold," which can likely be attributed to the climate-change-driven intensification of droughts (U.S. Fish and Wildlife Service, 2013, para. 2). Furthermore, numerous studies have found that the recurrence of wildfires has the capacity to decrease the prices of affected real estate: in California, Oregon, and Washington, real estate deemed to be at low fire-risk sells at prices 3.9% higher than its high-risk counterparts (Strum, 2020). Although, SLR and the increased frequency of flooding have been able to offset the transactional volume of Oregon's residential real estate market, "belief-updating" specific to the flooding aspect of climate change must occur before sellers are willing to adjust their prices in regards to increased flood-risk.

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Unbalanced Unpaid Work: Women's Household Work and the Persistence of the Gender Pay Gap

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Abstract

The unpaid labor gap between women and men is one aspect of research on women's labor market outcomes that seeks to understand the link between discrimination in the workforce and discrimination in the home. Using data from the American Time Use Survey between 2003 and 2019, a series of Oaxaca-Blinder decompositions show that approximately 90% of the unpaid labor gap is unexplained by demographic, human capital, and employment variables. Of this group of controls, employment is the most effective at explaining the unpaid work gap. Based on a series of regressions that account for household characteristics and job market information, the time women spend on unpaid work is more responsive to changes in household composition than that of men.
JEL Codes: J10, J16, J30, J70, J71

1 Introduction

In 2019, women earned 84 cents for every dollar earned by men (Semega et al. 2020). This figure is necessarily oversimplified because of substantial variation in the gender wage gap due to demographics, workforce status, and other factors. Meara, Pastore, and Webster find a gender pay gap of about 15% between October 2017 and March 2018, which grows to 27% between women working part-time and men working full time (2020). The gender pay gap is just one aspect of labor market inequalities between women and men, but because of its overarching impact on women's economic status, it is one of the most widely studied. As the gender wage gap narrows, the remaining difference between men's and women's wages becomes more difficult to explain. Exploring the driving forces behind the gender imbalance in unpaid work is one of the next steps toward a better understanding of the connection between unpaid work and the remaining gender wage gap.

By building on existing research that focuses on how industry and occupational traits impact the gender wage gap, it is possible to connect the unpaid labor that women perform to the paid labor they are compensated for. Drawing on data from the American Time Use Survey, this paper uses several Oaxaca-Blinder decompositions to explore how specific variables contribute to the difference in time spent on unpaid work between men and women. The Oaxaca-Blinder decomposition highlights that a large portion of the gender gap in unpaid work is unexplained when considering demographic, household, and employment variability in this dataset. This suggests that gender bias plays a significant role in the unpaid work gap. Analyzing the impact of changes in household composition on the unpaid labor performed by women and men finds that the amount of time women spend on unpaid work is more responsive to changes in household structure than the time men spend on unpaid work.

2 Literature Review

Gary Becker's "A Theory on the Allocation of Time" serves as the theoretical foundation for much of the modern scholarship on unpaid work. Becker's theory proposes that the amount of time used per dollar of goods and cost per unit of time are most important in determining how people spend their time (1965). This paper was one of the first to explicitly include leisure time in economic analysis, though previous research had done so implicitly. Becker's later research on the sexual division of labor identified the benefits of specialization in human capital and the resulting division of labor between married men and women (1985). Through interviews with dozens of couples in the 1970s and 1980s, Arlie Hochschild's The Second Shift provided a more individual perspective in its exploration of the "leisure gap" between men and women, attributing the additional time that men have for leisure to strong social norms that pushed women to perform all the traditional duties of a stay-at-home wife and mother while also working outside the home (1989). Like Hochschild, most early economic research on unpaid labor largely focused on the gap in women's labor force participation and resulting outcomes.

Current research on gender and unpaid work shows that while time amount of time women spend on unpaid work varies by age, race, and region, that the gap between men and women's unpaid work is pervasive across the country. Over the last 50 years, the amount of time spent on unpaid work has generally decreased while the amount of time spent on leisure has increased. While technological improvements contribute to the decrease in hours of unpaid work, women's increased labor force participation has also decreased the time spend they spend on unpaid work (Fang and McDaniel, 2017). The increase in men's time spent on unpaid work is likely tied to both changing attitudes toward unpaid work and increased responsibilities for men when women are more likely to work outside the home. Cross-border studies of the United States and Europe show a broad trend of gender convergence in unpaid work hours that is explained primarily by changes in behavior rather than demographic shifts (Bick, Fuchs-Schündeln, and Lagakos, 2018; Pailhé, Solaz, and Stanfors, 2021).

The gradual increase in women's workforce participation has been widely studied (Blau and Kahn, 2007; Elson, 2017; Gonzales et al., 2015). While women's labor force participation now approximately equals that of men (Blau and Kahn, 2017), the way women participate is distinct. Women are more likely to work part-time, concentrated into specific industries and occupations, less likely to rise to management positions, and more likely to take extended periods of time off work. Each of these trends contributes to the gender pay gap in a different way, but together they construct a labor market that makes it nearly impossible for women to reach wage parity. The gender pay gap is related not just to differences in workforce participation, but also to significant differences across industries and occupations.

Francine Blau and Lawrence Kahn use data from the Panel Study of Income Dynamics to demonstrate that human capital variables like education and work experience do not explain the existence of the gender pay gap (2017). Industry and occupation alone account for 51% of the 2011 wage gap (Blau and Kahn, 2017). Comparing their findings to explanations of the gender wage gap, Blau and Kahn find that the importance of the labor force participation rate decreased, as did the importance of education and other human capital variables. Most of the gap between men's and women's pay is no longer explained by women working less or being less educated. Labor-force experience and work hours remain important, but gender parity in these variables has increased over time. Gender differences in formal training and turnover are closely related to disparities in experience and work hours.

In one study of these industry-based variations, Claudia Goldin (2014) finds that a flexible schedule, which is often required for women because they take on a disparate amount of childcare and housework, is associated with a lower salary in some industries. The gender wage gap is largest in industries where hours are worth more at a specific time of day. This contributes to the higher wage gaps for MBAs and JDs, whereas pharmacists and similar professions see more equal earnings. Goldin suggests that reshaping the labor market to allow for more substitution between workers, as is the case in pharmacies, would make the relationship between hours worked and earnings more linear and help close the gender pay gap. This finding is consistent with sociological research on the time constraints of women's unpaid work (Davis and Greenstein, 2013).

Studies of unpaid work commonly use self-reported data, due largely to the limited alternatives for measuring individual-level time use. Rachel Krantz-Kent (2009) uses the American Time Use Survey (ATUS) to understand gendered time use dynamics in the United States. The ATUS categorizes time use into 434 distinct categories, 127 of which Krantz-Kent identifies as unpaid household work. Unpaid household work includes activities that have a viable market substitute and are performed for one's household. This measure also includes travel time related to unpaid household activities (i.e., driving to the grocery store). Krantz-Kent finds that between 2003 and 2007, women performed an average of 10.8 more hours of unpaid household work per week than men. The amount of time spent on unpaid household work was highest for people in their mid-thirties, due in part to the amount of time spent caring for children. Fathers' time use was less responsive to the number of children in the household than mothers' time use.

Large portions of the body of literature available on the gender pay gap and women's unpaid work fall outside the bounds of economics and highlight the limitation of a purely economic approach to studying unpaid work. This research highlights the gendered division of housework and differences between the types of work women and men perform: traditionally feminine work such as laundry is repetitive, nondiscretionary, and time-consuming (Jung and O'Brien, 2019). In contrast, the unpaid work performed primarily by men, such as yard work, is more likely to be infrequent, less time consuming, and more flexible in when they can complete it. The role of power in intimate relationships is also key to understanding the relationships between unpaid work and gender. For instance, psychological research on intimate relationships argues that social norms are translated into power dynamics that drive the distribution of unpaid work within a household (Davis and Greenstein, 2013).

Commonly noted as "discrimination" and "gender bias" within economic research, the social forces that drive women to perform such a large portion of unpaid household work in the United States are the focus of a large body of non-economic research (Bianchi et al., 2012; Ungerson, 1997; Himmelweit, 1995; Sayer, 2005; Kroska, 2004; Hook, 2006). Without the broader context of sociological, psychological, and other non-economic research, it would be more difficult to understand why there are significant gaps in the explanatory ability of economic research. While the impact of gender bias cannot be easily quantified in economic research, understanding its root causes improves the quality of economic models used in feminist economic research.

Because analyses of the gender pay gap must account for the impact of gender bias, which is not directly measurable, several techniques have been developed to explain the unexplained. To estimate the impact of discrimination on the wage gap between male and female workers, Ronald Oaxaca developed a statistical technique to analyze the sources of the wage gap. He found that at the time, much of the wage gap was explained by women's concentration in low-paying jobs and other demographic factors (Oaxaca, 1973). The technique he used has since been refined and is known as an Oaxaca-Blinder decomposition. While it has most commonly been used to better understand the causes of the gender wage gap, the Oaxaca-Blinder decomposition has more recently been applied to the gender gap in unpaid work (Kolpashnikova and Kan, 2020; Khitarishvili and Kim, 2014).

The application of this technique to the gender gap in unpaid work occurs because the ways that unpaid work and the gender pay gap are measured, as well as the factors that contribute to both gaps, are structurally similar. The Oaxaca-Blinder decomposition helps analyze the unpaid work gap because it drives a deeper understanding of the causes of the unpaid work gap and quantifies the limitations of the existing explanatory variables. The unexplained gap in the Oaxaca-Blinder decomposition is not a perfect measure of gender bias, but given a set of practical control variables, it is a rough proxy for how much of the resulting gap can be attributed to such unmeasurable variables. While the specific causes of the unexplained gap are impossible to determine, past research concurs that gender bias is one of the main unmeasurable variables.

3 Data

The American Time Use Survey (ATUS) is a nationally representative time use survey that provides estimates of how Americans spend their time collected through the Bureau of Labor Statistics. Data has been collected from over 200,000 interviews conducted between 2003 and 2020. ATUS data is linked to the Current Population Survey (CPS), which is the main source of labor force statistics in the United States and is also collected by the Bureau of Labor Statistics. The American Time Use Survey data is extracted from the Bureau of Labor Statistics' microdata using IPUMS, a University of Minnesota platform that aggregates census and survey data to increase access to family and community data. Detailed descriptions of variables and time use variables can be found through IPUMS or in the Bureau of Labor Statistics ATUS documentation.

I build a dataset with the variables detailed in Table 1 and all variables from the Activity Coding Structure and BLS Published Tables for the sample years 2003-2019. Data available for 2020 is not harmonized with previous years due to gaps in data collection during the COVID-19 pandemic and is excluded from this dataset. Where both CPS and ATUS variables are available, this analysis uses the CPS variable (noted by "_CPS8") to align labor market activity variables with industry and occupation data, which are only available through CPS. To eliminate incorrect and incomplete data from the resulting dataset, all observations with a data quality flag as indicated by the DATAQUAL variable are removed, as are all observations with less than 1380 minutes (22 hours) of time reported because gaps in reported time may result in incomplete reporting of unpaid work.

Table 1: Extracted ATUS Variables

Variable	Label
RECTYPE	Record type
YEAR	Survey year
CASEID	ATUS Case ID
STATEFIP	FIPS State Code
MSASIZE	MSA/PMSA size
FAMINCOME	Family income
HH_NUMKIDS	Number of children under 18 in household
HH_SIZE_CPS8	Number of people in household (CPS)
PERNUM	Person line number
LINENO_CP8	Person line number (CPS)
WT06	Person weight, 2006 methodology
AGE	Age
SEX	Sex
RACE	Race
EDUC	Highest level of school completed
EMPSAT_CPS8	Labor force status (CPS)
OCC2_CPS8	General occupation category, main job (CPS)
IND2_CPS8	General industry classification, main job (CPS)
UHRSWORKT_CPS8	Hours usually worked per week (CPS)
EARNWEEK_CPS8	Weekly earnings (CPS)
SPOUSEPRES	Spouse or unmarried partner in household
SPEDUC	Highest level of school completed (spouse or partner)
SPEMPSTAT	Employment status (spouse or partner)
SPUSUALHRS	Usual work hours (spouse or partner)
SPEARNWEEK	Weekly earnings (spouse or partner)
DATAQUAL	Interview should not be used

The unpaid work time use variable is constructed based on Rachel Krantz-Kent's methodology and the BLS Published Tables time use variables. This measure of unpaid work accounts for time that is unpaid and spent on activities that have a readily available market substitute (childcare, cleaning, etc.), as well as travel time related to the unpaid household activity (driving to the grocery store) (Krantz-Kent, 2009). Unpaid work that benefits another household, such as unpaid care work for a neighbor's children, is excluded from this measure, as is consistent with other measures of unpaid household work. The time use variables included in constructed variables for daily minutes of unpaid work and weekly hours of unpaid work are detailed in Table 2.

In some instances, weekly hours of unpaid work are a more helpful measure because it is easier to conceptualize the impact of such gaps.

Table 2: Time Use Variables Included in Unpaid Household Work

Time Use Variable	Label
BLS_HHACT	BLS: Household Activities
BLS_CAREHH_ADULT	BLS: Caring for and helping household members: Caring for and helping household adults
BLS_CAREHH_KID	BLS: Caring for and helping household members: Caring for and helping household children
BLS_CAREHH_TRAVEL	BLS: Caring for and helping household members: Travel related to caring for and helping household members
BLS_PURCH_BANK	BLS: Purchasing goods and services: Financial services and banking
BLS_PURCH_CONS	BLS: Purchasing goods and services: Consumer goods purchases
BLS_PURCH_GROC	BLS: Purchasing goods and services: Grocery shopping
BLS_PURCH_HHSERV	BLS: Purchasing goods and services: Household services
BLS_PURCH_HOME	BLS: Purchasing goods and services: Home maintenance, repair, decoration, and construction (not done by self)
BLS_PURCH_TRAVEL	BLS: Purchasing goods and services: Travel related to purchasing goods and services

Based on the ATUS data, women perform an average of 10 hours more unpaid household work than men. Women in the workforce perform an average of 8.3 hours more unpaid work than men in the workforce, and 8.7 more hours than men overall, as detailed in Table 3. Women who are employed work fewer paid hours, an average of 37 compared to the average of 42.2 for employed men. Employed women also have lower weekly earnings than employed men by $223. These findings are consistent with other estimates of the gender gap in unpaid and paid work, as well as the gender pay gap (Blau and Kahn, 2017; Krantz-Kent, 2009; Bick et. al, 2018).

Table 3: Average Weekly Time Use and Earnings

	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Weekly Hours of Unpaid Work (Full Sample)	19.38	0.07	29.33	0.07
Weekly Hours of Unpaid Work (Employed Only)	19.78	0.09	28.09	0.1
Typical Hours Worked per Week	42.23	0.05	37.01	0.05
Typical Weekly Earnings	916.14	3.11	693.27	2.37

3.1 Data Limitations

Any self-reported data may be biased by errors in reporting accuracy or people's memory. Selection bias is a common concern in survey data, but the American Time Use Survey provides weights to account for demographic variation and populations with low response rates. This minimizes such concerns in the data. Data quality flags in the ATUS also provide a simple way to filter out data that has been identified as unreliable by the survey staff. Beyond the accuracy of time use data, there are limitations on the types of analysis that can be performed with time use data. Because time use data is recorded by one person for one day, it does not account for variability in time use for that specific person across different days. When considering long-term trends, this means that time use data should be understood as a report of person-days spent on a specific activity. Most concerns surrounding the use of time use variables are relevant when using time use variables as a dependent variable, which is not the case in this analysis (Frazis and Stewart, 2012).

4 Methodology

The analysis is divided into two parts. First, a series of Oaxaca-Blinder decompositions is used to understand which variables have the most impact on the gender gap in unpaid work. These decompositions also compare the influence of variables based on whether the observations being analyzed are individuals in the workforce or the population at large. The second part of the analysis uses a set of regressions to understand how the composition of a household is related to the amount of time spent on unpaid work within that household. While these questions are interesting for the population at large, this research focuses specifically on individuals in the labor force because of the focus on the link between unpaid work and the gender pay gap.

4.1 Oaxaca-Blinder Decompositions

An Oaxaca-Blinder decomposition is employed to help understand what causes the gap in unpaid work performed by women and men. The Oaxaca-Blinder method is commonly used to analyze the gender wage gap and is suitable in this labor market-adjacent instance because of the similarities between the gender wage gap and analysis of unpaid work. It generates a measure of the change in *unpaid_work* when men are assigned the same characteristics as women, which is the "Endowments" effect. The characteristics assigned to men are the coefficients of the underlying regression that shows the change in women's unpaid work based on different explanatory variables. This technique uses two ordinary least squares (OLS) regressions, in this case separated by male and female respondents. In the simplified model:

$$Y_m = X_m \beta_m + u_m \tag{1}$$

$$Y_f = X_f \beta_f + u_f \tag{2}$$

Y is the minutes of unpaid work, X is the control variable, and u is the error term. Where b is the OLS estimator of β, $\bar{X}$ is the predicted value of X, and $\bar{Y}$ is the predicted value of Y given b and $\bar{X}$,

$$\bar{Y}_m - \bar{Y}_f = b_m \bar{X}_m - b_f \bar{X}_f = b_m(\bar{X}_m - \bar{X}_f) + \bar{X}(b_m - b_f) \tag{3}$$

In this model, $b_m(\bar{X}_m - \bar{X}_f)$ is the "impact of gender differences in explanatory variables evaluated using male coefficients," and $\bar{X}(b_m - b_f)$ is the "unexplained differential" (Blau and Kahn, 2017, 799-800).

