UNIVERSITY OF COPENHAGEN
FACULTY OF SOCIAL SCIENCES

Bachelor Thesis

Industrial Policy and Economic Transformation: The Impact of South Korea's 1970s Heavy Chemical Industry Drive on Long-Term Growth

Research Question: How did South Korea's 1970s Heavy Chemical Industry (HCI) drive influence its long-term GDP per Capita growth?

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Industrial Policy and Economic Transformation: The Impact of South Korea's 1970s Heavy Chemical Industry Drive on Long-Term Growth

A Bias-Corrected Synthetic Control Method Approach to Understanding South Korea's Divergence in the Late 20th Century

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Abstract

This thesis investigates the long-term impact of South Korea's Heavy Chemical Industry (HCI) drive, initiated in 1972, on the country's economic development, specifically GDP per capita growth. Employing the Bias-Corrected Synthetic Control Method (BC-SCM), the study constructs a counterfactual scenario to isolate the effects of the HCI policy by comparing South Korea's trajectory to a synthetic counterpart derived from a donor pool of comparable countries. The findings reveal that the HCI drive significantly contributed to South Korea's economic divergence from its contemporaries in Asia, with GDP per capita rising well above synthetic estimates in the decades following the intervention.

Robustness checks, including Leave-One-Out (LOO) analysis and temporal placebo tests, further validate the results, showing consistent evidence of the policy's positive impact on long-term growth. Supplementary analysis of sectoral growth and employment trends highlights how the manufacturing and industrial sectors drove this transformation, with labour productivity surging as resources were reallocated to high-growth industries.

The results contribute to the broader discussion on the effectiveness of targeted industrial policy in fostering rapid economic development and suggest that South Korea's experience holds valuable lessons for emerging economies seeking structural transformation.

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1 Introduction

The question whether, and if so how, government intervention and action can be a net positive has been widely debated over the past half century. Industrial policy and its effects has been a continuous discussion point amongst economists and has seen a resurgence in later years. In the field of emerging economies, the case of South Korea's Heavy Chemical Industry (HCI) drive in the 1970s is a notable example; cited both as a decisive policy that transformed the country's economy or as something the South Korean economy had to overcome. The HCI drive selected several key sectors to channel development resources into, these were: steel, petrochemicals, auto-mobiles, machine tools, shipbuilding, and electronics. Understanding the long-term impacts of this policy could yield valuable insights into the potential role of state intervention in industrialization.

The primary research question of this study is: *"How did South Korea's Heavy Chemical Industry drive influence its long-term GDP per capita growth?"* To address this, I employ the Synthetic Control Method (SCM), originally developed by Abadie and Gardeazabal (2003); Abadie et al. (2010), and further refines the analysis using the Bias-Corrected Synthetic Control Method proposed by Ferman et al. (2020), which enhances the robustness and reliability of the results.

While substantial research has been conducted on the so called "Miracle on the Han River", there is limited empirical analysis that attempts to isolate the effects of the HCI drive from other contributing factors. This paper aims to address this gap, by using the Synthetic Control Method (SCM) to assess how South Korea's GDP growth would have evolved in the absence of the HCI drive, using data from Penn World Tables and a carefully constructed synthetic control group; based on historical and economic factors. Data from the World Bank Group (WBG) and the International Labour Organization (ILO) is used for a supplementary descriptive statistical analysis of sectoral data in order to contextualize, and enhance, the findings from the SCM. Using indexed values for GDP contributions and employment trends across different sectors, the statistical analysis provides a clear visualization of the structural economic transformation during both pre- and post-treatment periods in South Korea.

The analysis of the HCI-drive reveals substantial long-term impacts on South Korea's economic development. South Korea's GDP per capita growth diverged significantly from a synthetic control group in the decades following the introduction of the HCI policy; with an estimated increase of approximately 90 percent in GDP per capita by 1980. This divergence continued to widen over the following years, culminating in 1990 at more than 200 percent, suggesting persistent and significant long-term effects on growth. Supplementary analysis of sectoral growth shows that the manufacturing and industrial sectors experienced substantial increases in value added during the HCI period, with manufacturing output multiplied more than 65 times between 1960 and 1990. During the same period a larger section of the labour force transitioned towards these high-growth sectors. In contrast, the agricultural sector displayed relatively modest changes, once again indicating that the HCI drive's focus on heavy industry was instrumental in South Korea's economic transformation. Based on these findings, I suggest that targeted industrial policy not only accelerated South Korea's growth but also contributed to its long-term divergence from most of its economic contemporaries in Asia.

The thesis is organized as follows: Section 2 provides a brief historical context, Section 3 outlines the methodology, Section 4 presents the data. Section 5 presents the results and robustness test. Section 6 discusses the findings and their implications. Finally, section 7 concludes.

This thesis has leveraged ChatGPT in the following ways: Spellcheck, creating and adjusting various tables, figures and sections, finding and sorting references. Any and all information given by ChatGPT has manually been verified, and checked by myself.

2 Policy Background: The Heavy Chemical Industry Drive

Historical Context - End of the Korean War and the Asian Economic Miracle

Today South Korea is known for a wide variety of things. From world famous bands like BTS and Blackpink to industry leaders such as Samsung and Hyundai, it seems that South Korea has a knack for producing sophisticated products and services that are enjoyed the world over. But how was it that a fledgling nation, which less than 75 years ago was embroiled in devastating civil war and purportedly had a gross national income per capita of less than 70 USD [1], transformed itself into an economic powerhouse with a GDP per capita of more than 33,000 USD today[2]?