The first part of this analysis explores the impact of employment on the gender gap in unpaid work. The initial regression accounts for household characteristics. This model is represented by:

$$unpaid\_work = \beta_0 + \beta_1 age + \beta_2 race + \beta_3 hh\_numkids + \beta_4 spouse + \beta_5 spouseemp + u \quad \text{(A)}$$

where *unpaid_work* is the minutes of unpaid work per day, *age* is the age of the individual, *race* is the respondent's race, *hh_numkids* is the number of children under 18 in the household, *spouse* accounts for the presence of a spouse or unmarried partner in the household, *spouseemp* is the employment status of the spouse, and u is the error term. Unmarried partners living in the household are considered spouses because this model assumes that cohabitation influences the distribution of work more than marriage. In addition to the variables in regression (A), the second model includes variables that account for basic employment characteristics as follows:

$$\begin{aligned} unpaid\_work = {} & \beta_0 + \beta_1 age + \beta_2 race + \beta_3 hh\_numkids + \beta_4 spouse \\ & + \beta_5 spouseemp + \beta_6 employed + \beta_7 hrsworkt + \beta_7 earnweek + u \quad \text{(B)} \end{aligned}$$

In this model, *unpaid_work* is the minutes of unpaid work per day, *age* is the age of the individual, *race* is the respondent's race, *hh_numkids* is the number of children under 18 in the household, *spouse* accounts for the presence of a spouse or unmarried partner in the household, *spouseemp* is the employment status of the spouse, *spouseemp* is the employment status of the spouse, *hrsworkt* is the average weekly hours worked, *earnweek* is the average weekly earnings, and u is the error term.

The portion of the same that is in the labor force is isolated using another pair of Oaxaca-Blinder decompositions. In understanding how unpaid work is related to the gender pay gap, this section of the sample is most relevant. Regression (A) is used for the first half of this analysis, where is it applied to only those observations in the labor force. The third model is represented by:

$$\begin{aligned} unpaid\_work = {} & \beta_0 + \beta_1 age + \beta_2 race + \beta_3 hh\_numkids \\ & + \beta_4 spouse + \beta_5 spouseemp + \beta_6 hrsworkt + \beta_7 earnweek + u, \quad \text{(C)} \end{aligned}$$

where *unpaid_work* is the minutes of unpaid work per day, *age* is the age of the individual, *race* is the respondent's race, *hh_numkids* is the number of children under 18 in the household, *spouse* accounts for the presence of a spouse or unmarried partner in the household, *spouseemp* is the employment status of the spouse, *hrsworkt* is the average hours of work per week, *earnweek* is average weekly earnings, and u is the error term.

4.2 Time Spent on Unpaid Work

This section of the paper focuses only on individuals in the workforce, so it analyzes only those observations where employed is equal to 1. The impact of the presence of a spouse and children on weekly hours of unpaid work is represented by:

$$\begin{aligned} unpaid\_weeklyhrs = \beta_0 + \beta_1 age + \beta_2 race + \beta_3 hh\_numkids + \beta_4 spouse \\ + \beta_5 spouse * spouseemp + \beta_6 hrsworkt + \beta_7 earnweek + u \end{aligned} \quad \text{(D)}$$

where *unpaid_weeklyhrs* is the respondent's hours of unpaid work per week, *age* is the age of the individual, *race* is the individual's race, *hh_numkids* is the number of children under 18 in the household, *spouse* accounts for the presence of a spouse or unmarried partner in the household, *spouse*spouseemp* is an interaction term between the presence of a spouse and the employment status of the spouse, *hoursworkt* is the average hours of work per week, *earnweek* is average weekly earnings, and u is the error term. The interaction between spouse presence and spouse's employment status is used to account for observations with no spouse. Next, this regression is modified to account for the interaction between the number of children and the presence of a spouse. This model is represented by:

$$\begin{aligned} unpaid\_weeklyhrs = \beta_0 + \beta_1 age + \beta_2 race + \beta_3 hh\_numkids + \beta_4 spouse \\ + \beta_5 spouse * hh\_numkids + \beta_6 hrsworkt + \beta_7 earnweek + u \end{aligned} \quad \text{(E)}$$

where *unpaid_weeklyhrs* is the respondent's hours of unpaid work per week, *age* is the age of the individual, *race* is the individual's race, *hh_numkids* is the number of children under 18 in the household, *spouse* accounts for the presence of a spouse or unmarried partner in the household, *spouse*hh_numkids* is an interaction term between the presence of a spouse and the number of children in the household, *hoursworkt* is the average hours of work per week, *earnweek* is average weekly earnings, and u is the error term. The interaction term between *spouse* and *hh_numkids* is used to understand how the presence of a spouse impacts the change in unpaid work associated with children's presence in the household.

5 Results

The purpose of the Oaxaca-Blinder decomposition in this analysis is to understand which variables drive the gender gap in unpaid work. In the first decomposition, which only accounts for household and demographic characteristics, implementing the Oaxaca-Blinder decomposition shows that men's unpaid work would increase by an average of 1.5 minutes per day if they had the same demographic characteristics as women (Table 4). This explained portion of the unpaid work gap is very small (1.5 minutes of the 85-minute gap) but statistically significant at $p < 0.05$. When accounting for household, demographic, and employment characteristics in the Oaxaca-Blinder decomposition, this analysis shows that men's unpaid work would increase by an average of 7.6 minutes per day if they had the same characteristics as women (Table 5).

This result is statistically significant and, over a week, accounts for almost an hour of the unpaid work gap between men and women. While most of the gap in unpaid work remains unexplained and may be attributed to gender bias or discrimination within the home, the impact of employment is comparatively much larger than that of household characteristics. This is consistent with existing literature that highlights the different employment choices that women make to care for their children (Anderson and

Levine, 1999; Ribar, 1992; Connelly, 1992). This also suggests that the characteristics of different workplaces may have an outsized impact on the way women chose to allocate their time (Goldin, 2014).

Table 4: Oaxaca-Blinder Decomposition (Full Population)

Variables	(1) Differential	(2) Decomposition
Prediction_Male	166.1***	
	(0.617)	
Prediction_Female	251.4***	
	(0.628)	
Difference	-85.33***	
	(0.881)	
Endowments		-1.493***
		(0.418)
Coefficients		-84.15***
		(0.878)
Interaction		0.313
		(0.373)
Observations	188437	188437

Note: Standard errors in parentheses: ***p<0.001, **p<0.05, *p<0.1

Table 5: Oaxaca-Blinder Decomposition including Demographic Variables (Full Population)

Variables	(1) Differential	(2) Decomposition
Prediction_Male	166.1***	
	(0.617)	
Prediction_Female	251.4***	
	(0.628)	
Difference	-85.33***	
	(0.881)	
Endowments		-7.607***
		(0.519)
Coefficients		-84.45***
		(0.912)
Interaction		6.732***
		(0.548)
Observations	188437	188437

Note: Standard errors in parentheses: ***p<0.001, **p<0.05, *p<0.1

For the second set of Oaxaca-Blinder decompositions, which consider only those observations that are employed, there would be small but statistically significant increase in men's unpaid work if they had the same household and demographic characteristics as women. In this case, 2.7 minutes of the 73-minute gap in daily unpaid work can be explained (see Table 6). In this subset of observations, the household and demographic characteristics explain a larger portion of the gender gap in unpaid work than they do when considering all observations. The Oaxaca-Blinder decomposition that considers demographic, household, and employment characteristics for the employed subset of the data only explains 0.4 minutes of the unpaid work gap and is not statistically significant (Table 7). These results highlight the strong role of unexplained factors in the gender gap in unpaid work. While gender bias is not the only excluded variable and is not the entire explanation, it likely plays a significant role in accounting for the remaining gap.

Table 6: Oaxaca-Blinder Decomposition (Employed Population)

Variables	Differential	Decomposition
Prediction_Male	169.6***	
	(0.757)	
Prediction_Female	240.7***	
	(0.816)	
Difference	-71.17***	
	(1.113)	
Endowments		2.783***
		(0.551)
Coefficients		-73.23***
		(1.113)
Interaction		-0.724
		(0.515)
Observations	112276	112276

Note: Standard errors in parentheses: ***p<0.001, **p<0.05, *p<0.1

The Oaxaca-Blinder decomposition is limited by the number of unobserved variables that influence the data. A model that accounts for additional variables such as metropolitan area and elder care would be more detailed, but it is possible that even a more comprehensive model would only explain limited portions of the unpaid work gap. Compared to the gender pay gap, there are fewer potential explanatory variables that can be easily measured and analyzed because factors that influence the unpaid labor gap are often non-market factors that are less frequently measured or tracked. This influences both how comprehensive the Oaxaca-Blinder decomposition is and the potential omitted variable bias in other regressions.

Table 7: Oaxaca-Blinder Decomposition incl. Demographic Variables (Employed Population)

	(1)	(2)
Variables	Differential	Decomposition
Prediction_Male	169.6***	
	(0.757)	
Prediction_Female	240.7***	
	(0.816)	
Difference	-71.17***	
	(1.113)	
Endowments		-0.403
		(0.684)
Coefficients		-74.23***
		(1.165)
Interaction		3.457***
		(0.743)
Observations	112276	112276

Note: Standard errors in parentheses: ***p<0.001, **p<0.05, *p<0.1

While the Oaxaca-Blinder decompositions find that household and demographic characteristics play a small role in explaining the unpaid work gap, this does not mean that they are unimportant. Because the composition of a household is the primary factor that influences how much work is required for the household to function, studying how that work is distributed when the household changes can highlight continued inequities in unpaid work. This section of the analysis uses only data from ATUS respondents who are employed because the driving force of this research is the connection between unpaid work and the gender pay gap.

Using a regression that controls for age, race, number of children, weekly hours, spouse presence, and whether the spouse is employed, women's unpaid work increases by an average of 3.3 hours per week when a spouse or unmarried partner is present in the household and does not work, compared to an increase of 3.5 hours per week when the spouse does work. For men, unpaid work increases by 2.2 hours when a spouse is present and does not work, versus only 2.1 hours when an employed spouse is present in the household. Because women's baseline for time spent on unpaid work is higher (11.6 hours versus 8 hours), this unequal distribution of additional work is especially notable. Full regression results are detailed in Table 8. The low R-squared value is likely related to a high level of unexplained variation in the Oaxaca-Blinder decomposition and is reflective of the numerous variables influencing time allocation. This analysis uses a set of variables that are consistent with other time use studies and the low R-squared value should not be a cause for concern.

Table 8: Predicted Hours of Unpaid Work

Variables	(Male) unpaid_weeklyhrs	(Female) unpaid_weeklyhrs
age	0.0970***	0.166***
	(0.008)	(0.00947)
race	0.000424	-0.0229***
	(0.00745)	(0.007)
hh_numkids	2.362***	5.308***
	(0.111)	(0.128)
spouse	2.174***	3.339***
	(0.291)	(0.428)
0b.spouseemp#co.spouse	0 (0)	0 (0)
1.spouseemp#c.spouse	2.138***	3.500***
	(0.263)	(0.428)
earnweek_cps8	-1.32e-05***	2.61e-05***
	(3.21e-06)	(4.93e-06)
Constant	8.048***	11.68***
	(0.86)	(0.923)
R-squared	0.042	0.107
Observations	55173	57103

Note: Standard errors in parentheses: ***p<0.001, **p<0.05, *p<0.1

Using the same controls variables and an interaction term between the presence of a spouse and the number of children, this analysis shows that women with spouses spend an additional 6.3 hours per week on unpaid work if they have one child, 6.8 hours if they have two children, and 5.9 hours if they have three children. Men with spouses spend an additional 4 hours per week on unpaid work if they have one child, 4.8 hours if they have two children, and 4.1 hours if they have three children. For this regression, women's baseline for unpaid work is 12.5 hours and men's is 8.6. Full regression results are detailed in Table 9. These results follow the same pattern as the model that considers the interaction between the presence of a spouse and the spouse's employment status. Overall, the increase in unpaid work associated with a change in household characteristics is much larger for women than it is for men.

Table 9: Predicted Hours of Unpaid Work, Including Number of Children

Variables	(Male) unpaid_weeklyhrs	(Female) unpaid_weeklyhrs
age	0.102***	0.171***
	(0.00806)	(0.00927)
race	-0.00232	-0.0248***
	(0.00737)	(0.00694)
hh_numkids	1.046***	4.093***
	(0.211)	(0.211)
spouse	2.169***	3.562***
	(0.268)	(0.299)
0b.hh_numkids#co.spouse	0 (0)	0 (0)
1.hh_numkid#c.spouse	4.008***	6.262***
	(0.385)	(0.429)
2.hh_numkids#c.spouse	4.851***	6.810***
	(0.513)	(0.553)
3.hh_numkids#c.spouse	4.115***	5.919***
	(0.755)	(0.857)
4.hh_numkids#c.spouse	3.017***	1.494
	(1.145)	(1.608)
5.hh_numkids#c.spouse	3.503*	-0.153
	(1.873)	(2.969)
6.hh_numkids#c.spouse	17.30**	-3.438
	(7.543)	(5.723)
7.hh_numkids#c.spouse	-0.577	5.196
	(4.047)	(8.79)
8.hh_numkids#c.spouse	1.206	-24.99**
	(8.003)	(10.31)
9.hh_numkids#c.spouse	53.84***	0 (0)
	(7.947)	
10.hh_numkids#c.spouse	25.79***	0 (0)
	(2.103)	
earnweek_cps8	-1.28e-05***	2.81e-05***
	(3.22e-06)	(4.95e-06)
Constant	8.597***	12.47***
	(0.853)	(0.926)
Observations	55173	57103
R-squared	0.045	0.114

Note: Standard errors in parentheses: ***p<0.001, **p<0.05, *p<0.1

This finding is consistent with other studies that find that the amount of time women spend on unpaid work is more responsive to changes in household structure than men's (Blau and Kahn, 2017; Fang and McDaniel, 2017). While men take on some additional unpaid work as the amount of work required for the household to function increases, they take on comparatively less work than women. Based on the limited impact of household characteristics in the Oaxaca-Blinder decomposition, this difference is due to unexplained factors. These unexplained factors may include either unmeasured variables or the more general presence of "discrimination" in unpaid work expectations. Because of the significant role that gender bias plays in determining how time is allocated within the home, gender bias is likely the cause of much of this

6 Conclusion

Over time, the portion of the gender pay gap that is explained by education, experience, and labor force participation has fallen significantly. The line between the personal and professional is often blurry, but it is especially blurry in conversations about the relationship between women's unpaid work and labor market outcomes. The way women spend their time within the home is closely related to women's decisions to enter and exit the job market, but also to the decisions they make about industry, occupation, and number of hours worked. The influence of time allocation within the home does not stop after women decide to enter the job market. Unpaid work and other responsibilities within the home influence women's labor market outcomes throughout their careers.

Two Oaxaca-Blinder decompositions highlight the underlying causes of the gender gap in unpaid work: one that accounts for household and demographic characteristics and one that accounts for household, demographic, and employment characteristics. These decompositions find that a small but statistically significant portion of the unpaid work gap is explained by the variation in household and demographic characteristics between women and men, but that a larger portion of the gap is explained by employment characteristics (employment status, earnings, and hours worked). The significant portion of the gender gap in unpaid work that is unexplained indicates that there are unaccounted for variables that play a much larger role in determining how men and women spend their time within the home. Based on existing economic and sociological research, it is likely that this unexplained portion of the difference in unpaid work is driven by social expectations, power dynamics in intimate relationships, and other factors that together are best characterized as gender bias.

The three main regression models illustrate how the relationship between unpaid work and household characteristics to understand how changes in unpaid work vary for people who are employed. The presence of children in the household is associated with more of an increase in unpaid work for women than for men. Similarly, the presence of a spouse and a spouse's employment status are associated with a larger change in women's unpaid work than in men's unpaid work. This is consistent with the Oaxaca-Blinder decomposition, which finds that changes in unpaid work are not explained by household characteristics alone. This is also consistent with existing research that finds that women take on a disproportionate burden when the quantity of household work changes (Fang and McDaniel, 2017). This disproportionate burden-sharing is also reflected in the model that includes the impact of children and the interaction between the presence of a spouse and the number of children.

Future research should focus on exploring other potential variables that can decrease the unexplained portion of the Oaxaca-Blinder decompositions. The links between unpaid work and industry-specific labor market factors, like the ability to work flexible hours, could be an important step to understanding why the remaining gender pay and unpaid work gaps exist. Especially because industry and occupation account for much of the remaining pay gap, a careful analysis of women's unpaid work across industries and occupations may explain more of the unpaid work gap than household characteristics. Industries that have more equal distributions of unpaid work can serve as a starting place for designing workforce and welfare policies that facilitate more equal distributions of work within the household. Accounting for unpaid work burdens should be a focus of policies designed to address the gender pay gap, and research that explores the nuances of the gender pay gap is an important step toward designing suitable policy interventions.

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The Effects of Quantitative Easing on Income Inequality in Japan

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Abstract

This research paper demonstrates that asset purchases through quantitative easing (QE) by the Bank of Japan (BOJ) increased the size of the central bank balance sheet by 874 percent and caused unintended consequences for income inequality. Over the past two decades, the Japanese economy experienced low inflation and stagnant economic growth, while the BOJ's traditional policy tools were constrained by the liquidity trap at the effective lower bound of interest rates. In response, the BOJ initiated an enormous QE program to prevent a deflationary spiral. At the same time, income inequality—measured by the Gini coefficient—expanded by 9.3 percent. The traditional literature provides abundant evidence for the benefits of QE to inflation and economic stability but neglects the potential consequences on income inequality. How and to what extent have the BOJ's unconventional monetary policies affected income inequality in Japan? This research study utilizes a vector auto regression (VAR) model to determine the impact of QE on income inequality. The model reveals that QE substantially increased income inequality and caused around 15.3 percent of Japan's income inequality growth over the past two decades. Additionally, the current pace of QE will continue to expand income inequality over the next decade. These findings have significant implications for the well-being of Japanese society and the trade-offs faced by both fiscal and monetary policymakers.

JEL Codes: D60, E25, E52, E58, F33

1 Introduction

This research paper demonstrates that the Bank of Japan's (BOJ) quantitative easing (QE) increased income inequality in Japan. The traditional literature for QE is centered around the impacts to inflation and output, but neglects to effectively consider the distributional consequences of QE. In order to evaluate the relationship between QE and income inequality, this research paper utilizes a vector auto-regression (VAR) model that analyzes and forecasts the relationships between multiple variables over time as a matrix of interconnected linear regressions. The findings from the model conclude that QE substantially increased income inequality in the past and will continue to increase income inequality in the future.

In Japan, the problems of declining economic growth and rising income inequality pose significant challenges. Over the past two decades, Japan's income inequality rose by over nine percent (Statistics Bureau 2021). At the same time, real GDP grew at a sluggish pace by one-half percent on average per year (International Monetary Fund 2021). The low economic growth in Japan was coupled with deflationary pressures from an aging and shrinking population (Han 2019 p.3). These pressures constrained the BOJ's traditional monetary policy tools at the effective lower bound for interest rates (Ulate and Loften 2021 p.4). The effective lower bound prevents the BOJ from cutting interest rates during an economic crisis, which forces the central bank to consider new policy channels (Bernanke et al. 2004). In order to prevent a deflationary spiral and declining economic growth, the BOJ began to implement a series of unconventional monetary policies—including QE, which is the large-scale purchase of financial assets in order to inject money into the economy and stimulate economic activity.

This research paper utilizes the Japanese monetary system as a case study because the BOJ is the most innovative central bank in the world. In 2001, the BOJ became the first central bank to deploy QE. These monetary interventions increased the size of the BOJ's balance sheet by 874 percent, as seen in figure 1 (Bank of Japan 2021a). The extraordinary growth of the balance sheet demonstrates the unprecedented nature of these interventions. In 2021, the total value of assets purchased through QE by the BOJ was equivalent to 128.59 percent of Japan's GDP, as seen in figure 2 (Atlantic Counsel 2021). This means that the BOJ's asset purchases are by far the largest in the world as a percent of GDP. These monetary interventions are the subject of intense debate by academics and policymakers. The traditional literature for QE focuses primarily on the impacts to inflation and output. Although these metrics provide a general evaluation of monetary policy, researchers have neglected to effectively consider the unintended consequences for income inequality. Do these massive monetary interventions benefit everyone equally or are there winners and losers? This research paper will use Japan as a case study to understand the important relationship between QE and income inequality.

Figure 1: Bank of Japan Balance Sheet from 2000 to 2021

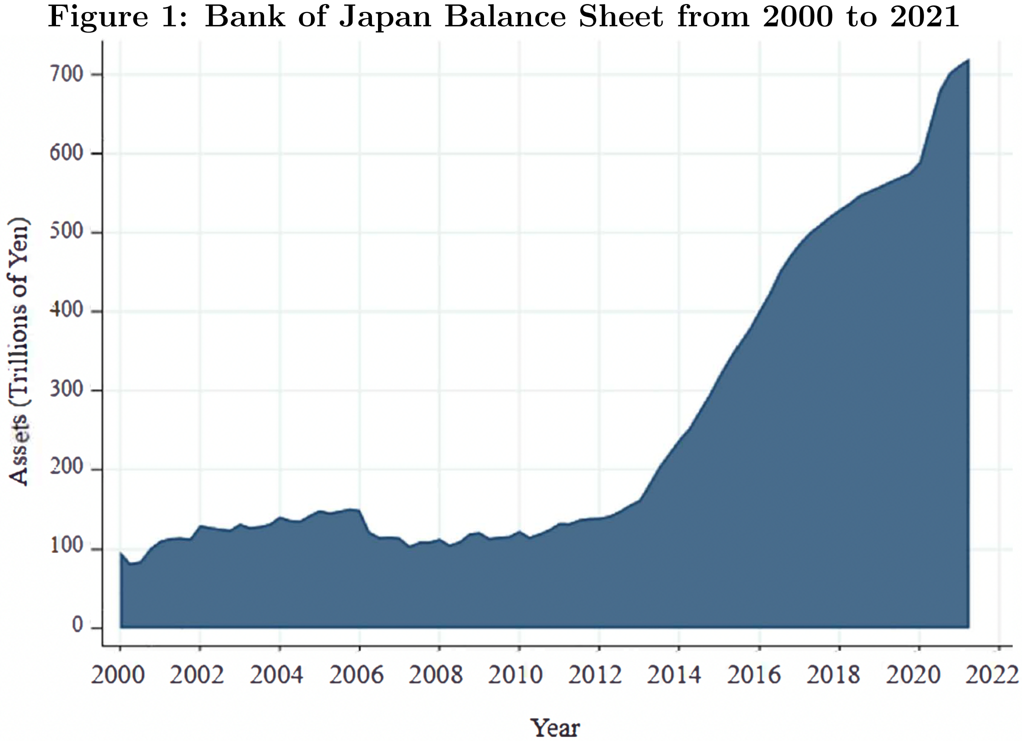
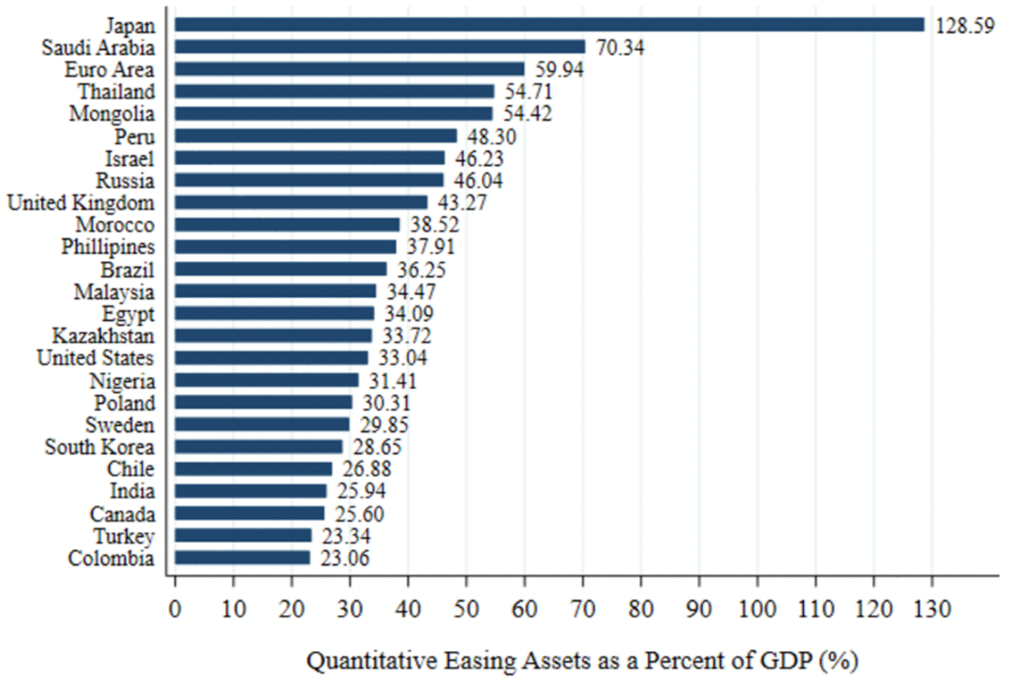


Figure 2: Top 25 Countries by Quantitative Easing as percent of GDP



Despite its importance, the distributional effects of QE have been largely neglected by researchers and policymakers. Many critics argue that the BOJ's financial asset purchases caused the value of the stock market to rise but left the rest of the economy behind. In Japan, high-income earners invest a greater proportion of their income in the financial markets and control the vast majority of financial assets (Fujiki et al. 2012 p.4-6). This means that QE could disproportionately benefit high-income earners without improving the circumstances of other people. The size and composition of the BOJ's interventions are also notable. In 2010, the BOJ began to directly inject money into the stock market by purchasing exchange traded funds (ETFs), which are indexes containing many individual stocks. At the start of 2021, the BOJ's aggregate ETF holdings exceeded 454 billion dollars, making the BOJ the single largest shareholder in the Japanese stock market (Kihara 2021). The current value of the BOJ's ETF holdings account for an astonishing eight percent of the entire Japanese stock market. Therefore, it is important to consider the impact of these interventions on income distributions and Japanese society. The journalist William Pesek wrote, "It's great the wealthy have [BOJ Governor] Kuroda to protect them from losing. If only the other 99 percent were so lucky" (Pesek 2015 p.8). Another journalist concluded, "central banks sowed the seeds of the populism that now threatens to engulf them" (Funabashi 2019 p.7). Evidently, there is a tumultuous debate over the unprecedented levels of QE in Japan.

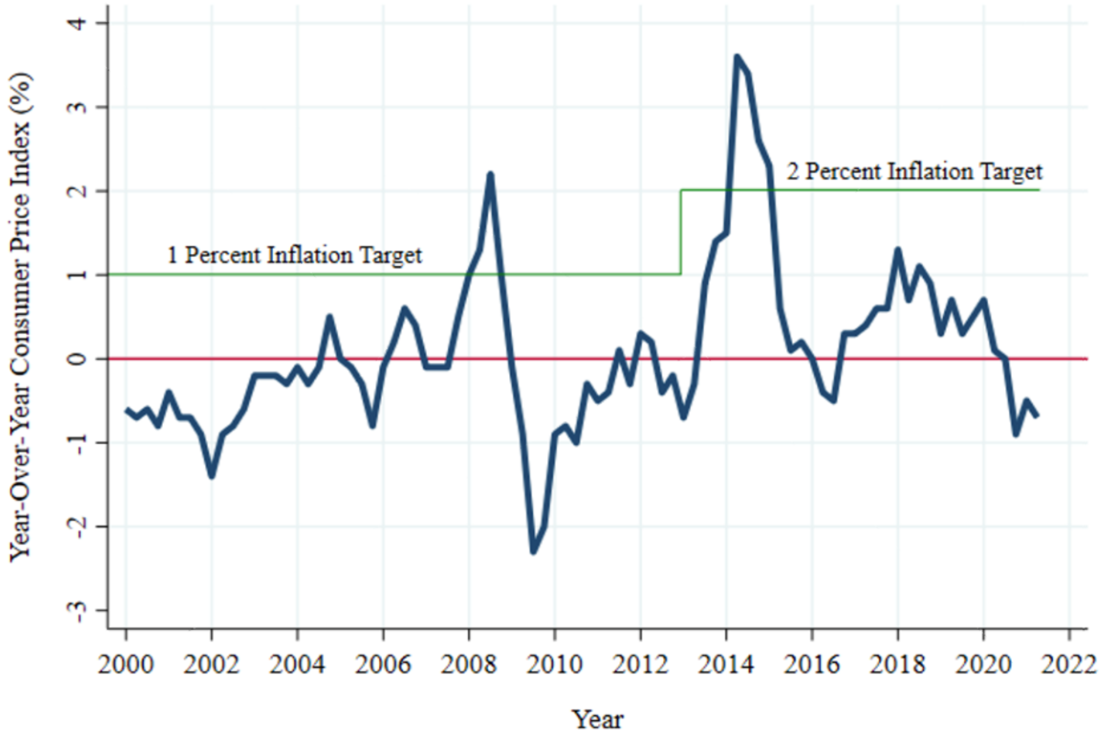
There are also important international implications from the impacts of QE in Japan. Many countries across the world are following the path of Japan's economy. This trend of "Japanization" occurs when a country faces stagnant economic growth, secular stagnation, lower nominal interest rates, and deflation (Ito 2016 p.5-6). All of these features are present in Japan and emerging in other developed economies. One of the primary pressures towards "Japanization" is the declining global interest rate environment, which forces central banks across the world to utilize more QE because traditional policy tools are increasingly constrained by the effective lower bound (Hong and Shell 2019). This means that QE is being used by the vast majority of central banks, including the Federal Reserve, European Central Bank, and the Bank of England. Additionally, income inequality is expanding across the world over time. According to the World Inequality Report, income inequality rose in nearly all countries since the 1980s (Alvaredo et al. 2018 p.9). The expansion of income inequality is the source of profound social tension and controversy. Substantial evidence indicates that higher levels of income inequality can cause major political shifts, including populist revolts and the spread of authoritarianism (O'Connor 2017). Income inequality also reduces overall economic growth and household welfare. Researchers from the Organization for Economic Co-operation and Development (OECD) found a negative and statistically significant impact from income inequality on economic growth for the thirty-eight countries in the OECD (Cingano 2014 p.28).

Additional research shows that income inequality leads to greater levels of consumption inequality, which is a crucial measure of household welfare (Krueger and Perri 2006 p.186-188). Therefore, the global trends of "Japanization" and widening income inequality have major implications for political leaders and academics across the world. According to the renowned French economist, Thomas Piketty, "the current economic system is not working when it comes to solving the problem of rising inequality" (Piketty 2020). Thus, policymakers face trade-offs between rising income inequality and declining economic growth. Given these circumstances, it is important to understand the relationship between QE and income inequality. Going forward, this research paper will begin with an introduction, review the current literature, explain the methodology of the model, summarize the findings, and provide a conclusion.

2 Literature Review

The traditional literature for QE is generally focused on the impacts to inflation and output because these are the most important measures for successful monetary policy. This traditional literature provides compelling evidence that QE in Japan successfully increased the level of inflation, but the impacts to economic growth are not statistically significant (Wang 2021). Although QE increased the level of inflation in Japan, as measured by the year-over-year consumer price index (CPI), the BOJ was not able to reach its target for inflation (Statistics Bureau 2021). As shown in figure 3, the actual inflation level over the past two decades remained consistently below the inflation target even after the central bank increased the inflation target from one percent to two percent (Bank of Japan 2013). This suggests that QE helped to prevent a deflationary spiral that would harm the economy but failed to achieve the BOJ's price stability objective. In a speech to Parliament, former Prime Minister Abe admitted, "It's true the BOJ has yet to hit its two percent inflation target" (Kihara 2019). Abe's comments underscore the harsh reality that the BOJ cannot obtain price stability, even with massive QE programs. The impacts of QE on long-term economic growth are even more concerning. A study by the Bank for International Settlements demonstrates that Japan's QE programs failed to produce a significant increase in aggregate demand or nominal GDP (Iwata and Takenaka 2012 p.157). This means that the Japanese economy continues to grow at a sluggish pace with looming deflationary pressures that could threaten economic stability.

Figure 3: The Consumer Price Index and Inflation Targeting by the Bank of Japan



Given the challenging economic circumstances in Japan, it is understandable why the BOJ deployed a series of untested and extraordinary QE programs. Despite the importance of these programs, the traditional research on QE fails to effectively consider the distributional effects from central bank asset purchases. Several economists have begun to research these effects and there are a wide range of findings. In 2014, economists from De Nederlandsche Bank published the first paper considering the distributional effects of QE in Japan (Saiki and Frost 2014). This paper found a positive relationship between QE and income inequality, however the metrics for income inequality were limited and the time frame failed to capture the largest interventions by the BOJ. After this paper was published, several other academics began to research the distributional effects of QE in a variety of different monetary systems. This research ignited a controversial and contested debate between academics. Several economists found a positive relationship between QE and income inequality (Montecino and Epstein 2015; Mumtaz and Theophilopoulou 2017; Guerello 2017; Dolado et al. 2021). These economists generally argue that QE increases income inequality by inflating the value of wealth stored as financial assets. The increased value of financial assets tends to benefit upper income households that hold a greater share of their wealth in financial markets. The capital earnings from these households expand income inequality while wages and employment stagnate. In contrast to this research, several other economists found a negligible or negative relationship between QE and income inequality (Lenza and Slacalek 2018; Hohberger et al. 2020). These researchers argue that QE compresses the income distribution by increasing overall employment levels. These contradictory findings raise further questions about the effects of QE on income inequality.