Table 1: Key Economic and Political Events Leading to the HCI-Drive

Year	Event/Policy	Description
1948	Proclamation of Republic of Korea	Syngman Rhee becomes the first president after the adoption of a new constitution and UN-supervised elections.
1953	Korean Armistice Agreement	Ended three years of civil-war, splitting the Korean Peninsula at the 38th parallel.
1961	Military Coup	General Park Chung-Hee overthrows the Second Republic, laying the groundwork for his long-term presidency.
1962	First Five-Year Economic Plan	Focused on building infrastructure to establish a self-reliant economy and foster rapid modernization. Key areas included basic industries and export-driven growth.
1965	Normalization Treaty with Japan	Provided access to Japanese funds through loans and compensation for colonial damages, boosting industrial capacity. ("Treaty on Basic Relations between Japan and the Republic of Korea", 1965)
1967	Second Five-Year Economic Plan	Initiated a shift toward heavy industries such as steel and petrochemicals to increase global competitiveness.
1972	Yushin Constitution and Martial Law	Park declared martial law, dissolved the National Assembly, and suspended the constitution. The regime emphasized control over economic policy and launched the HCI drive.
1973	Heavy Chemical Industry (HCI) Policy Implementation	Targeted key industries including electronics, shipbuilding, machinery, petrochemicals, and non-ferrous metals. The government borrowed heavily to ensure that it maintain control, rather than allowing direct foreign investment. (HORIKANE, 2005)
1979	Park's Assassination	After calling for the violent suppressing of demonstrations for democratization and equity, Park was assassinated by the Korean Central Intelligence Agency director. ("Park Chung-hee's Yushin: Road to Dictatorship", 2010). .

[1] Gross National Income is reported as being 67 USD in 1953, The Korea Herald (2015)
[2] Data sourced World Bank, South Korea Country Data, accessed November 2024.

South Korea and its Contemporaries[3]

South Korea is counted as one of the countries in The East Asian miracle, eight high-performing Asian economies, which from 1965 to 1990 underwent dramatic economic growth, improved human welfare, and more equitable income distribution.[4] But even among the so-called Asian Tigers - South Korea, Hong Kong, Taiwan and Singapore - South Korea stands somewhat out. In 1960, South Korea's GDP per capita (constant 2017 USD) was approximately $1,250, lagging significantly behind Hong Kong (approximately $6,000), Taiwan (approximately $2,600), and Singapore (approximately $2,760). By 1972 South Korea's GDP per capita had reached $2,828, surpassing Thailand ($2,578) but still trailing the Tigers. Eighteen years later, in 1990, South Korea's GDP per capita had soared to $13,819, eclipsing its regional contemporaries, such as the Philippines ($4,103) and Indonesia ($3,436), and closing in on the other Asian Tigers: Hong Kong ($32,684), Taiwan ($22,476), and Singapore ($28,637). A striking feature of South Korea's development was its sustained annual GDP growth, which averaged around 9% during the 1960s, peaked at 10% in the 1970s, and moderated to 6% in the 1980s. The industrial policies implemented during the HCI drive played a pivotal role, channelling resources into high-growth sectors like heavy chemicals and shipbuilding, while leveraging foreign capital and technical expertise from Japan and the United States.

Economists widely refer to this extraordinary transformation as the "Miracle on the Han River." Much of the literature credits *targeted or strategic industrial policies*, particularly the focus on heavy and chemical industries during the 1970s, as a fundamental driver of this success. However, other factors, including export-driven industrialization, human capital development, and a strong partnership between the state and private enterprises also played pivotal roles. Together these elements laid the foundation for South Korea's path to a become leading market economy and eventually to its status as high income country and member of the organization of advances economies, the OECD (Organization for Economic Cooperation and Development), in 1996 - just a little over 40 years after the fighting on the Korean peninsula stopped.

3 Empirical Method

Synthetic Control Method

This paper aims to evaluate the effects of the HCI-drive policy in South Korea. The typical Difference-in-difference (DiD) approach requires reasonable counterfactual, which can be a problem when evaluating national policy effects. I leverage a version of the synthetic control method by Abadie et al. (2010), which presents a synthetic control unit by estimating a counterfactual control unit from a weighted average of donor control countries.[5] This, ceteris paribus, allows for the creation of a hypothetical South Korea where the HCI-drive never took place. I direct readers to those text, for a more detailed explanation of the method, and simply briefly outline the method here (Abadie and Gardeazabal, 2003; Ferman and Pinto, 2021b).

Imagine a sample of $C+1$ units (e.g., countries), all indexed by c, where unit $c = 1$ is the one of interest, and the remaining units, $c = 2$ to $c = C+1$, are potential comparison units. All these units are

[3]All data is from Data sourced from Penn World Tables (version 10.01) and author's own calculations.