There are also profound disagreements between policymakers about the distributional effects of QE. In 2012, economists from the Bank of England issued a working paper conceding that QE primarily benefited the top five percent of households because this segment of British society holds over forty percent of all assets (Bank of England 2012). After a controversial public discourse, the Bank of England reevaluated the research and concluded that QE does not have a clear impact on income inequality (Pugh et al. 2018). Additionally, former Federal Reserve Chairman Ben Bernanke, who introduced QE to the United States during the global financial crisis, argued that "the effects of monetary policy on inequality are almost certainly modest and transient" (Bernanke 2015). Bernanke's comments underscore the growing consensus among policymakers that QE does not have a distributional effect on income. However, the current research does not provide a clear basis for these statements and the debate is far from over. In a recent speech, Governor Richard Macklem from the Bank of Canada stated, "QE can boost wealth by increasing the value of assets such as the investments Canadians have in their registered retirement savings plans or company pension plans. But of course, these assets aren't distributed evenly across society" (Macklem 2021). These comments underscore the emerging recognition among some policymakers that QE could have distributional consequences.

These policy differences are especially important for Japanese society in the aftermath of the pandemic. In May 2021, BOJ Governor Haruhiko Kuroda stated, "The impact of the pandemic appears to be uneven and regressive, as the negative impact has been more tilted toward low-income earners and young workers. There are therefore concerns over an increase in income and wealth inequality" (Kuroda 2021). Other political leaders in Japan share Kuroda's concern over rising income inequality. During Fumio Kishida's campaign to become Prime Minister, he promised a "new Japanese-style capitalism" that would reduce the "division between the rich and the poor" (Kyodo News 2021). These comments indicate a growing concern among political leaders over rising income inequality in Japan. However, reducing asset purchases through QE would slow the pace of recovery from the pandemic and unleash deflationary pressures. In the October 2021 monetary policy statement, the BOJ committed to "continue with Quantitative and Qualitative Monetary Easing (QQE) with Yield Curve Control, aiming to achieve the price stability target of 2 percent, as long as it is necessary for maintaining that target in a stable manner" (Bank of Japan 2021c p.2). The BOJ's policy statement suggests that the central bank will continue to utilize QE in order to avoid a deflationary spiral. Therefore, the growing need for QE and the expansion of income inequality pose significant problems to the Japanese economy and society.

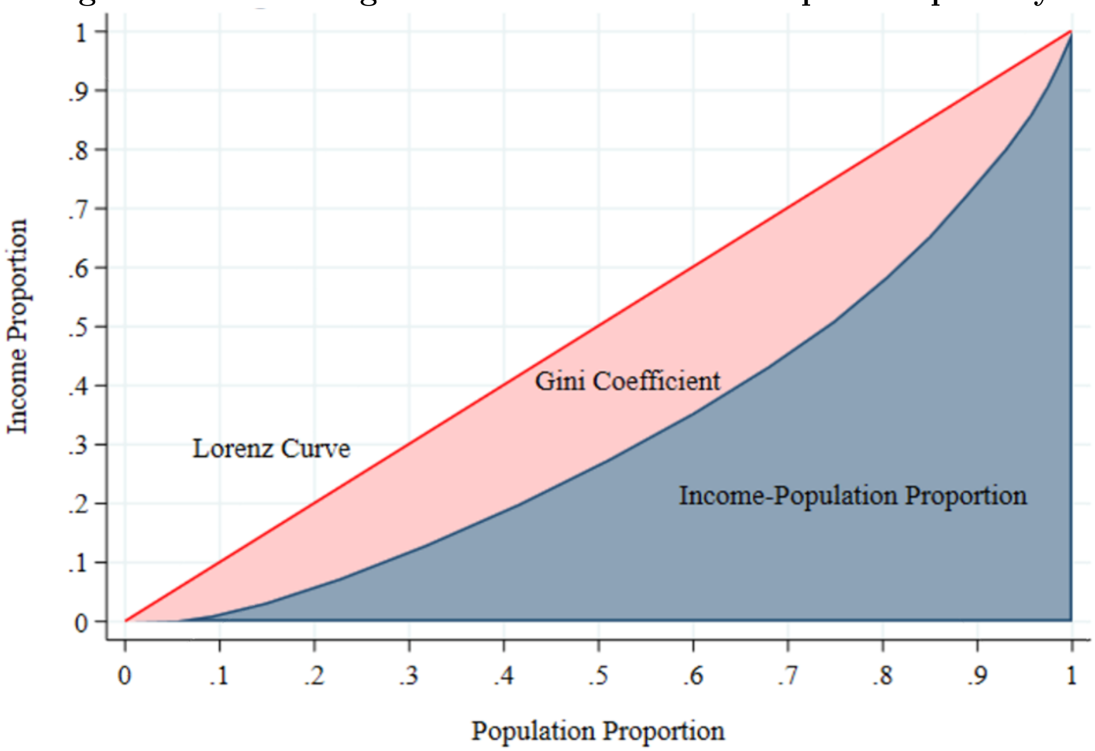
3 Methodology

In order to evaluate the relationship between QE and income inequality, this research paper utilizes a variety of statistical methods. This methodology section will start by discussing how the Household Income and Expenditures Survey is utilized to measure income inequality in Japan. Afterwards, this section will explain the theoretical and statistical basis for the vector autoregression (VAR) model, which will be used to measure the impacts from an exogenous shock to QE on income inequality. This methodology section provides the logical basis for this research study.

3.1 Measuring Income Inequality

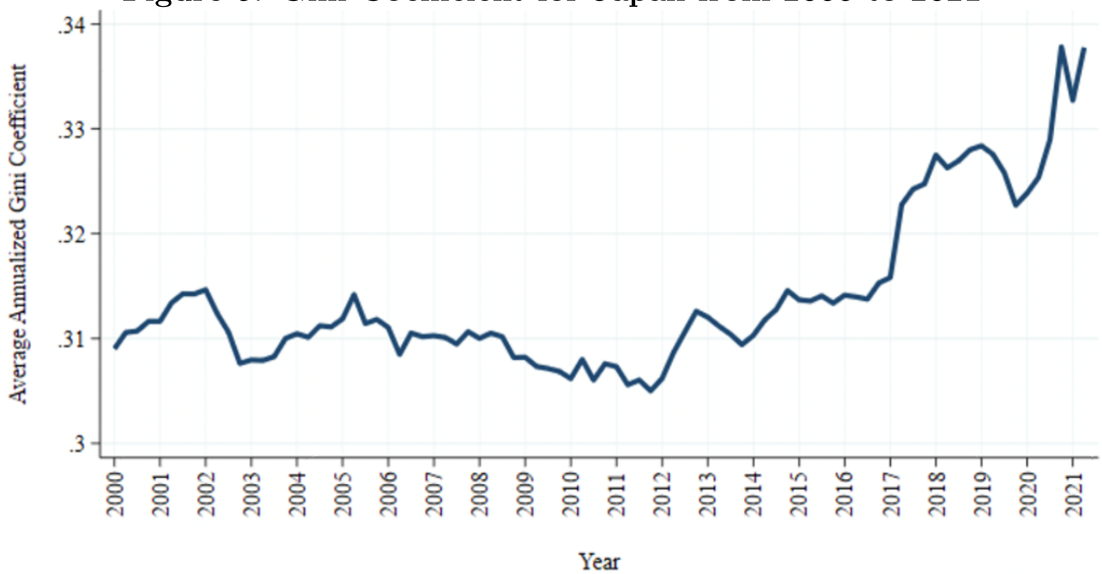
Japan does not regularly publish statistics on income inequality, so a new measure of income inequality was created for this research project. The primary tool used to measure a nation's income inequality is the Gini coefficient, which ranges from 0 to 1 with larger numbers corresponding to greater income inequality. For this research project, the income data from the Household Income and Expenditures Survey was used to create the Gini coefficient for Japan. The survey provides the average income levels for eighteen income brackets from 2000 to 2021 based on the responses from approximately ten thousand randomly selected households in Japan (Statistics Bureau 2021). The proportion of total income earned for each of the income brackets is used to create the income-population proportion curve, as seen in figure 4. The Gini coefficient is the area between the income-population proportion curve and the Lorenz curve, which is a line that represents a society with a perfectly equitable income distribution. Adjustments were also made to account for the average fiscal redistributions provided to each income bracket. These fiscal redistributions include the tax and spending policies implemented by the government that tend to shift earnings from high-income groups to low-income groups. By removing the effects of fiscal redistributions on income inequality, the impact from QE on income inequality can be isolated through further analysis.

Figure 4: Generating the Gini Coefficient for Japan Graphically



The data for the Gini coefficient shows that income inequality increased by approximately nine percent over the past two decades, as seen in figure 5. This means that the Gini coefficient rose from 0.309 in 2000 to 0.338 in 2021. The data also reveals that income inequality grew at an accelerating pace after 2013, which is when the BOJ began to substantially increase the level of asset purchases through QE. The data also demonstrates that the current redistributive effects of fiscal policy in Japan are not large enough to counteract the rising level of income inequality. These findings for the Gini coefficient have significant implications beyond the scope of this research paper. Going forward, this research project will construct a model that is used to evaluate the relationship between QE and income inequality.

Figure 5: Gini Coefficient for Japan from 2000 to 2021



3.2 Creating the Model

In order to evaluate the effects of QE on income inequality, this paper utilizes a vector autoregression (VAR) model. The VAR model is a forecasting algorithm that determines the relationship between multiple bi-directional time series variables. This means that the variables in the model influence each other over time. For a simplified example, an increase in QE leads to an increase in the value of the stock market. The rising stock market prices cause an increase real GDP, which causes prices to rise through inflation. After observing inflation, the central bank adjusts the level of QE and the cycle repeats. With this modeling system, policymakers are able to respond to the conditions of the economy as they change. Additionally, the model is autoregressive because each variable is a function of its own prior values. The VAR model assumes that each variable is a linear combination of its own past values and the past values of other variables in the system. For this reason, all of the variables in the model are endogenous over time. This makes the VAR model well-suited to evaluate the effects of QE on income inequality because there are generally time differentials between the implementation of monetary policy and the economic outcomes. Research demonstrates that the lag between an interest rate cut and the peak impacts to both output and inflation typically takes between two and six quarters (Cagan and Gandolfi 1969 p.277). This research supports the utilization of a dynamic model because the lagging effects of monetary policy enables variables to interact with each other over time.

Importantly, the system of variables satisfies the four preconditions required for a VAR model. First, the error terms have a mean of zero and there is no correlation between the error terms over time. This means that the error terms are not autoregressive

(Hatemi-J 2004 p.661-683). Second, the augmented Dickey-Fuller (ADF) tests demonstrate that the time series is stationary over a four-quarter lag period. This means that the variables properties for mean, variance, and autocorrelation are approximately constant in the time series and the model can assume that the manner in which the variables change over time remains consistent.

Additionally, the optimal number of lags for the model is a period of four quarters based off of the Akaike information criteria (AIC) test, which estimates the prediction error based on the number of parameters and the function of maximum likelihood for the model (Akaike 1969). The results for the AIC test are shown in Table 1 below.

Table 1: Akaike Information Criteria (AIC) Lag Order Test

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2686.32				2.2e+22	65.6419	65.7009	65.7887
1	-2232.22	708.2	25	0.000	6.3e+17	55.1761	55.5296*	56.0566*
2	-2201.55	61.334	25	0.000	5.5e+17	55.0379	55.686	56.6521
3	-2173.82	55.469	25	0.000	5.3e+17	54.9712	55.9139	57.3192
4	-2140.34	66.95*	25	0.000	4.4e+17*	54.7645*	56.0017	57.8462

Note: Sample: 2001q1 thru 2021q2, Number of obs = 82, *optimal lag
Endogenous: GDP Inflation QE Nikkei_225 Gini, Exogenous: _cons

Third, the data does not exhibit perfect multicollinearity. This means that no variables in the model are a perfect linear function of any other explanatory variable. Fourth, large outliers are generally unlikely for each of the variables in the model. This is confirmed through an interquartile region test on each of the variables. These preconditions allow the model to assume that the regression estimates are consistent, can be evaluated through a confidence interval, and jointly respond to shocks across multiple equations. A simplified K-variate vector autoregressive model of lag length p, denoted VAR(p), is shown in equation 1.

$$y_t = v + A_i y_{t-1} + ... + A_p y_{t-p} + u_t \tag{1}$$

Where:

$v = (v_1, ..., v_k)$ is a fixed vector of intercept terms

A_i are a fixed group of coefficient matrices

$u_t = (u_1, ..., ukt)$is a K-dimensional white noise with a nonsingular covariance matrix

There are five variables in the model, as seen in the table below. These variables are used to estimate the transmission of a monetary shock from QE on the Gini coefficient. The sequence of the regressions for the variables are determined by the Cholesky decomposition, which is the most efficient way to solve for a system of linear equations (Higham 2009 p.251-254). The sequence supports the general theory behind the model since it assumes that monetary policy decisions are based on the circumstances of output and inflation. It also assumes that the Gini coefficient is based on the estimated value for each of the variables following an increase in QE. This sequencing makes logistical sense and provides the foundation needed to generate the model. The variables for the VAR model are shown with the order provided by the Cholesky decomposition in equation 2.

$$y_t = [GDP_t, pi_t, QE_t, N_t, Gini_t] \tag{2}$$

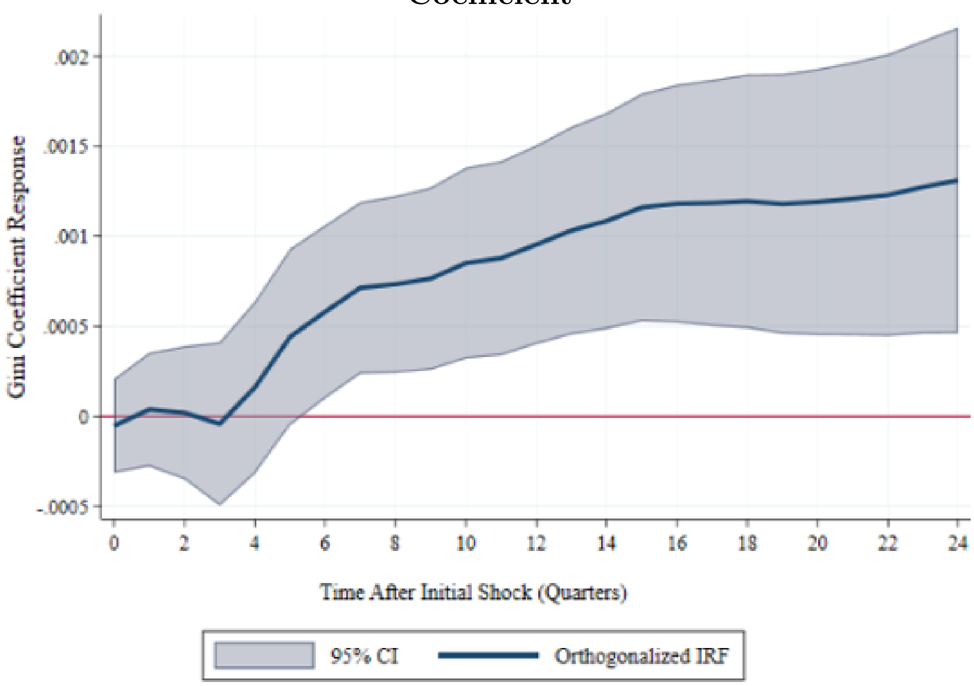
Table 2: VAR Model Variables

Variable	Label
GDP_t	Real GDP product per capita (Source: International Monetary Fund)
pi_t	Year-over-year consumer price index (Source: Statistics Bureau of Japan)
QE_t	Assets on the central bank balance sheet (Source: Bank of Japan)
N_t	Nikkei 225 stock index closing price (Source: Nikkei 225)
$Gini_t$	Gini coefficient (Source: Statistics Bureau of Japan)

4 Summary of Findings

The model shows that QE increases income inequality over time. The impulse response function (IRF) demonstrates that increasing the assets purchased through QE by one-standard deviation leads to an increase in the Gini coefficient by 0.0013 over the course of six years, as seen in figure 6. These results are substantial, and they are significant at the ninety-five percent confidence level. The IRF also evaluates the impacts of QE on income inequality over the past two decades. The model estimates that QE accounts for 15.3 percent of the income inequality growth over the past two decades in Japan. This is a substantial portion of the overall increase in income inequality, which underscores the significance of QE on income distributions. The model also provides a unique story for how an exogenous shock to QE impacts income inequality over time. After the level of QE is increased, there are no effects to income inequality for approximately three quarters. This is most likely caused by time delays in the transmission of monetary policy through an economy. After three quarters, there is a sharp increase in income inequality that decelerates slowly over time. The end result is a higher level of income inequality caused by an increase in QE.

Figure 6: Impulse Response Function for Quantitative Easing on the Gini Coefficient



The model also provides forecasts for the future effects of QE in Japan. For example, if the BOJ decided to increase the total assets purchased through QE by 500 trillion yen ($4.3 trillion) the model predicts that the Gini coefficient would increase by around one percent over the next six years. This would cause the Gini coefficient to rise from 0.3378 to 0.3412, which is statistically and substantively significant. In conclusion, the BOJ's asset purchases through QE expanded income inequality over the past two decades and will continue to expand income inequality in the future. These findings are important because the BOJ continues to utilize QE in order to respond to the deflationary pressures on the Japanese economy. According to the model, the BOJ's current and future interventions will continue to expand income inequality in Japan.

Table 3: Vector Autoregression Model Equation Input Results

Equation	Parms	RMSE	R-Sq	Chi-Sq	P>Chi-Sq
GDP	21	7093.62	0.9220	969.2427	0.0000
Inflation	21	0.469649	0.8315	404.6525	0.0000
QE	21	83390.5	0.9986	58047.25	0.0000
Nikkei_225	21	1010.71	0.9715	2791.617	0.0000
Gini	21	0.001406	0.9749	404.0742	0.0000

Note: Sample: 2001q1 thru 2021q2, Number of obs = 82
Log likelihood = -2140.343, AIC = 54.76445, FPE = 4.43e+17, HQIC = 56.00174,
Det(Sigma_ml) = 3.23e+16, SBIC = 57.84623

The findings from the model are supported by the equation input results and the forecast error variance decomposition (FEVD). The equation input results show that each of the five endogenous variables have a high R-squared value, as seen in table 3. In particular, the R-squared value for the Gini coefficient is 0.97, so around ninety-seven percent of the variation in the Gini coefficient is explained through the model's system of regressions. This means that the model successfully explains the variation for the Gini coefficient and supports the finding that QE expands income inequality in Japan. Additionally, the FEVD indicates that the model's forecast explains a substantial portion of the forecast error variation that occurs after the BOJ increases the level of QE. The FEVD is a form of structural analysis that evaluates the performance of a model when explaining the actual variation over time. The FEVD shows that around sixty-two percent of the total variance in the forecast for the Gini coefficient can be explained by the increase in QE after six years, as seen in table 4. The high R-squared values and the large FEVD results support the findings that QE increased income inequality in Japan. If the R-squared or FEVD values were lower, there could be problems with the assumptions for the model.

Table 4: Orthogonalized Impulse Response Function (OIRF) and the Forecast Error Variance Decomposition (FEVD) for Six Years with a Ninety-Five Percent Confidence Interval

	(1)	(1)	(1)	(1)	(1)	(1)
Step	orif	Lower	Upper	fevd	Lower	Upper
0	-0.000052	-0.000313	0.000209	0	0	0
1	0.000038	-0.000278	0.000355	0.001836	-0.016602	0.020274
2	0.00002	-0.00035	0.00039	0.001771	-0.008561	0.012102
3	-0.000042	-0.000497	0.000413	0.001073	-0.006005	0.008152
4	0.000161	-0.000317	0.000639	0.001157	-0.005065	0.007379
5	0.000441	-0.00049	0.000931	0.00489	-0.016806	0.026586
6	0.000581	0.0001	0.001063	0.031349	-0.04426	0.106957
7	0.000715	0.000237	0.001192	0.071091	-0.059282	0.201464
8	0.000734	0.000243	0.001225	0.11717	-0.052252	0.286592
9	0.000765	0.000259	0.001272	0.160622	-0.041066	0.036209
10	0.000852	0.000321	0.001383	0.199688	-0.024354	0.42373
11	0.000879	0.00034	0.001418	0.23992	0.001213	0.478628
12	0.000954	0.000402	0.001506	0.277882	0.028808	0.526956
13	0.001032	0.000455	0.00161	0.314375	0.060277	0.568472
14	0.001086	0.000485	0.001687	0.353045	0.095604	0.610486
15	0.001161	0.000529	0.001793	0.391254	0.132419	0.650088
16	0.001182	0.000522	0.001843	0.429362	0.170492	0.688231
17	0.001186	0.000502	0.00187	0.465232	0.206481	0.723984
18	0.001195	0.000489	0.0019	0.496153	0.23834	0.754472
19	0.001181	0.000459	0.001903	0.524243	0.266522	0.781963
20	0.001192	0.000451	0.001932	0.548802	0.292498	0.805105
21	0.001209	0.00045	0.001969	0.569966	0.31594	0.823992
22	0.00123	0.000447	0.002013	0.589172	0.338669	0.839676
23	0.001274	0.00046	0.002088	0.605683	0.359383	0.851983
24	0.001312	0.000463	0.002161	0.620241	0.378165	0.862317

Although the findings for the model are substantive and compelling, there are some predictive and analytical limitations. First, the model is only accurate in the short- and medium-term because of limitations to available data. The current data on QE is not sufficient to make accurate predictions beyond ten years from the initial shock. This means that the model cannot be used to consider the long-term effects of QE on income inequality. Second, the model does not distinguish between the different types of assets that the BOJ purchases through QE. This is a significant problem because the composition of asset purchases almost certainly impacts the outcomes for income inequality. For example, there might be different effects to income inequality from purchasing government bonds compared to individual stocks or ETFs. The composition of asset purchases is important because different income groups tend to hold different types of assets. Additional research is required to consider the role of QE asset composition on income inequality. Third, the range of the model's predictions increase with the size of the intervention. This means that the model produces a wide range of outcomes with a very large increase in QE, which poses general predictive limitations. For these reasons, it is important to understand that the model's forecasts are estimations that rely on simplified assumptions about the world. Therefore, readers should take into account the statistical limitations from the model when they are considering the findings from this research paper.

5 Conclusion

This paper is not an indictment or criticism of QE in Japan. The BOJ's unprecedented interventions helped to prevent a deflationary spiral that could have caused substantial harm to the Japanese economy. However, there are unintended consequences from these interventions on income inequality that require additional attention. The VAR model developed in this research paper reveals that QE substantially increased income inequality in Japan. The expansion of income inequality was caused by asset purchases that disproportionately increase the value of financial assets when compared to economic fundamentals, such as wages and employment. The rising financial asset prices tend to benefit higher-income earners that hold a greater percentage of their savings in financial markets. This leads to capital income gains for high-income households and widens the distribution of incomes in Japan. The VAR model provides statistically and substantially significant evidence that QE increased income inequality in Japan over the past two decades and will continue to increase income inequality in the future. It is important for policymakers to consider and respond to these unintended consequences from government-led interventions.

The problems associated with income inequality in Japan will continue to get worse over the course of time. In a September 2021 interview, Governor Kuroda told reporters, "We will continue our present measures of monetary easing, and help with companies' financing. If necessary, we are prepared to take additional easing measures without hesitation" (Kawanami et al. 2021). These statements signal that the BOJ will continue to engage in QE and the magnitude of their interventions will increase with the persistence of deflationary pressures. Therefore, QE will continue to play a significant role in the Japanese economy, and it will continue to expand income inequality. However, QE is not the only factor contributing to rising income inequality in Japan. There are a variety of other long-term trends that are expanding the distribution of Japanese incomes. Demographic changes from an aging and shrinking population increase income inequality by reducing overall factor productivity and expanding consumption-based disparities between age groups (Yamada 2012 p.63-84). Technological change and globalization expand the income gaps between low and high skill workers (Jaumotte et al. p.271-309). The impacts of climate change expand the disparities in economic growth between rural and urban communities (Hayashi 2015 p.260-271). All of these factors contribute to expanding income inequality in Japan.

Most importantly, the BOJ is not responsible for reducing income inequality. The BOJ is a politically independent central bank whose sole objective under the Bank of Japan Act is "aimed at achieving price stability" (Bank of Japan 2021b p.2-3). The problems associated with income inequality are beyond the scope of the central bank's statutory obligations. Fortunately, Japanese fiscal policymakers can implement changes to address income inequality. The fiscal policy conducted by the Japanese Diet and Ministry of Finance can redistribute earnings through tax and spending proposals. A more progressive tax system would increase the share of government revenues collected from high-income earners. The benefits from these higher tax revenues could finance programs that are targeted towards low- and moderate-income households. In conclusion, the policies established by the Japanese Diet and the Ministry of Finance should take into account the unintended consequences of QE on income inequality. A part-time kindergarten bus driver named Aoki summarized the problem perfectly. He said, "With Abenomics, the finance minister talked about wealth trickling down. But there was no such thing, was there? Almost nothing" (Komiya and Kihara 2021). If the Japanese Diet and Ministry of Finance do not respond to the rising levels of income inequality caused by QE, the problem will continue to get worse.

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Asymmetric Effect of Fluctuating Oil Prices on Remittance Inflows to the Philippines

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Abstract

This paper analyzes the effect of crude oil prices on remittance inflows to the Philippines from Gulf Cooperation Council (GCC) countries by conducting an OLS linear regression for overall trends and then generating a variable of the difference in oil prices to focus on what happens when there are negative and positive shocks to oil prices. Using monthly data spanning from 2000 to 2020, this paper finds a weak negative association between crude oil prices and remittance inflows and an asymmetric relationship, in which negative shocks have a more significant positive effect on remittance inflows than positive shocks.

JEL Codes: F24, J30, J61, Q41, Q43

1 Introduction

Since the 1980s, Overseas Filipino Workers (OFWs) have been hailed as *bagong bayani*, 'modern-day heroes', for keeping the Philippine economy afloat. In 2019, there were 2.2 million OFWs scattered worldwide, accumulating 30 billion US dollars worth of remittances, surpassing net inflow of foreign direct investments, and contributing to nearly 10 percent of the Philippine economy (World Bank). Remittances are the financial transfers, usually made up of overseas workers' earnings, sent to family members struggling financially in their home countries. Given that oil-rich Gulf Cooperation Council (GCC) countries (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates) are a large source of migrant remittances in the Republic of the Philippines, this paper examines the effects of oil price shocks on the Philippines. The Philippine Statistics Authority's (PSA) 2019 Survey of Overseas Filipinos reports that nearly 50 percent of OFWs were employed in the Western Asia region, primarily in Saudi Arabia (22 percent) and the UAE (13 percent). The GCC countries heavily rely on migrant populations, so much so that there are more expatriates in most GCC countries than there are nationals (Shayah and Sun 2019). By running a linear regression accounting for various controls, overall, this paper finds a weak negative association between crude oil prices and remittance inflows into the Philippines, with observed asymmetry between negative and positive shocks. Both shocks have a positive association, but negative shocks in oil prices have a much more significant positive effect on remittance inflows than their counterpart.

2 Literature Review

There is a plethora of studies seeking to investigate the empirical relationship between remittances and broader macroeconomic variables. The Philippines has a culture of migration that is characterized by an increased export of human labor that has become the country's "lifeline whenever hard times hit" (Sison 2001). The history of OFWs in the Middle East has emerged in the 1970s when there was an added demand for construction work to build infrastructure. Since then, Reside (2009) considers the effects of oil prices on remittances as a minor inclusion of shocks, relating to exchange rates, inflation and interest rates, whereas authors like Yang (2008) focus solely on the exchange rate shock during the 1997 Asian financial crisis. Literature specifically examining the relationship between oil prices and personal remittances are growing, but there is a gap in studying the Philippines' case, a developing country that ranks fourth among the top five remittance recipient countries in the world, alongside India, China, Mexico, and Egypt. Additionally, the Philippines is a strong case study given its governments' consistent release of detailed survey findings in English.

With almost a third of the world's oil produced in the Middle East, GCC countries generally rely on oil prices and exports on their economic performance. Snudden (2018) explains that GCC countries' large migrant worker population and its large share of financial transfers suggest an intrinsic association between migrant flows, remittance outflows, and the global market for crude oil. Existing literature mainly assesses the linear or symmetric relationship between crude oil prices and remittances, with a focus on the remittance sender or recipient countries. The underlying assumption is that an increase in oil prices is expected to generate oil revenues in oil-exporting and labor-importing countries. This will enhance activities and increase aggregate demand for migrant workers, and thus spur higher remittance outflow (Naufal and Termos, 2009). Looking at the cross elasticity of remittances from the GCC economies to price of oil, Naufal and Termos (2009) find a positive inelastic relationship between oil price changes and remittance outflows.

On the contrary, increasing oil prices also influence oil-importing, migrant-exporting countries; it increases the cost of production and price level, which increases the domestic cost of living (John, 2018). Analyzing the case of Sri Lanka, Lueth and Ruiz-Arranz (2007) reveal a positive relationship between remittance inflow and crude oil prices. Given this perceived positive association, many assume that a drop in oil prices can create the inverse (Akçay, 2021), where oil revenue will decrease in oil-exporting countries, reduce demand for migrant workers, and in turn, lower remittance outflows.

However, recent developments in the field have pushed back against this assumed linearity between crude oil prices and remittance flows. Akçay & Karasoy (2019) and Akçay (2021) pioneered the concept of asymmetry between this link; asymmetry emerges when positive and negative shocks in oil prices impact remittances differently. Akçay (2021) found that remittance outflows are positively affected by an increase in oil prices, but a decrease has no significant impact. Some notable studies highlight the asymmetric relationship on the oil-exporting side (Akçay, 2019) and oil-importing side (Akçay & Karasoy, 2019; Abbas, 2020; Khodeir, 2015).

While there has been substantial research on remittance outflows from GCC countries to other Asian recipient countries, the asymmetric oil-remittance relationship has not yet been evaluated in the context of the Philippines. One of the few research papers that analyzes the effect of oil price shocks on the Philippine economy's output growth specifically looks at the 2008/9 and 2014/5 oil price drops (Brucal and Abrigo, 2016). This paper assumes that the effect of oil prices on remittances is symmetric, meaning that once they find an association when oil prices rise, they neglect to examine the inverse relationship when oil prices drop. And so, this research distinguishes itself in its aims to assess the asymmetric relationship between crude oil prices and remittances and its scope on the Saudi Arabia-Philippines and more largely, the GCC-Philippines remittance corridors.

This paper has been organized in the following way to uncover the relationship between oil price fluctuations and remittances in the Philippines: Section 3 describes data collection and methodology; section 4 presents the results and analysis, section 5 conducts robustness checks, and section 6 provides conclusion statements and implications this research has on overall development efforts in the Philippines.

3 Empirical Strategy

3.1 Data Collection

Following Abbas (2020), this study utilizes a multivariate regression model that assesses the relationship between remittance inflows and oil prices, along with other explanatory variables. The data for this study span monthly from January 2000 to December 2020 and are derived from various American, Filipino, and international databases. The remittance inflow data is in million USD and is collected from the external accounts of the Bangko Sentral Ng Pilipinas (BSP), the Philippines' central bank. These values are personal remittances, computing the sum of net compensation of employees, personal transfers, and capital transfers between households. This remittance data is aggregated from bank records by land and sea-based workers across the world. Although this data does not explicitly look at remittances coming directly from GCC countries, the aggregate sum of remittance inflows into the Philippines is a strong measure reflective of the nearly 20-25% of remittances sent from GCC countries (Table 1).

Table 1: GCC Remittances to the Philippines (millions of USD)

Year	Bahrain	Kuwait	Oman	Qatar	S. Arabia	UAE	Total GCC	Global	TR**
2010	157	106	55	246	1544	775	2885	18762	15.7
2011	155	139	66	282	1613	877	3135	20116	15.6
2012	166	157	56	321	1728	960	3391	21391	15.9
2013	184	235	77	412	2109	1263	4282	22984	26.4
2014	172	455	115	698	2843	2224	6509	24628	26.4
2015	144	617	173	708	2844	2030	6517	25606	25.5
2016	175	856	412	1059	2630	2155	7290	26899	27.1
2017	229	806	345	1110	2508	2450	7540	28059	26.9
2018	234	689	228	1008	2230	2035	6425	28943	26.2
2019	323	759	229	758	2098	1592	5760	30133	19.1
2020^p	228	580	386	820	1811	1287	5114	29903	17.1

Note: ^{p}=preliminary, **TR = Percentage of Remittances in GCC/World

Source: Bangko Sentral Ng Pilipinas (2019)

Moreover, there might be some potential misreporting and under reporting of remittances given the difficult nature in measuring international migration and cash transactions. There is an assumption that remittances process through informal channels.

However, given that migration is so integrated within Filipino society and that nearly all OFWs work abroad with an existing contract, the internal reporting measures of the Filipino government are more accurate and precise than more macro-level data of remittances. Additionally, employing a monthly frequency rather than an annual frequency improves the model's precision and enables for exact estimates of oil price shocks.