[4]World Bank. (1993). *The east asian miracle: Economic growth and public policy.* Oxford University Press

[5]The synthetic control method was first introduced by Abadie and Gardeazabal (2003). I adopt the Bias-Corrected Synthetic Control Method (BC-SCM) as developed by Ferman et al. (2020) and expanded by Ferman and Pinto (2021b) to address limitations in standard synthetic control methods

observed for T periods. A dummy variable, d_{ct}, indicates if unit c is receiving treatment during period t; taking value 0 for all control units. The pre-intervention period is defined as $t \in \{1, ..., T_0\}$ and T_1 the post-intervention period, where $d_{dt} = 1$. The total amount of observed periods is $T = T_0 + T_1$.

From the **Rubin Causal Model** and the theory of potential outcomes. Briefly explained, it states that to measure causal effect of a given treatment, one needs to compare the observed outcome of the treated unit with its counterfactual. The formula for the effect of treatment is then:

$$\tau_{ct} = Y_{ct} - Y_{ct}^0 \tag{1}$$

with τ_{ct} as the treatment effect, Y_{ct} is the observed outcome of treated unit at time t, and Y_{c1}^0 is the counterfactual outcome of treated unit in the absence of treatment. However, since Y_{c1}^0 does not naturally exist, I instead estimate the treatment effect as such:

$$\hat{\tau}_t = Y_{1t} - \sum_{c=2}^{C} w_c Y_{ct} \tag{2}$$

where $\sum_{c=2}^{C} w_c Y_{ct} = Y_{ct}^{SC}$ is a synthetic counterfactual, created by a weighted (w_c) average of observed outcomes, $Y_{ct}, c \neq 1$, from the donor pool at time t. This synthetic control can be represented by a $C \times 1$ vector of weights $\mathbf{W} = (w_2, ..., w_{c+1})$, where combining the untreated outcomes amongst the donor pool will create a reasonable approximation of the counterfactual for y_{ct}, in the post-intervention periods T_1. I include an added restraint of $0 \leq w_c \leq 1$ for $c = 2, ..., C$ and $w_2 + ... + w_{c+1} = 1$, to ensure that results are more interpretable. Here $\mathbf{X}_1$ is a $k \times 1$ vector containing the selected pre-intervention characteristics of unit $c = 1$ that I want to match as closely as possible. $\mathbf{X}_0$ is a $k \times j$ matrix which collects the values of the same variables from the units in the control pool; pre-intervention characteristics in $\mathbf{X}_1$ and $\mathbf{X}_0$ may include pre-intervention values of the outcome variable. From Abadie et al. (2010) and Abadie et al. (2015), I choose a set of weights ($\mathbf{W}^*$) that minimizes the following equation:

$$\mathbf{W} = \min_{w} \sum_{m=1}^{k} v_m \left(\mathbf{X}_{1m} - \mathbf{X}_{0m}\mathbf{W}\right)^2 \tag{3}$$

here v_m is a weight, which reflects the relative importance that is assigned to the m-th variable, when measuring the discrepancy between $\mathbf{X}_1$ and $\mathbf{X}_0\mathbf{W}$, for $m = 1, ..., k$ variables, where m functions as a indicator for which m-th variable is valued at a given time. The goal is to minimize the sum of the squared differences between pre-intervention characteristics of treated unit ($\mathbf{X}_1$) , and SC ($\mathbf{X}_0\mathbf{W}$). Note that this can be done automatically through the synth code in Stata. A key metric for evaluating pre-treatment fit is the Root Square Mean Prediction Error (RMSPE), which measures the difference between the observed and synthetic control. The formula for calculating RMSPE across the pre-treatment period is:

$$RMSPE = \sqrt{\frac{1}{T_0} \sum_{t=1}^{T_0} \left(Y_{1t} - \sum_{c=2}^{C+1} w_c^* Y_{ct}\right)} \tag{4}$$

For a more in-depth explanation on the application, I refer readers to Abadie et al. (2010). This paper will utilize RMSPE as a key metric of model fit, alongside additional robustness test to validate results

Assumptions of Traditional SCM

There are several key assumptions, behind the SCM, as laid out in Abadie et al. (2010).

1. **Stable Unit Treatment Value Assumption, SUTVA**: The treatment must not have any spill effects. This ensures that that the synthetic control remains unaffected by the intervention.
2. **Parallel Trends**: The predictor variables must capture enough relevant factors that in the absence of of treatment, the synthetic and treated unit would follow similar outcome trajectories.
3. **Stability of Predictor-Outcome Relationship**: The relationship between the predictor variables and outcome, ln(GDP Pr Capita PPP.$2021), must remain stable over time. Any structural changes in the relationship would serve to invalidate the results; this is also crucial in choosing predictor variables, so not to choose variables which diverge in their relative importance over the period.
4. **Convex Hull Condition**: The predictor variables of the treated unit must lie within the convex hull of the predictor variables of the donor pool units. This ensures that a feasible weighted combination of donor pool units, will be able to approximate the treated units characteristics.
5. **Unconfoundedness**: Assignment to treatment is as good as random, conditional on the predictors included in the construction of the synthetic control. From Rubin's Causal Model: $(Y(0), Y(1)) \perp T \mid X$

Traditional SCM, as described by Abadie et al. (2010), relies heavily on achieving a near-perfect pre-treatment fit. However this assumption can fail, for example in complex cases where one donor country coincidentally mimics pre-treatment characteristics, but then diverges post-treatment due to unique developments. This can result in biased treatment effect estimates ($\hat{\tau}_t$) , as post-intervention gaps may reflect systemic differences rather than noise (Ferman & Pinto, 2021b). In such scenarios, particularly for South Korea's HCI-drive — a policy implemented during a period of rapid structural and economic transformation — achieving a robust synthetic control becomes challenging.