Monthly data of imported crude oil prices are for West Texas intermediate (WTI), which serves as one of the main global oil benchmarks. This global price of WTI Crude, not seasonally adjusted, is measured in USD per barrel and is sourced from the US Federal Reserve Bank of St. Louis. As a proxy for GDP, the industrial production index accounts for the Philippines' economic activity. This includes the output of industrial establishments with a base year of 2010=100 that expresses change in the volume of production output. Data for this indicator, along with the inflation rate of the Philippines (measured yearly as average consumer prices); and the interest rate on deposits, are derived from the International Financial Statistics of the International Monetary Fund (IMF). The official exchange rate domestic currency of Philippine peso relative to the USD is collected from the World Development Indicators of the World Bank (WDI); the total number of Overseas Filipino Workers is offered annually from the PSA Survey of Overseas Filipinos reports; and final household consumption expenditure sourced from the BSP that was interpolated from quarterly data to monthly data using Cubic Spline Interpolation. This model also includes OECD-recession indicators calculated by FRED from the peak through the trough taking on a binary form, equaling 1 during a global recession and 0 otherwise. These indicators signify a recession for OECD member and non-member economies, consisting of 35 countries spread out across five continents, excluding South America and Antarctica. On the remittance-sending side, this paper accounts for a variable that can affect individuals' ability to send back money in relation to financial technology. The total number of transactions made monthly using Automated Teller Machines in Saudi Arabia (the top destination within the region) is included as a proxy for the ease in which migrant workers can access banking services. This variable is an aggregate sum of all transactions, including but not limited to remittance transfers. This data is accessed from the Eldridge data hub Knoema and provide a good indication of internal transaction infrastructure, especially considering limited data on banking capabilities in GCC countries and on broader fintech trends. Table 2 features the summary statistics for all the variables outlined in this section that are used in the empirical analyses. Other factors that could drive remittance inflows could include migrant wages, social and legal factors in the destination countries, remittance transaction fees, and measures of financial development (Abbas, 2020).

Table 2: Summary Statistics

Statistics	N	Mean	Std. Dev.	Min.	Max.
Log of monthly remittance inflow (millions USD)	252	21.05439	0.6057515	19.63559	21.8914
Global WTI crude oil prices	252	60.70335	26.06697	16.80727	133.9271
Manufacturing Index in the Philippines	252	99.05815	25.9664	15.28	187.65
Exchange Rate	252	48.40738	4.437907	40.427	56.3414
Inflation Rate	252	3.919048	4.437907	40.427	56.3414
Interest rates on deposits	240	3.987917	2.21714	1	12.78
Log of OFWs Worldwide	252	13.5463	0.563717	12.52424	14.1359
Log no. of ATM transactions in Saudi Arabia	237	9.688464	0.7052423	7.950502	10.73248
Recession binary indicator	252	0.488095	0.500853	0	1
Log of final household consumption expenditure (Philippines)	240	1758619	868650.2	583785	14380382

3.2 Empirical Specification

This study uses a multivariate log-log OLS model to estimate how crude oil prices affect the volume of remittance inflows to the Philippines. Running a two-step process, this research first explores overall bivariate and multivariate trends between oil prices and remittances, and then accounts for how oil prices can influence remittances differently during negative and positive shocks.

3.2.1 Section A

Following Abbas (2020), this paper constructs a complex model for remittance inflow that incorporates oil prices along with the other explanatory variables, which is presented as:

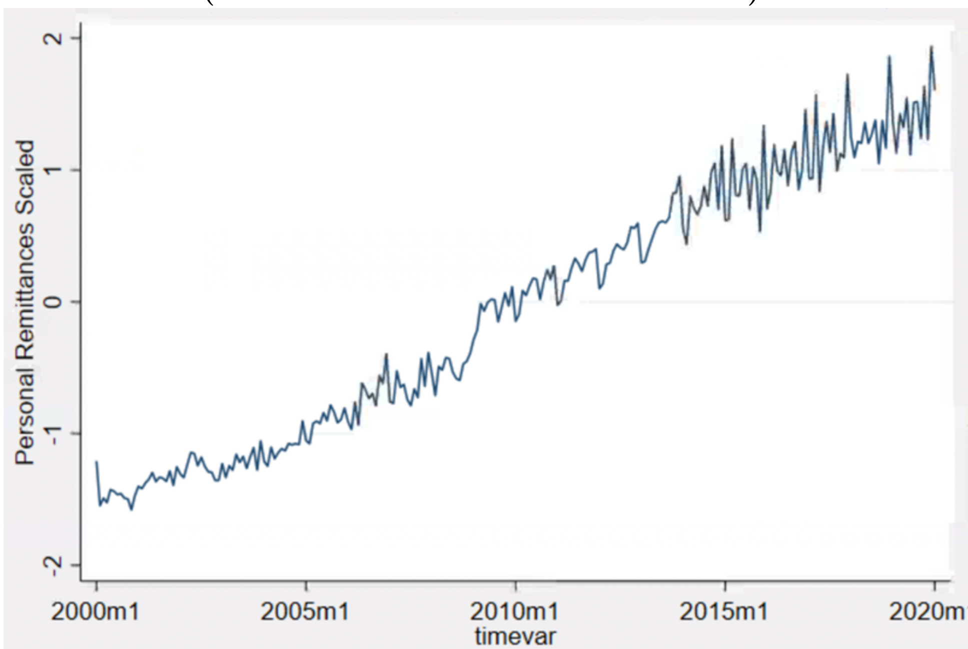
$$\begin{aligned} \ln(REM_{itd}) = \beta_0 + \beta_1(\ln(OIL_{it})) + \beta_2(\ln(PROD_{itd})) \\ +\beta_3(\ln(ER_{it})) + \beta_4(INFL_{it}) + \beta_5(INT_{it}) + \beta_6(OFW_{itsd}) \\ +\beta_7(\ln(ATM_{jtd})) + \beta_8(\ln(CONS_{it})) + \beta_9(RECESSION_t) + u_{it} \end{aligned} \tag{1}$$

where $ln(REM_{\text{itd}})$ is the detrended logarithm of workers' remittances (current USD) sent to the Philippines, country i; $ln(OIL_{\text{it}})$ is the logged price of imported WTI crude oil; $ln(PROD_{\text{itd}})$ is the detrended logarithmic value of industrial production, manufacturing index of the Philippines; $ln(ER_{\text{it}})$ is the official exchange rate; $INFL_{\text{it}}$ is the inflation rate (a proxy for macroeconomic instability); INT_{it} is the interest rate on deposits; OFW_{itd} is the detrended standardized value of OFWs; $ln(ATM_{\text{jtd}})$ is the detrended logarithm number of ATM transactions in Saudi Arabia, country j; and $ln(CONS_{\text{it}})$ is the logarithm of household consumption expenditure in the Philippines. The variable d indicates detrended, t represents time and u is the random error. All values in the model are reported monthly, besides the inflation rate and number of OFWs that are reported annually.

To remove the cyclical component within the time series data, Hodrick-Prescott (HP) filters, a widely used tool in macroeconomic analysis, were added. The HP filter smoothens the curves of four different variables in the dataset: personal remittances, industrial production, the number of OTWs, and the number of ATM transactions.

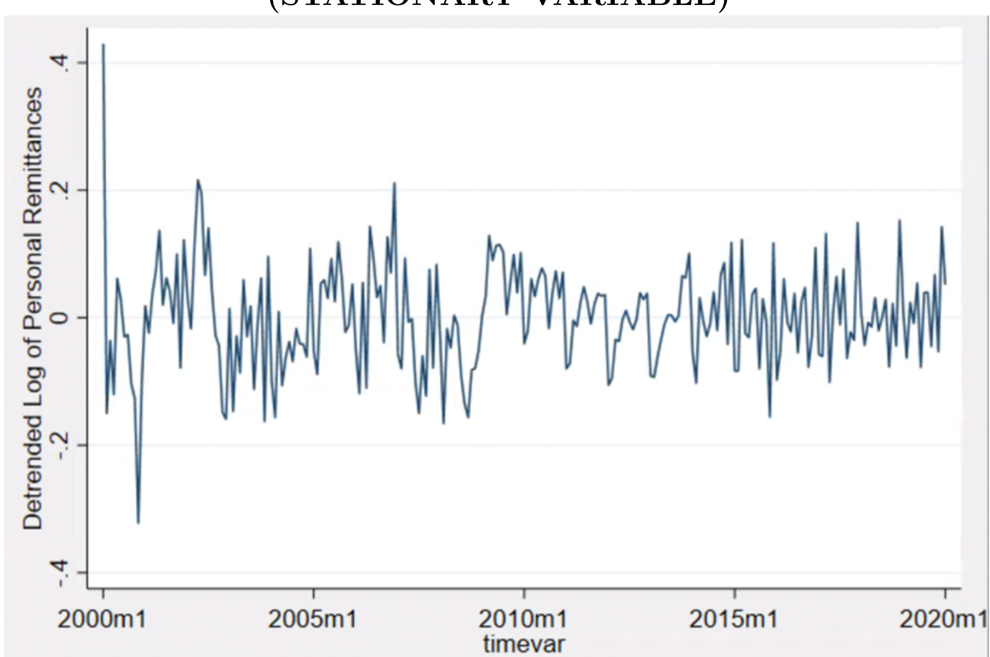
Figure 1a showcases the general deterministic global trends of remittances inflows into the Philippines in its non-stationary form and Figure 1b reflects its shift to a stationary variable once detrended.

Figure 1a: Personal Remittances into the Philippines 2000-2019 (NON-STATIONARY VARIABLE)*



*Y-axis represents the standardization of the variable (calculated by subtracting the mean from the original values and dividing it by its standard deviation).

Figure 1b: Personal Remittances Detrended with an HP Filter 2000-2019 (STATIONARY VARIABLE)



3.2.2 Section B

Another multivariate log-log OLS model is developed to understand how the magnitude of an oil drop or boost affects the value of remittances. This section aims to explore the asymmetric relationship of crude oil prices along with other explanatory variables on remittance inflows to the Philippines from GCC countries. This study runs two variations of this following regression for two instances, indicated by different conditional if statements:

$$\begin{aligned} \ln(REM_{itd}) = \beta_0 + \beta_1(\ln(OIL_{it})) + \beta_2(\ln(PROD_{itd})) + \beta_3(\ln(ER_{it})) \\ +\beta_4(INFL_{it}) + \beta_5(INT_{it}) + \beta_6(OFW_{itsd}) + \beta_7(\ln(ATM_{jtd})) \\ +\beta_8(\ln(CONS_{it})) + \beta_9(RECESSION_t) + u_{it}, \\ \text{if } \Delta OilPrice_{it} < 0 \text{ (or } \Delta OilPrice_{it} > 0) \end{aligned} \tag{2}$$

where $ln(REM_{\text{itd}})$ is the detrended logarithm of remittances inflows to the Philippines; $ln(OIL_{\text{it}})$ is the logged price of imported WTI crude oil, controlling for the lagged effects for the three months prior to when the drop occurs; $ln(PROD_{\text{itd}})$ is the detrended logarithmic value of industrial production of the Philippines; $ln(ER_{\text{it}})$ is the official exchange rate; $INFL_{\text{it}}$ is the inflation rate; INT_{it} is the interest rate; OFW_{itd} is the detrended standardized value of OFWs; $ln(ATM_{\text{jtd}})$ is the detrended logarithm number of ATM transactions in Saudi Arabia; and $ln(CONS_{\text{it}})$ is the logarithm of household consumption expenditure in the Philippines. $\Delta OilPrice_{\text{it}}$ represents the difference in oil prices, signifying that there is a drop in oil prices when this value is less than 0 and an increase in oil prices when the value is greater than 0. Similarly, the study performs two regressions, one accounting for the four main explanatory variables and the second including all the nine regressors.

4 Results

The overarching aims of this study are to assess how imported crude oil prices impact remittance inflows generally and during specific shocks. When running a bi-variate regression with remittances as the dependent variable and crude oil prices as the sole explanatory variable, there is no observed relationship between the two variables at all (Table 3).

Table 3: Bivariate Regression Results

Variables	(1) Non-Stationary[a]	(2) Stationary[b]
Log of Global Price of WTI Crude	0.70***	0
	(0.07)	(0.01)
Constant	18.24***	0
	(0.29)	(0.06)
Observations	252	252
R-squared	0.28	0

Note: [a]Dependent Variable - Remittances (log), [b]Dependent Variable - Remittances (detrended log)
Robust standard errors in parentheses: ***p<0.001, **p<0.05, *p<0.1

Once the additional main controls are included in the regression, a weak negative association between oil prices and remittances that is close to 0 and not statistically significant is observed(Columns 3 and 4 in Table 4). A 1 percent increase in oil prices per barrel is associated with either a 0.01 or 0.04 percent decrease in remittances. The table features the non-stationary results alongside the stationary results to showcase the value of detrending the time series. The coefficients of the non-stationary model firmly support the hypothesis that increasing oil prices are linked to increasing remittance inflows. However, the R-squared value of 0.98 in Column 2 suggests that these perceived strong findings might be inflated (Table 4). This nearly perfect link is unlikely in a regression that includes so many variables, especially those that are largely unexplained macroeconomic variables. The short-term fluctuations within the time series data produces these inaccurate results. By using HP filters, the model becomes more sophisticated and reflective of occurrences in the real world.

Another interesting feature in comparing the non-stationary to stationary results is the difference in sign (Table 4). Without a time trend, the data implies a positive association between oil and remittances but once it is added, there is a weak negative association, suggesting that an increase in oil prices is affiliated with a decrease in remittance inflows. This goes against the consensus within existing literature that assumes rising oil prices lead to greater economic activity within oil-exporters, thus prompting larger demand for migrant workers, and increasing remittances (Naufal and Termos, 2009; Akçay, 2021).

Table 4: Multivariate OLS Regression Results (Section A)

Variables	(1) Non-Stationary^a Main Controls	(2) Non-Stationary^a All Controls	(3) Stationary^b Main Controls	(4) Stationary^b All Controls
Log of Global Price of WTI Crude	0.64***	0.07**	-0.01	-0.04
	(0.1)	(0.03)	(0.02)	(0.03)
Log of Manufacturing Index	0.4	-0.16***		
	(0.27)	(0.05)		
Log of the Exchange Rate	0.26	0.2	-0.03	-0.02
	(0.39)	(0.17)	(0.1)	(0.12)
Annual Inflation Rate		-0.01*		0
		(0.01)		(0)
Interest Rate on Deposit		-0.01*		-0.01*
		(0.01)		(0.01)
Binary OECD-Recession Indicator	0.16**	-0.05***	-0.02	-0.02
	(0.06)	(0.01)	(0.01)	(0.01)
Scale of OFWs Worldwide		0.22***		
		(0.04)		
Log of Household Consumption Expenditure in the Philippines		0.49***		-0.01
		(0.12)		(0.03)
Log Number of ATM Transactions in Saudi Arabia		0.18*		
		(0.11)		
Detrended Log of Manufacturing Index			0.04	
			(0.03)	
Detrended Scale of OFWs Worldwide				0.02
				(0.14)
Detrended Log Number of ATM Transactions in Saudi Arabia				0.02
				(0.13)
Constant	15.59***	12.05***	0.16	0.45
	(2.19)	(0.56)	(0.46)	(0.61)
R-squared	0.34	0.98	0.02	0.04
Observations	252	237	252	237

Note: ^{a}Dependent Variable - Remittances (log), ^{b}Dependent Variable - Remittances (detrended log)
Robust standard errors in parentheses: ***p<0.001, **p<0.05, *p<0.1

Although Section A did not garner a large coefficient once the HP filters were added, this paper still attempts to explain this potential negative association that is often unobserved or neglected within the field. One plausible explanation as to why oil prices and remittances might be negatively correlated is a fundamental flaw in the leading assumption – although increased oil prices lead to more economic activity, it does not necessarily lead to higher demand for migrant workers, nor does it guarantee an increase in wages. Authors Keane and Prasad (1996) report that oil price increases lead to substantial wage cuts for all workers, but only raises the relative wage of skilled workers. Taking on a similar approach, Kisswani (2017) finds that oil price increases lead to higher services and production costs, lowering productivity, and thus "causing some companies to take cost-cutting measures such as a reduction in employment.... and wages." Given that most OFWs are unskilled workers with nearly 40 percent tasked with "elementary occupations" or simple and routine tasks (PSA), this literature suggests that because of the nature of their work, they could be negatively impacted by rising oil prices, thus lowering their disposable income/remittances behaviors.

Beyond this theoretical question of what effect wages might have on remittances, the oil-remittance relationship remains largely unexplained in Section A, marking a gap in the research for future papers. In splitting up the data into negative and positive shocks, denoted by a respective shift in difference of oil prices per month, this paper finds that that both shocks generate a positive effect. However, negative shocks in oil prices have a much more significant positive effect on remittance inflows than positive shocks do (Table 5).

For negative shocks, once accounting for a three-month lag in oil prices, a 1 percent decrease in oil prices is associated with a 0.31 percent decrease in remittances or a 0.24 percent decrease with additional controls, that are statistically significant at the 1 percent and 5 percent levels, respectively. Using the formerly mentioned regression, Column 1 (Table 5) showcases that a 1 percent decrease of Philippine's manufacturing index is associated with a decrease of 0.05 percent in remittances; a 1 percent decrease of the exchange rate is associated with a decrease of 0.07 percent in remittances; and if there is a global recession, remittances are expected to decrease by 0.02 percent, holding all else constant. Once adding more controls, the coefficient on oil prices retains its statistical significance and the recession indicator also becomes statistically significant at 10 percent. Regarding the other variables, inflation and interest rates, and population of OFWs abroad have negligible coefficients, while a 1 percent decrease in ATM transactions in Saudi Arabia is expected to decrease remittances by 0.15%. In contrast, the regressions on the positive shocks are not as substantial. A 1 percent increase in oil prices is expected to increase remittances by either 0.01 percent or 0.08 percent depending on which regression is used. Both findings reveal a positive association that is not statistically significant at any level. In conducting this comparison, this study uncovers an asymmetric relationship between oil prices and remittances, in which there is more evidence that remittance inflows to the Philippines are positively affected by a decrease in oil prices rather than an increase in oil prices. Interestingly, these findings vary from the existing literature on this topic. Akçay (2021) has found evidence of the opposite – oil price increases have a larger effect on remittances than oil price drops. The main reason for this variation can be explained in the frequency of our data sets. Akçay observes the annual oil prices changes over a 35-year period, while this paper observes the monthly variations over a 20-year period. The fluctuation of WTI crude oil prices is the main reason as to why negative shocks have a larger magnitude effect on remittances than positive shocks (Figure 2).