Bias-Corrected SCM

To address these limitations, I employ the Bias-Corrected Synthetic Control Method (BC-SCM) proposed by Ferman et al. (2020). This method improves upon traditional SCM by incorporating adjustments to pre-treatment residuals, thereby reducing biases in the estimated treatment effects. Unlike traditional SCM applications - which may produce biased results when pre-treatment discrepancies persist - the BC-SCM explicitly adjusts for these discrepancies, thus ensuring a more robust analysis. This makes it particularly well-suited in cases like South Korea's HCI-drive, where rapid economic changes and systemic shocks might otherwise compromise the reliability of synthetic control estimates.

Proposed by Ferman et al. (2020), and elaborated in Ferman and Pinto (2021b), the Bias-Correct Synthetic Control Method (BC-SCM) addresses limitations in SCM when pre-treatment is imperfect. To mitigate for this, the BC-SCM includes an additional adjustment term, based on the discrepancy in the pre-treatment fit.

$$\epsilon_{1t} = Y_{1t} - \hat{Y}_{1t}^{SC} = \mathbf{Z}_t\beta + u_t, \quad u_t \sim \mathcal{N}(0, \sigma^2) \tag{5}$$

where ϵ_{1t} is the residual from for treated unit at time t. $\mathbf{Z}_t$ is a matrix of pre-treatment predictor variables. β is a vector of regression coefficients. u_t is the error term - and assumed to be uncorrelated to $\mathbf{Z}_t$ - capturing random noise in the relationship between pre-treatment residuals and predictors. For this paper, standard OLS will be used when regressing. The bias-corrected treatment effect is now calculated as

$$\hat{\delta}_t = \mathbf{Z}_t\hat{\beta}, \quad \text{where} \quad \hat{\beta} = (\mathbf{Z}^\top \mathbf{Z}^{-1}\mathbf{Z}^\top \epsilon) \tag{6}$$

where $\hat{\beta}$ is the estimated coefficient from a regression of said residual on the predictors.[6]

$$\hat{\tau}_{1t}^{BC} = Y_{1t} - \hat{Y}_{1t}^{SC} - \hat{\delta}_t \tag{7}$$

$\hat{\delta}_t$ is the adjustment term that corrects for residual bias. (Ferman et al. (2020); Abadie (2021))

I leverage the Allsynth wrapper in Stata - by Wiltshire (2024) - to implement the Bias-Corrected Synthetic Control Method (BC-SCM). The Allsynth wrapper automates the bias-correction process, ensuring accurate adjustments for pre-treatment residuals in accordance with the theory outlined above; and conducts robustness checks such as placebo tests.

Placebo Test and Probability

Unfortunately, establishing causality is not as simple as just evaluating the size of $\hat{\tau}_{1t}$, neither for traditional or Bias-corrected. It is important to ensure that the results aren't a case of a string of false positives. This has been been argued by several people, to name one Abadie (2021).[7] This is certainly relevant in this case, where even with a large donor pool the issue of heterogeneity arises. In the case of Jones and Marinescu (2022) and Abadie et al. (2010), the synthetic counterfactual of, respectively Alaska and California ran into issues of heterogeneity with a donor pool consisting of the remaining 49 US states. In the case of South Korea, every country and comparison will have its unique challenges in exactly mimicking the pre-intervention trends. Therefore, I will employ bias-correction, as well as several robustness checks (Leave-one-out with subsequent placebo-test, as well as an brief look into employment data from various sectors in South Korea) to enhance the plausibility of the results.

The null hypothesis and alternative are stated as such:

$$\mathcal{H}_0 : \text{Observed intervention effect is due to random chance}$$
$$\mathcal{H}_1 : \text{The observed intervention effect is not due to random chance}$$

if $\mathcal{H}_0$ is discarded that would imply a causal impact of the intervention. To calculate the probability (p), from Abadie (2021), I calculate the p-value as:

$$p = \frac{\#\{\text{placebo gaps equal or more extreme than observed gap}\}}{\text{Total number of placebos}} \tag{8}$$

The number of placebo gaps used are the bias-corrected ones, to mitigate both likelihood of false positives and negatives, and to ensure the observed intervention effect isn't exaggerated by any systematic pre-intervention discrepancies, as explained in Abadie (2021).

[6]The OLS estimator $\hat{\beta}$ is derived by minimizing the sum of squared residuals: $SSR(\beta) = (\epsilon - \mathbf{Z}\beta)^\top(\epsilon - \mathbf{Z}\beta)$. Taking the derivative with respect to β and setting it to zero: $\mathbf{Z}^\top\mathbf{Z}\beta = \mathbf{Z}^\top\epsilon$. Solving for β , one obtains: $\hat{\beta} = (\mathbf{Z}^\top\mathbf{Z})^{-1}\mathbf{Z}^\top\epsilon$, where $\mathbf{Z}$ is the matrix of predictors and ϵ is the vector of pre-treatment residuals.

[7]Notable other sources are: Ben-Michael et al., 2021, Firpo and Possebom, 2018, Chernozhukov et al., 2019, Cunningham, 2021

4 Data

Penn World Tables

This study primarily utilizes data from the Penn World Table (PWT) version 10.01, a commonly used database in macroeconomic research. It provides harmonized data on key economic indicators across countries, making it ideal for cross-country comparative analysis. The dataset spans 1950–2019, but this analysis focuses on 1960–1990 for two primary reasons:

1. Data Limitations: Several key countries in the donor pool lack reliable data before 1960.
2. Avoiding Contamination from External Shocks: Major global economic events, such as the Asian Financial Crisis (1997), could distort post-treatment trends and confound the analysis.

While the HCI drive has been dated to both 1973 and 1972, this paper assigns the treatment period to 1972, as several key policies were implemented during this year that directly contributed to South Korea's industrial transformation. These include the previous five-year plans, the nationalization of banks - facilitating preferential credit allocation - and the official launch of the HCI-drive. The 1972 date is thus chosen to capture the early effects of these policies, supported by a lower pre-treatment RMSPE and improved synthetic control fit. Extending the analysis beyond 1990 risks attributing unrelated economic changes, such as those caused by external shocks, to the HCI-drive. Furthermore, during the 1980s, South Korea transitioned towards broader market liberalization. For these reasons, I find that including data from beyond 1990 risks conflating the effects of the HCI-drive. A key assumption of the SCM is that post-intervention effects can be attributed to the intervention itself, not to external shocks.

The primary outcome variable is Log of Real GDP per Capita (PPP-adjusted, constant 2017 USD). Taking the natural logarithm accounts for non-linear relationships and ensures comparability across countries. Key control predictors include:

- Log of GDP per Capita (Lagged once): Captures historical economic performance.
- Annual GDP Growth: Reflects recent economic trends.
- Real Total Factor Productivity at constant national prices (RTFPNA), where United States in 2017=1 . Allows for capturing productivity increases
- Consumption Shares: Includes the shares of household and government consumption.
- Share of Gross Capital Formation: Reflects investment levels.
- Trade Openness: Defined as the net sum of share of merchandise exports and imports.

The donor pool consists of countries with available and comparable data during this period. All predictor variables are constructed as five-year rolling averages to smooth out short-term fluctuations and better reflect structural trends, as argued by Abadie et al. (2015). The PWT data is supplemented with additional sources for robustness checks, ensuring the validity of both the synthetic control and bias-corrected synthetic control estimates

Donor Pool

There are two main parts to ensuring that SUTVA is upheld. The first, no interference. Treatment effect must no spill over to any control units. The second, consistency, each unit has a well-defined potential outcome; in other words the observed outcome matches the potential outcome under assigned treatment conditions. The donor pool for the SCM model is constructed by selecting comparison countries which share similar characteristic traits with South Korea, as argued by Abadie (2021). Below is a shorten explanation and justification for certain groups of countries inclusion in the donor group, with a larger - individual - version found in table 6 in the appendix.

- Japan and Taiwan: Included for their historical similarities in industrialization paths but require careful consideration due to strong economic linkages with South Korea, posing potential risks of interference.
- Southeast Asia (Indonesia, Malaysia, Thailand, Philippines): Added due to their structural similarities as developing economies and shared geographic proximity, with a low risk of spillover effects.
- China and India: Incorporated as they represent large, industrializing economies with minimal economic integration with South Korea during the period, thus reducing the risk of interference.
- Hong Kong and Singapore: Selected for their comparable export-driven industrialization patterns and shared regional development models, with limited direct overlap with South Korea's policies.
- Brazil, Mexico, and Burkina Faso: Chosen due to their distinct economic strategies and geographic distance from South Korea, ensuring minimal risk of policy interaction or spillover.
- Chile, Peru, and Turkey: Included for their structural similarities in industrial development, despite their geographic and economic isolation from South Korea.
- Egypt and Iran: Added as industrializing economies with limited direct interaction with South Korea during the period.
- Sri Lanka: Selected for its developmental trajectory which aligns with low-income economies in the donor pool, and with minimal trade integration with South Korea.

The selected donor group is constructed to ensure comparability and minimize potential biases. By including a diverse range of countries, I enhance the reliability of the model and support the validity of treatment effect estimates, as argued by Abadie et al. (2010) and others[8].

5 Empirical Analysis: The Effect of HCI-drive on the Korean Economy

I have selected eight predictor variables that I find not to violate any of the core assumptions and minimized pre-treatment RMSPE fit.[9] Table 3 outlines the predictor variables, including basic category and a brief description of the variable. To asses the validity of the synthetic control, I start by evaluating the pre-intervention fit between South Korea and its synthetic counterfactual. Table 4 presents the predictor balance between treated and synthetic units. While most predictors, such as GDP growth and lag exhibit minimal deviation, the larger gaps of RTFPNA (48.8%) and Trade Openness (32.6%) still fall within the range of donor countries; confirming that the convex hull condition is satisfied, and the synthetic control is not relying on extrapolation. Still, while the convex hull

[8] Several papers have stated the importance of a large donor pool, in regards to creating a credible synthetic. See Gardeazabal and Vega-Bayo, 2016; Cavallo et al., 2013