Table 5: Positive and Negative Shocks Results (Section B)[a]

VARIABLES	(1) Negative Shock Main Controls	(2) Negative Shock All Controls	(3) Positive Shock Main Controls	(4) Positive Shock All Controls
Log of Global Price of WTI Crude Oil	0.31***	0.24*	0.01	0.08
	(0.1)	(0.14)	(0.13)	(0.17)
Log of Global Price of, WTI Crude Oil = L1	-0.37**	-0.36*	0.08	-0.09
	(0.17)	(0.21)	(0.13)	(0.18)
Log of Global Price of WTI Crude Oil = L2	-0.04	0.04	-0.05	-0.08
	(0.15)	(0.17)	(0.1)	(0.13)
Log of Global Price of WTI Crude Oil = L3	0.11	0.08	-0.06	0.06
	(0.1)	(0.11)	(0.06)	(0.08)
Detrended Log of Manufacturing Index	0.05	-0.09	0.04	0.07
	(0.05)	(0.09)	(0.03)	(0.07)
Log of the Exchange Rate	0.07	0.13	-0.04	0.07
	(0.11)	(0.12)	(0.1)	(0.11)
Annual Inflation Rate		-0.01		0.01
		(0.01)		(0.01)
Interest Rate on Deposit		0		-0.02***
		(0.01)		(0.01)
Detrended Scale of OFWs Worldwide		0.01		0
		(0.06)		(0.05)
Detrended Log Number of ATM Transactions in S. Arabia		0.15		0.17*
		(0.1)		(0.1)
Log of Household Consumption Expenditure in the Philippines		0.03		-0.03
		(0.04)		(0.03)
Binary OECD-Recession Indicator	-0.02	-0.04*	0	0
	(0.02)	(0.02)	(0.01)	(0.02)
Constant	-0.27	-0.93	0.21	0.31
	(0.47)	(0.67)	(0.44)	(0.53)
R-squared	0.15	0.15	0.04	0.1
Observations	100	93	149	141

Note: [a]Dependent Variable - Remittances (detrended log)
Robust standard errors in parentheses: ***p<0.001, **p<0.05, *p<0.1

Figure 2: Crude Oil Prices 2000-2019[a]

[a]The red reference lines on the graph signify the two major precipitous drops within this time period; the first major drop occurred during the 2008 Global Financial Crisis for a span of six months and the great oil crash of 2014 lasted for eleven months.

Oil price drops occur at a much steeper rate than oil price increases. Most notably, there are two major precipitous drops within the data that coincide with the 2008 Global Financial Crisis and the 2014 "great oil crash" that last for a span of six and eleven months, respectively. These two precipitous drops are mechanically affecting this research. The oil-remittance relationship reflects on these abrupt variations in oil prices drops, making the negative shock findings more significant and valid than the positive shocks. While this model gives added weight to the steep decreases in oil prices, Akçay's models put more weight on the steep increases in oil prices that he observes.

5 Robustness Check

One potential criticism of these results might be the use of monthly data instead of quarterly or annual data. The monthly frequency causes the steepness of certain shifts in oil prices to appear differently, with more weight given to the negative shocks than the positive shocks (Figure 1a). While some of this variation is adjusted using the HP filters (Figure 1b), the monthly model picks up on the nuances and minute variations within oil price increases, whereas Akçay's (2021) annual model displays the oil price increases as steep upward trends. While both methods are valuable, using monthly observations offers a larger sample size, adds specificity to the model, and discerns trends that other literature overlooks. Moreover, by adding lags in oil prices, this model accounts for delayed effects of oil price shocks. The consensus is that oil price increases aggregate demand for migrant workers, which increases remittance outflows. Labor economics supports this notion; heightened demand for labor also rises the level of employment and wage rate. Since the profound effects of oil prices on the economy and society take time to actualize, a 12-month interval more accurately represents these broad changes than a 1-month period. However, adding a three-month lag in the model pushes back the oil price up to 3 months, controlling for this delayed impact in labor within GCC economies.

Given how closely labor economics is linked to remittance flows from GCC countries to the Philippines, it would be interesting for future research to investigate the effects of rising oil prices on OFW's wages. Adopting similar methodology as Keane and Prasad (1996), future papers could specifically assess how oil price fluctuations effect the demand and wages of skilled versus unskilled workers. Though, this study might be heavily limited given the underreporting of migrant wages in GCC countries. Perhaps more straightforward, it would also be interesting to evaluate the incorporation of explanatory variables that can affect OFW's financial, technological, or logistical ability to send remittances rather than broad macroeconomic indicators. Such variables can include cost of living in GCC countries and remittance transaction costs, such as fees associated with international money transfer applications.

6 Conclusion

With rapid globalization and governmental policies promoting labor migration, remittance inflows to the Philippines have been consistently trending upwards. Nearly half of all OFWs are employed in GCC countries and nearly a third of the aggregate remittance inflows come from this region. This paper is original in its quest to evaluate the asymmetric oil-remittance relationship in the context of the Philippines that has not been evaluated within existing literature. Utilizing multivariate OLS regression models to estimate how crude oil prices affect the volume of remittance inflows to the Philippines, this study analyzes overall trends and trends during negative and positive shocks. Each section is divided into two regressions, the first of which includes the main controls (crude oil prices per barrel, industrial production, exchange rate, and a recession indicator) and the second of which includes additional controls(inflation and interest rates, number of OFWs, number of ATM transactions in Saudi Arabia, and final household consumption expenditure). Applying stationary variables using Hodrick-Prescott filters, this paper finds a weak negative association between crude oil prices and remittance inflows into the Philippines. While both shocks have positive associations, negative shocks in oil prices have a much more significant positive effect on remittance inflows than positive shocks.

Accounting for a three-month lag in oil prices, this study reveals that a 1% decrease in oil prices is associated with a 0.31% decrease in remittances (or 0.24% with additional controls). These results are statistically significant at the 1% and 5% level, respectively. This varies from the effects on remittances during a positive shock – a 1% increase in oil prices is expected to increase remittances by either 0.01% or 0.08% with the added controls, not statistically significant at any level. Given that the fluctuations in crude oil prices consist of steeper drops than increases, this paper observes a different asymmetric relationship than Akçay (2021).

These findings have implications on the role that remittances, comprising nearly 10 percent of the Philippine economy, have on development efforts in the Philippines. With over 2 million OFWs working overseas, migrant workers enact trickle-down change for their family members, households, and communities. There is considerable literature that showcases the effect of remittance inflows on various elements of Filipino society (Ahmad and French, 2014), with evidence that higher remittances are expected to increase investment in education, housing, and healthcare (Tabuga, 2007). Understanding that negative shocks to oil prices can significantly impact remittance inflows offers greater insight as to what drives remittances, which can guide future policy recommendations.

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Do Overseas Development Assistance and Foreign Direct Investment Impact The Carbon Dioxide Emissions Of Developing Countries?

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Abstract

This paper analyzes the effects of overseas development assistance (ODA) and foreign direct investment (FDI) on carbon dioxide (CO_2) emissions between 2007 and 2018 on 118 aid-receiving countries. It builds upon the work of Lim (2014), who analyzed the impact of ODA and FDI on sulfur dioxide (SO_2) between 1980 and 2005, instead running ordinary least squares (OLS) estimations focusing on CO_2 emissions' relationships with ODA and FDI. The models in this paper control for GDP, the presence of carbon taxes and emissions trading systems, and add country and time-fixed effects. The results of the equations find a small and statistically insignificant, but negative association between CO_2 emissions and ODA, which is similar to Lim's findings of a negative and statistically significant relationship between the variables for small-aid-recipient countries. Meanwhile, a statistically significant and positive association does exist between CO_2 emissions and FDI. JEL Codes: F20, F21, F30, F31, O10, O19, Q50, Q53, Q56

1 Introduction

The relationships that overseas development assistance (ODA) and foreign direct investment (FDI) have with carbon dioxide (CO_2) emissions is key for policymakers to understand. Since the late 20^{th} century, world leaders have expressed concern about the future of the earth's environment and climate. While many politicians recognize the environmental problem and the role of CO_2 in creating this problem, many are reluctant to act. At its core, clean environments are often viewed as a normal good (Mak Arvin, 2009), meaning that countries will only prioritize environmentally focused policies when they are financially secure.

With today's international dialogue on the causes and effects of climate change, countries with increased wealth will typically choose environmentally friendly policies. Because lower-income countries cannot yet afford environmentally focused policies, developed countries have an incentive to increase the wealth of lower-income countries for their own future well-being.

A common and direct way for wealthy countries and their institutions to assist developing countries is through overseas development assistance. ODA's ability to cause true economic growth has been disputed by some economists, though its effectiveness depends on the climatic and governance situations within the recipient country (Dalgaard, 2004).

Developing countries similarly receive foreign direct investment (FDI), which differs from ODA in that it is typically given as a private investment. To receive FDI, countries usually have locational advantages and cheap labor for businesses to utilize (Wang, 2011). Because of questions regarding the overall effectiveness of ODA, Moyo (2010) argues that donor countries should reduce ODA while developing countries should work towards receiving more in FDI. Wang disputes this claim, instead arguing that the two should be paired and well-balanced. This paper utilizes updated data from 118 countries between 2007 and 2018 and an ordinary least squares (OLS) model based off Lim's 2014 study on sulfur dioxide (SO_2), ODA, and FDI to verify these relationships. Four main regressions analyze the relationships between CO_2 emissions, ODA, and FDI with combinations of GDP and the presence of carbon taxes and emissions trading systems as control variables in addition to country and time fixed effects. This paper's findings suggest that policymakers interested in promoting decarbonization in the Global South could use ODA as a tool to accomplish this goal but should focus more on cautiously utilizing FDI.

2 Literature Review

This paper analyzes the effects that ODA and FDI have on CO_2 emissions in ODA and FDI receiving countries. Both variables are necessary to include due to the different procedures countries go through to receive both.

As outlined by Wang, FDI requires recipient countries to be competitive. One way developing countries will attempt to compete for investment is through relaxed environmental regulations, commonly known as the "pollution haven" hypothesis. Levinson and Taylor (2008) find that American environmental regulations between 1977 and 1986 caused a 10% increase in net imports. The pollution haven hypothesis challenges the normal good assumption of a clean environment, as developing countries with booming export economies may not have the incentive to strip themselves of their comparative advantage. Previous analyses show a positive relationship between FDI and pollution (Yousef, 2016).

If the pollution haven hypothesis holds true as the primary reason for a positive relationship between CO_2 emissions and FDI, then it is important to distinguish between the investment itself and the agency of the country's government to act, specifically on environmental matters. When countries with high levels of foreign direct investment additionally have strong governance metrics, CO_2 emissions continue to decrease (Farooq, 2021). Therefore, countries with both high amounts of CO_2 emissions and high amounts of FDI are likely to suffer from bad governance or a lack of environmental laws. One solution to this problem could be for developing countries to implement a market for pollution (Lim, 2014).

While countries must "compete" for FDI, they must fulfill other sets of objectives to receive and continue receiving ODA. Mak Arvin and Lew (2009) discuss the importance of donor countries' motives in giving aid. They find that donors between 1990 and 2002 rewarded recipient countries for certain environmental outcomes, such as forestation, while not emphasizing carbon dioxide emissions. Yet, their results show that higher sums of bilateral aid decrease carbon emissions to a greater magnitude than deforestation.

3 Data Description

This paper uses publicly available data from the World Bank's World Development Indicators and Carbon Pricing Dashboard. CO_2 emissions (measured in kilotons), FDI (measured in net inflows, current U.S. dollars (USD)), and ODA (measured in current USD) are found in the DataBank World Development Indicators database. Data from the 118 countries that report yearly ODA and FDI numbers between 2006 and 2017 (timeframe explained below) is included as well as yearly CO_2 emissions data between 2007 and 2018. Data on carbon taxes came from the World Bank's Carbon Pricing Dashboard. Model 1 below is used by Lim (2014) and is the basis for this paper's model:

$$SO_2Intensity_{i,t} = \phi_1 SO_2Intensity_{i,t-1} + \gamma_1 Aid_{i,t-1} + \gamma_2 GlobalizationFlow_{i,t-1} + \gamma_3 Aid * GlobalizationFlow_{i,t-1} + X_{1,t}\beta_1 + \alpha_i + \tau_t + \epsilon_{it}.$$

Lim's model follows theories developed by economists that ODA tends to decrease a country's carbon emissions, while FDI causes an increase. ODA is often tied to environmental programs and conditions applied by the donor country, while FDI is invested by private companies looking to maximize profits and sometimes evade environmental regulations. Therefore, greater sums of ODA will tend to decrease emissions while greater FDI sums increase emissions.

This paper makes several changes to Lim's model. First, since Lim used data on independent variables between 1980 and 2005, this paper uses updated data on the independent variables from 2006 to 2017. Secondly, CO_2 emissions replaces SO_2 emissions because recent international climate agreements such as the Kyoto Protocol and the Paris Climate Accords focus on reducing CO_2 emissions.

Lim's discussion on the importance of environmental laws leads to the addition of binary variables for two popular environmental policies. Lim specifically suggests a cap-and-trade or emissions trading system (ETS). However, as only one country (Kazakhstan) in this paper's dataset employed an ETS during the timeframe analyzed, a variable for a carbon tax, a policy that is still rare but more prevalent among ODA-receiving countries, is also added. Data on environmental laws follows the 1-year lagged timeframe for CO_2 emissions (2007-2018). For example, Mexico first enacted its carbon tax legislation in 2014. In order to capture the full affects of the legislation on CO_2 emissions from the moment it was enacted, the dataset constructed for this paper records a "1" from the year 2014 onward for CO_2 emissions, which corresponds to ODA, FDI, and GDP data from 2013.

Finally, two equations divide CO_2 emissions, ODA, and FDI by GDP while removing GDP as a control variable. These equations allow for an analysis of a hypothetical relationship between ODA and FDI as a fraction of a country's GDP.

Table 1 below describes each variable, while Table 2 provides descriptive statistics. Figure 1 displays a scatterplot with CO_2 emissions on the vertical axis and ODA on the horizontal axis, while Figure 2 displays a scatterplot for the relationship between

CO_2 emissions and FDI. Figure 3 shows the relationship between CO_2 emissions per USD of GDP and ODA per USD or GDP, with Figure 4 providing a zoomed in scale of the x-axis. Figure 5 shows the relationship between CO_2 per USD of GDP and FDI per USD of GDP.