[9] See *Arguments for Assumptions of SCM in appendix*

Table 2: Key Economic Indicators for Donor Pool Countries (Pre-1972 Average)

Country	GDP per Capita (2017 USD)	Trade Openness	Population Growth Rate	RTFPNA
South Korea	**1,688.84**	**-0.0614**	**2.61%**	**0.4426**
Japan	9,058.35	-0.0382	1.07%	0.4426
Taiwan	3,924.51	-0.0355	3.09%	0.7052
Thailand	1,668.54	-0.0541	3.02%	0.4911
Brazil	3,076.40	-0.0103	2.89%	1.1346
Hong Kong	8,244.22	0.1608	2.48%	0.6432
Burkina Faso	989.07	-0.0302	0.95%	0.9236
China	1,108.87	0.0038	2.37%	0.8533
India	1,302.26	-0.0107	2.21%	0.6611
Indonesia	1,313.45	0.1753	2.08%	0.9287
Malaysia	3,435.13	0.0829	2.59%	1.377
Mexico	7,962.19	-0.0176	3.17%	1.4959
Sri Lanka	3,019.27	-0.0058	2.41%	0.7974
Philippines	2,251.01	-0.0295	3.06%	1.1755
Peru	3,491.91	0.0256	2.87%	1.5126
Singapore	4,915.38	-0.6382	2.30%	1.1315
Turkey	6,127.84	-0.0087	2.39%	1.3784
Iran	5,587.96	0.4502	2.94%	3.8155
Egypt	964.53	-0.0591	2.27%	1.4936
Chile	6,226.77	-0.0526	2.09%	1.1836

Source: Data from Penn World Tables, version 10.0. (Feenstra et al., 2015), with additional transformations by author. *Note*: GDP per Capita is measured in constant 2017 USD. Trade Openness is calculated as the sum of exports and imports relative to GDP.

Table 3: Predictor Variables for Constructing the Synthetic Control

Variable Name	Category	Description
avg-GDPG	Economic Performance	Average annual GDP growth, reflecting economic performance.
avg-LagGDPC	Economic Performance	Lagged log GDP per capita (PPP 2017 USD), capturing economic trends.
avg-PR	Structural Factors	Average population growth, reflecting demographic changes.
avg-RTFPNA	Productivity	TFP at constant national prices (2017 = 1).
avg-csh-c	Structural Factors	Share of household consumption at current PPPs.
avg-csh-i	Structural Factors	Share of gross capital formation at current PPPs.
avg-csh-g	Structural Factors	Share of government consumption at current PPPs.
avg-to	External Factors	Trade openness (net export- and import share at current PPPs).

Source: All variables derived from the Penn World Tables 10.01 (Feenstra et al., 2015), with addtional transformations by author
Note: Variables are averages over a five-year pre-treatment period to smooth short-term fluctuations.

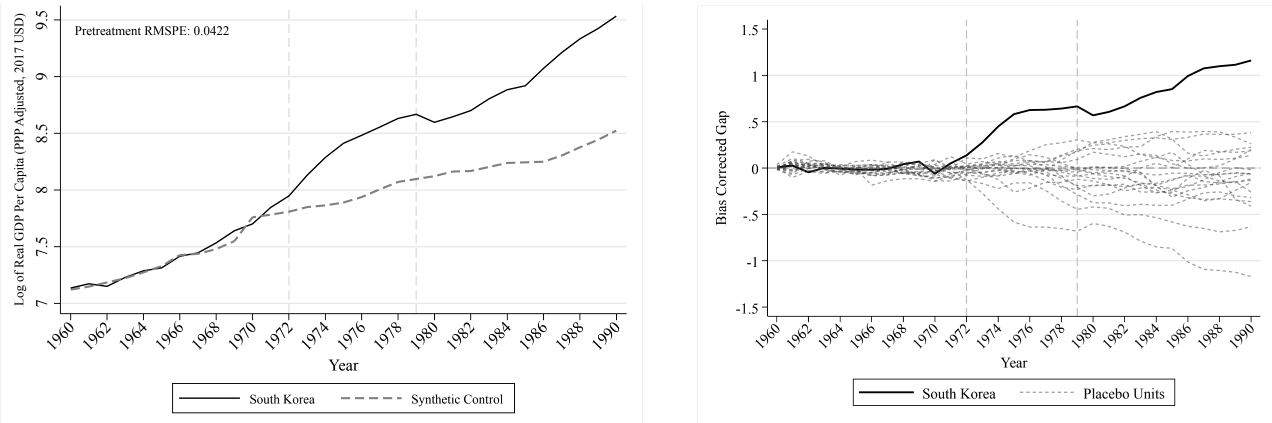
condition is met, the treated unit's avg-RTFPNA value is relatively close to the boundary of the donor pool range. Therefore, to strengthen the robustness of the analysis BC-SCM was used, adjusting for predictor imbalances and ensuring that the treatment effect more accurately reflects post-treatment dynamics. Additionally it is important to note that while these deviations exist, with a pre-treatment RMSPE of 0.0422, the synthetic control has more successfully then not, replicated pre-intervention GDP per capita trends, which as highlighted by Abadie et al. (2010) is critical.

Table 4: Predictor Balance Pre-Intervention: Treated vs. Synthetic

Variable	Treated	Synthetic	Percent Difference
avg_GDPG	8.17%	8.15%	0.3%
avg_Lag_GDPC	7.279	7.271	0.1%
avg_PR	2.81%	2.80%	0.2%
avg_rtfp	0.4317	0.6426	48.8%
avg_csh_C	0.726	0.703	3.1%
avg_csh_I	0.178	0.179	0.4%
avg_csh_G	0.158	0.151	4.8%
avg_to	-0.0610	-0.0809	32.6%

Notes: The table showcases the predictor balance between observed and synthetic predictor values, averaged over the pre-treatment period (1960-1972).

Figure 1: South Korea and Synthetic Control: Observed values and Placebo Test



(a) Pre- and Post-Treatment Trajectories of Log GDP per Capita for South Korea and the Synthetic Control.

(b) Bias Corrected Gaps: South Korea and Placebo Units

Note: The figure on the left shows the trajectory of South Korea's log GDP per capita (solid line) compared to its synthetic control (dashed line). Figure on the right is the Bias-corrected gaps, for both South Korea as well as placebo tests done on countries in the donor pool. First vertical dashed line indicate the start of Launch of the Third Five-year economic plan in 1972. Second vertical dashed line indicates assassination of Park Chung-hee and de-facto end of HCI-drive.

With a pre-treatment RMSPE of 0.0422, this indicates a strong fit between South Korea and its synthetic control. The donor weights, presented in Table 5, highlight key contributions from Thailand (0.719), Egypt (0.105) and India (0.059). Low pre-treatment RMSPE as a measure of fitness was established by Abadie et al. (2010), where they argued a low value indicates a robust synthetic control.

Figure 1(a) shows the observed divergence between South Korea and its synthetic counterpart, beginning around 1970, where South Korean GDP per Capita starts outperforming before the formal implementation of the HCI-drive in late 1972. This early divergence can possibly reflect preparatory measures taken by the South Korean government at the time, in preparation for the third Five-year economic plan (Horikane, 2005). The estimated average treatment effect over the post-treatment period (1973-1990) is approximately 0.15 log points, translating to a 16.2 % higher GDP per capita. The RMSPE-Ratio of 15.33 (Bias Corrected of 19.37) supports the significance of the observed divergence[10].

[10]The RMSPE-Ratio is derived by $\frac{\text{RMSPE(Post Treatment)}}{\text{RMSPE(Pre Treatment)}}$. Similar post-treatment divergence was documented by Abadie et al. (2010) when evaluating the impact of California's tobacco control program

The overall p-value for the placebo tests, calculated as the proportion of donor units with RMSPE ratios exceeding that of South Korea, is 5.26%. This value, while slightly above the conventional 5% threshold, still provides evidence supporting the significance of the effect[11].

Figure 1(b) illustrates the gap between South Korea's observed log GDP per capita and its synthetic control unit over time. The solid line represents South Korea, while the dashed lines correspond to placebo units from the donor pool. A placebo test works by assuming the treatment to units in the donor pool that were not actually treated, thus allowing the comparison of their estimated effects to the treated unit. This allows one to assess whether the observed treatment effect is statistically significant or due to random noise. The graph shows a notable divergence beginning in 1971 - coinciding with the ending of the second five-year plan - and grows rapidly in the following period in after the implementation of the HCI-drive. The divergence grows steadily throughout the post-treatment period, reaching a difference of 94.56 % in 1979 but dipping shortly in 1980 - which syncs up with the assassination of Park Chung-Hee - then continuously growing until 1990. By 1990 the difference was equal to an effect of 219.18%. The positive and increasing bias-corrected gaps suggest a sustained and significant economic impact attributable to the policy implementation. Importantly, the lack of any statistically significant gaps in the placebo test, supports the robustness of the observed treatment effect. This indicates that the result is unlikely to be driven by random fluctuations or pre-treatment characteristics[12].

Table 5: Synthetic Control Method for South Korea's HCI-drive

Statistic	**Pre-treatment Period**	**Post-treatment Period**	**Overall**	**RMSPE-Ratio**
MSPE (Mean Square Prediction Error)	0.00178	0.4295432	0.2639579	15.5307
Bias-Corrected MSPE:	0.0013777	0.5958242	0.3657159	19.3702
Placebo Test Results				
Average MSPE of Donor Units	0.0070388	0.197945	0.1240639	4.8878
Bias-Corrected Average of Donor	0.0028641	0.071695	0.0450507	4.2745
Overall P-value from Placebo Test		0.0526		
Country	**Synthetic Control Weight**	**Country**	**Synthetic Control Weight**	
Burkina Faso (BFA)	0.034	Brazil (BRA)	-	
Chile (CHL)	0.036	China (CHN)	-	
Egypt (EGY)	0.105	Hong Kong (HGK)	-	
Indonesia (IDN)	-	India (IND)	0.059	
Iran (IRN)	-	Japan (JPN)	-	
Sri Lanka (LKA)	-	Mexico (MEX)	-	
Malaysia (MYS)	-	Peru (PER)	-	
Philipines (PHL)	-	Singapore (SGP)	0.044	
Thailand (THA)	0.719	Turkey (TUR)	-	
Taiwan (TWN)	0.002			

Notes: The table shows the results from the Synthetic Control Method (SCM) analysis of South Korea's HCI drive. RMSPE values indicate the model fit, with lower values representing better fit. The weights of control units represent their contribution to the synthetic control. Placebo tests compare the treated unit's RMSPE to those of the donor pool units to assess significance. A higher RMSPE-Ratio value indicates a stronger divergence, thus stronger evidence of treatment significance.