Table 1: Variable Descriptions

Variable	Description	Source
Carbon dioxide Emissions	Kilotons emitted per year	World Bank: World Development Indicators
Overseas Development Assistance (ODA)	Net amount of aid received per year. Measured in current US dollars.	World Bank: World Development Indicators
Foreign Direct Investment (FDI)	Net inflows per year. Measured in current US dollars.	World Bank: World Development Indicators
Carbon Tax	Indicates whether or not country had a carbon tax law in a given year.	World Bank Carbon Pricing Dashboard
Emissions Trading System	Indicates whether or not country had an emissions trading system implemented in a given year.	World Bank Carbon Pricing Dashboard

Table 2: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Emissions (kt)	1,416	142741.2	858026	10	1.03e+07
Emissions per capita (kt)	1,416	.0021793	.0026445	.0000246	.0162839
ODA (current USD)	1,416	6.59e+08	9.58e+08	-9.90e+08	1.14e+10
FDI (current USD)	1,416	4.55e+09	2.11e+10	-1.02e+10	2.91e+11
GDP (current USD)	1,416	1.70e+11	8.11e+11	2.29e+07	1.23e+13

Figure 1

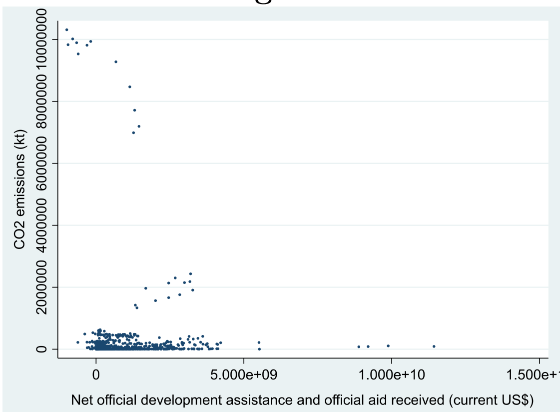


Figure 2

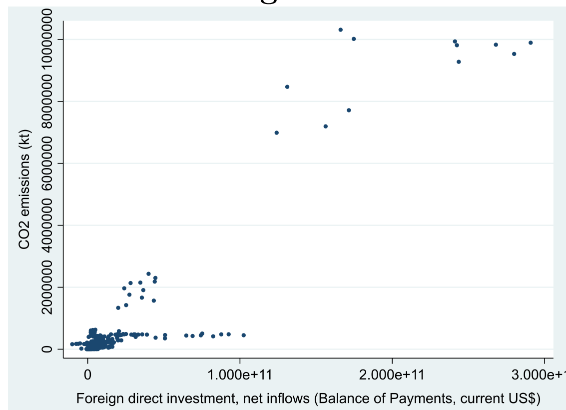


Figure 3

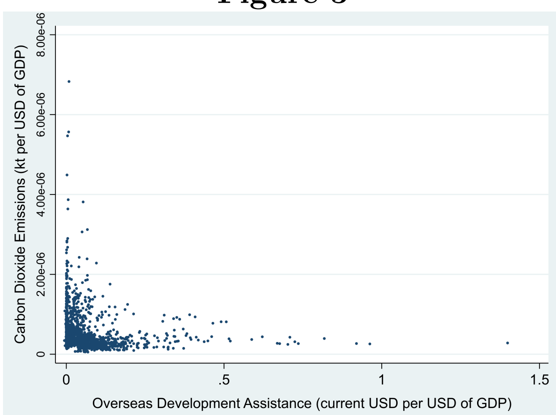


Figure 4

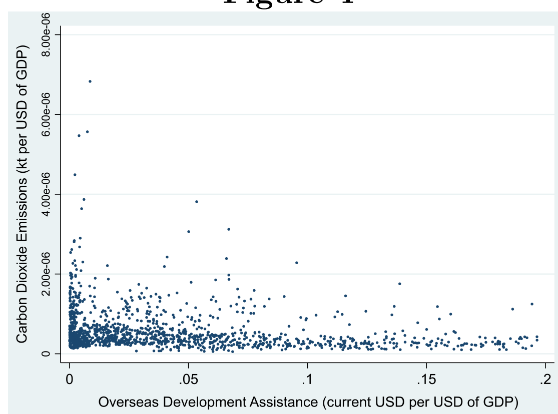
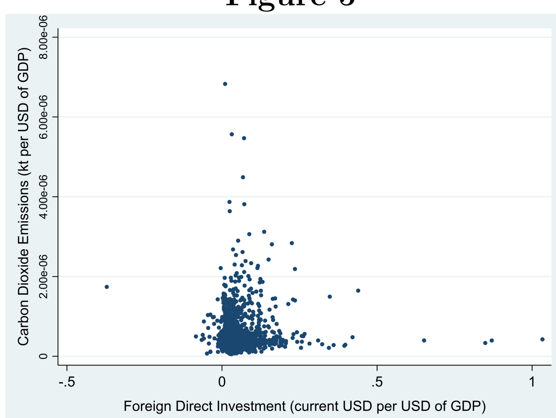


Figure 5



In order to test the theory that ODA causes CO_2 emissions to decrease while FDI causes CO_2 emissions to increase, 4 ordinary least squares (OLS) regressions are run with slight variations. Lim's 1-year lag on CO_2 emissions data is maintained, meaning the CO_2 data was collected between 2007 and 2018. This lag allows the model to better estimate the true effects of ODA and FDI since their potential effects on CO_2 emissions do not happen overnight. Equations (2) and (4) contain country and year fixed effects in order to control for potential country and year-specific qualities that could change the relationship between ODA, FDI, and CO_2. In (1) and (2), GDP is added as a control variable to prevent differing results between small and large countries. Meanwhile, in (3) and (4) GDP is removed as a control variable, and the rest of the equations' numerical variables are divided by GDP in order to measure intensity, or units per dollar of GDP. In (3) and (4), an interaction term for ODA/GDP and FDI/GDP is added in order to avoid the potential collinearity caused by a statistically significant relationship between the two variables (Table 3).

Table 3: Interaction Term

FDI/GDP	Coefficient	Robust SE	t	p > |t|	[95% Conf.	Interval]
ODA/GDP	.0805633	.0471554	1.71	0.088	-.0119387	.1730653
_cons	.0443104	.0025178	17.60	0.000	.0393714	.0492493

Below are the regression equations used in this paper:

$$(CO_2)_{i,t} = \beta_1 ODA_{i,t-1} + \beta_2 FDI_{i,t-1} + \beta_3 GDP_{i,t-1} + \beta_4 Tax_{i,t} + \beta_5 ETS_{i,t} + \alpha_{i,t} \quad (1)$$

$$(CO_2)_{i,t} = \beta_1 ODA_{i,t-1} + \beta_2 FDI_{i,t-1} + \beta_3 GDP_{i,t-1} + \beta_4 Tax_{i,t} + \beta_5 ETS_{i,t} + \alpha_{i,t} + \epsilon_i + \tau_t \quad (2)$$

$$\begin{gathered}(CO_2)_{i,t}/GDP_{i,t-1} = (\beta_1 ODA_{i,t-1})/GDP_{i,t-1} + (\beta_2 FDI_{i,t-1})/GDP_{i,t-1} \\ + \beta_4 Tax_{i,t} + \beta_5 ETS_{i,t} + \beta_6 (ODA/GDP) * (FDI/GDP) + \alpha_{i,t}\end{gathered} \quad (3)$$

$$\begin{gathered}(CO_2)_{i,t}/GDP_{i,t-1} = (\beta_1 ODA_{i,t-1})/GDP_{i,t-1} + (\beta_2 FDI_{i,t-1})/GDP_{i,t-1} \\ + \beta_4 Tax_{i,t} + \beta_5 ETS_{i,t} + \alpha_{i,t} + \epsilon_i + \tau_t\end{gathered} \quad (4)$$

Where α represents the error term, ϵ represents country fixed effects, and τ represents time fixed effects. Table 4 below displays the results of these regressions. The coefficients reported here are standardized, meaning a one-unit change in standard deviation of the independent or control variable causes a change in standard deviation equal to the coefficient's magnitude for CO_2 emissions. Numbers in parentheses below each coefficient represents that coefficient's robust standard error.

In each equation, the coefficient for ODA is negative, while the coefficient for FDI is positive, in accordance with previous literature and theory. While FDI's positive coefficient maintains at least some level of statistical significance in each equation, ODA's coefficient only has statistical significance in Equation (3). Moreover, the size of ODA's coefficients are minuscule, with a one-unit change in ODA only changing the standard deviation of CO_2 emissions in the thousandths. In Equations (1), (2), and (3), the standard error is greater than the coefficient, suggesting the unreliability of a consistently negative coefficient.

Table 4: Regression Results

Variable	(1) CO^2 Emissions (kt)	(2) CO^2 Emissions (kt)	Variable	(3) CO^2 Emissions (kt/GDP)	(4) CO^2 Emissions (kt/GDP)
ODA	-0.00081138	-0.00078225	ODA/GDP	-0.15372242***	-0.00293739
(USD)	(0.00586373)	(0.00299160)	(USD)	(0.02256842)	(0.01188576)
FDI	0.41700090***	0.07985355**	FDI/GDP	0.07462314**	0.03729267*
(USD)	(0.12076048)	(0.03355167)	(USD)	(0.03724286)	(0.02062566)
GDP	0.55198446***	0.28800860***			
(USD)	(0.09369789)	(0.02699875)			
Carbon Tax	-0.31215015**	-0.06242748***	Carbon Tax	0.82350164**	-0.15052729
	(0.12837643)	(0.01591567)		(0.34348577)	(0.17847225)
ETS	-0.03182098	-0.01415637	ETS	1.10428532***	-0.89996742***
	(0.04543385)	(0.01359590)		(0.18890021)	(0.29678803)
			ODA/GDPx	-0.00978873	-0.00507825
			FDI/GDP	(0.00994719)	(0.00430003)
Fixed Effects	No	Yes	Fixed Effects	No	Yes
Adj. R-sq	.90641936	.99745188	Adj. R-sq	.03732852	.79391393

Note: Robust standard errors in parentheses: ***$p<0.001$, **$p<0.05$, *$p<0.1$

Among the control variables, the coefficient for a carbon tax is statistically significant in (1), (2), and (3). However, (3) is also the only equation where the carbon tax has a positive coefficient, suggesting that the presence of a carbon tax increases the carbon intensity of a country by more than one standard deviation. Emissions trading systems gain statistical significance in (3) and (4) and experience the same phenomenon as carbon taxes with a positive coefficient in (3).

3.1 Robustness Checks

The adjusted R-squared statistic remains high for (1), (2), and (4); however, its value in (3) is 0.03732852, showing that the model explains very little of the variance in emissions. The positive coefficients given to both carbon taxes and ETS are therefore less verifiable, especially considering that their coefficients are negative in the three other equations with higher adjusted R-squared values.

Equations (2) and (4) have higher adjusted R-squared values than (1) and (3), respectively, suggesting the value of adding fixed effects to the equation. Therefore, I run additional regressions with only country and year fixed effects as independent variables. When emissions are measured in kilotons, the adjusted R-squared value is .98254381. When emissions are measured in kilotons per dollar of GDP, the adjusted R-squared value is .79204029. The massive jump in adjusted R-squared value between (3) and (4) show how the tremendous effect the fixed effects have in explaining the variance of (4).

An alternative control to fixed effects is population. To measure whether the fixed effects or population fit the model better, population replaces fixed effects in equations (2) and (3). Population additionally has a bivariate relationship with ODA, FDI, and

GDP, leading to the inclusion of interaction terms in both equations. Table 5 below shows the results. All numeric variables have standardized coefficients.

Notably, the adjusted R-squared in (6) remains low as with (3), suggesting that the fixed effects are unique in explaining the large variance in (4).

In (5), FDI notably has a statistically significant and negative coefficient with emissions, challenging previous literature and this paper's own results. It is possible that adding population creates extra noise in the model not present when fixed effects are added.

Residual plots for the primary 4 equations are displayed below. Figure 6 represents the residuals for emissions in (1), Figure 7 for emissions in (2), Figure 8 for emissions/GDP in (3), and Figure 9 for emissions/GDP in (4).

Table 5: Adjusted Regression Results

Variable	(5) Emissions (kt)	Variable	(6) Emissions (kt/GDP)
ODA (in USD)	-.0064367 (.0053012)	ODA/GDP	-.0915495*** (.0200637)
FDI (in USD)	-.2412494*** (.0512808)	FDI/GDP	.1176027* (.0586979)
GDP (in USD)	.3614664*** (.0827087)		
Population (total)	.2424995** (.0875618)	Population/GDP	-.0865683* (.0464095)
ODAxPopulation	-.0561615 (.0454101)	(ODA/GDP)x (Population/GDP)	-.0301333 (.0420544)
FDIxPopulation	.7657716*** (.1054359)	(FDI/GDP)x (Population/GDP)	-.0776304 (.0491268)
GDPxPopulation	-.0838641 (.0966372)		
Tax	.1435399*** (.0253904)	Tax	.7811195* (.3478016)
ETS	.2457018*** (.0285018)	ETS	1.034436*** (.1863496)
Adjusted R-squared	.97172433	Adjusted R-squared	.05180238

Note: Robust standard errors in parentheses: ***p<0.001, **p<0.05, *p<0.1

Figure 6: Emissions Residuals (1)

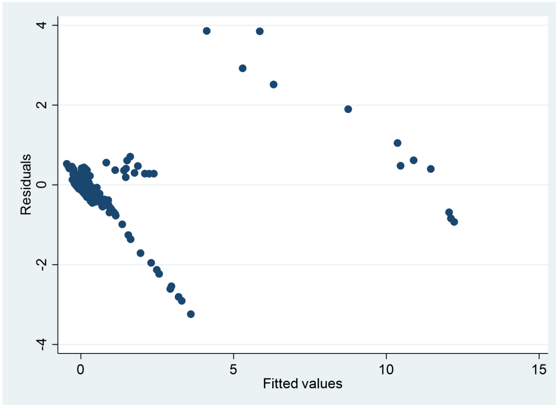


Figure 7: Emissions Residuals (2)

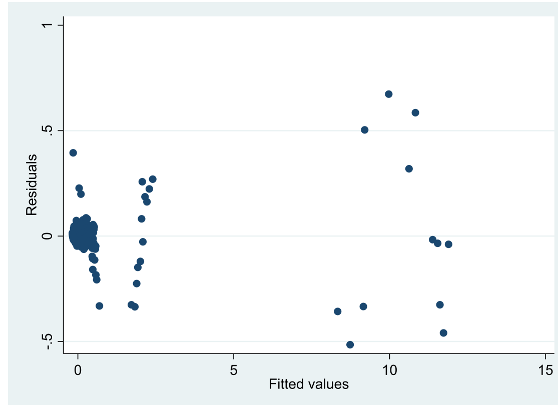


Figure 8: Emissions/GDP Residuals (3)

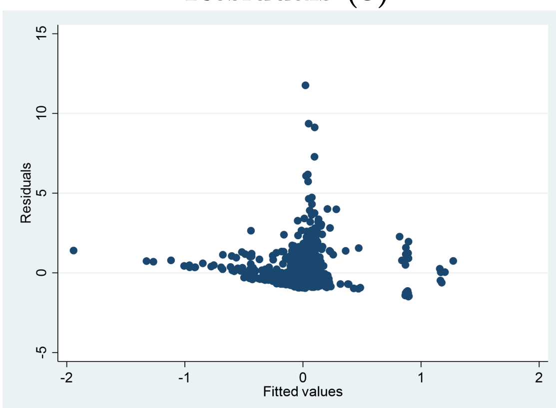
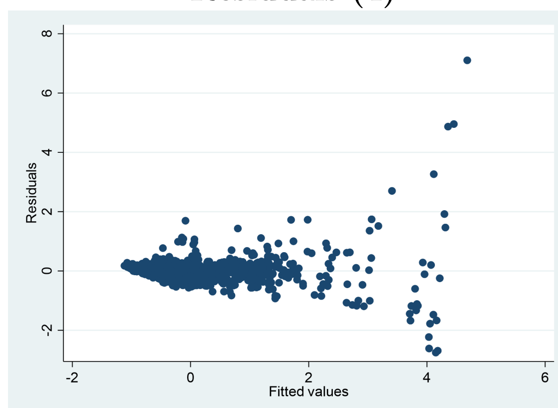


Figure 9: Emissions/GDP Residuals (4)



The absence of a polynomial form in each plot confirms that no logged terms are necessary in equations (1) through (4).

One major limitation of this study is that the data on ODA is the total value of bilateral and multilateral assistance received by the country in the given year. Development assistance often has conditions placed upon it by the donor country or agency. It is plausible that development assistance specifically earmarked for carbon mitigation projects or at least containing incentives for mitigation more strongly associates with reduced emissions.

While carbon taxes and emissions trading systems are innovative, market-based solutions touted by many economists as the most effective carbon mitigation policies, they are not the full breadth of environmental laws. It is possible that the countries denoted as implementors of carbon taxes or emissions trading systems are already more environmentally conscious than their contemporaries in this study. Thus, the true relationship between environmental laws and carbon mitigation could lie with other, unincluded laws and policies.

Inaccuracies within the data itself are likely considering the existence of rounded numbers within the dataset. Additionally, self-reporting countries and the World Bank have vested interests in ensuring future financial support, which could lead to higher tolerance of slightly inaccurate but believable data. However, due to the likely small nature of any inaccuracies, the relatively small change in magnitude by rounding, and the large number of countries included in the study, more accurate data likely does not change the overall conclusions of this paper.

The data could have reached a different conclusion with a longer lagging period. This paper's model lagged CO_2, carbon tax, and ETS data by one year in accordance with Lim's lagging of the dependent variable. It is possible that development assistance, investment, and wealth from two or more years prior has a greater influence over emissions than the same data from only one year prior.

Countries included in this study are those that had data on each variable for each relevant year. Likewise, many countries, especially smaller island countries which typically receive ODA, are not included. This exclusion could lead to an exclusion bias, though arguably the minimal impact these countries have on world net CO_2 emissions prevents their exclusion from tampering with any important policy conclusions derived from these results. Had smaller island countries been the difference maker causing an association between ODA and CO_2 emissions to occur, the statistically insignificant association in the larger countries included in the regression means this study could have overestimated the total impact of ODA on net CO_2 emissions.

4 Conclusion

This paper estimates the relationship between CO_2 emissions per capita and ODA, FDI, and carbon taxes and emissions trading systems in an OLS regression. The model is unable to confirm a statistically significant negative relationship between carbon emissions and ODA but can confirm a statistically significant and positive relationship between emissions and FDI. Meanwhile, the presence of carbon taxes and emissions trading systems negatively relates to emissions. Because of this relationship between the presence of environmental laws and emissions, the model's results echo claims of previous papers on the importance of strong governance and environmental enforcement to mitigate CO_2 emissions, regardless of FDI's true effect.

Future research should analyze the limitations outlined in the robustness checks section. Utilizing nonlinear regressions and increasing lag time could lead to more significant results, as would utilizing conditional ODA data, dividing the variable between environmentally-focused assistance and non-environmentally-focused assistance. Studies several years from now will likely see clearer results on environmental laws as well, as the relatively small selection of aid-recipient countries with carbon taxes and emissions trading systems inevitably grows.

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