Robustness Check

As mentioned earlier, the findings of BC-SCM - and SCM - shouldn't be taken at face value. To ensure the validity of my findings a series of additional robustness tests, beyond the standard treatment placebo tests, were conducted. These include: Leave-one-out (LOO) and Temporal Placebo tests. Each robustness test addresses potential concerns, such as over-reliance on specific donor countries, false-positives and more. These test fit the standard of earlier papers which also have employed the Synthetic Control Method.

[11] Both Abadie et al., 2010 and Ferman and Pinto, 2021a have argued that in context of SCM, a nuanced interpretation is required, due to the nature of how significance is influenced by pre-treatment fit and overall design of donor pool.

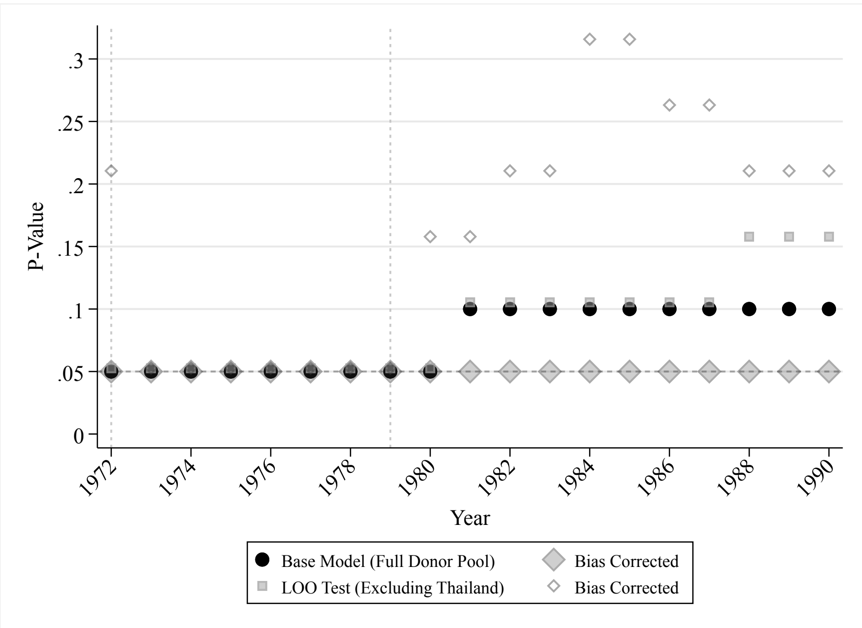
[12] No placebo ever achieved a p value under 10%, thus i am unable to reject the hypothesis that any effects are attributed to noise for the placebo tests.

Leave-One-Out Tests

The LOO tests revolves around excluding one donor country from the pool, then recalculating and running the BC-SCM, to asses the impacts of a donor on the results. Earlier I mentioned how Thailand, which contributed 71.9% of the synthetic weight, could potentially serve to void the results. Thailand happend to share a lot of economic similarities with South Korea in the pre-treatment period (1960-1971). During the pre-treatment period, the synthetic control closely tracked South Korea's log of GDP per capita, with a RMSPE of 0.0422 (Bias Corrected 0.037). Removing Thailand from the donor pool, results in a pre-treatment RMSPE of 0.067 (Bias Corrected 0.0813), thus still achieving a strong pre-treatment fit. [13] This validates the robustness of the synthetic control construction.

The post treatment period (1972-1990) showed a consistent and growing divergence appearing in figure 3(a). The the difference was 18.42% in 1972, growing to 147.75 %. in 1990. This growing divergence reflects the cumulative economic impact, where in the following decades after the HCI-drive's lingering effects held strong as targeted sectors grew and matured. While excluding Thailand reduced the post-treatment divergence it did not eliminate it. In the following 7 years after 1972, the effect remains marginally statistically significant with a p value of 5.26%, see figure 2. This suggest that while Thailand's inclusion in constructing the synthetic control is substantial, the found treatment effect is not solely driven by its inclusion. LOO test were run on all donor countries, with their subsequent placebo test can be seen in figure 3(a). Excluding the other donor countries, including Taiwan and Indonesia - which had lower weights - demonstrated minimal impact on the results. This consistency across iterations confirms the robustness of the synthetic control, and thus it's ability in capturing the counterfactual trajectory of South Korea.

Figure 2: P-Values for Base Model and Leave-One-Out (LOO) Test Excluding Thailand



Note: This figure presents p-values for the synthetic control model (SCM) using the full donor pool (Base Model) and excluding Thailand (LOO Test). Bias-corrected (diamonds) and uncorrected (circles/squares) p-values are shown for each year. The horizontal line at 5% marks threshold of statistical significance at a 5%. Significant p-values (marginally above 5%) during the HCI intervention period (1973–1979) suggest that the observed treatment effect is unlikely due to random chance.

[13] Appendix, Table 7 shows the results for LOO (Thailand) for South Korea

Temporal Placebo Test

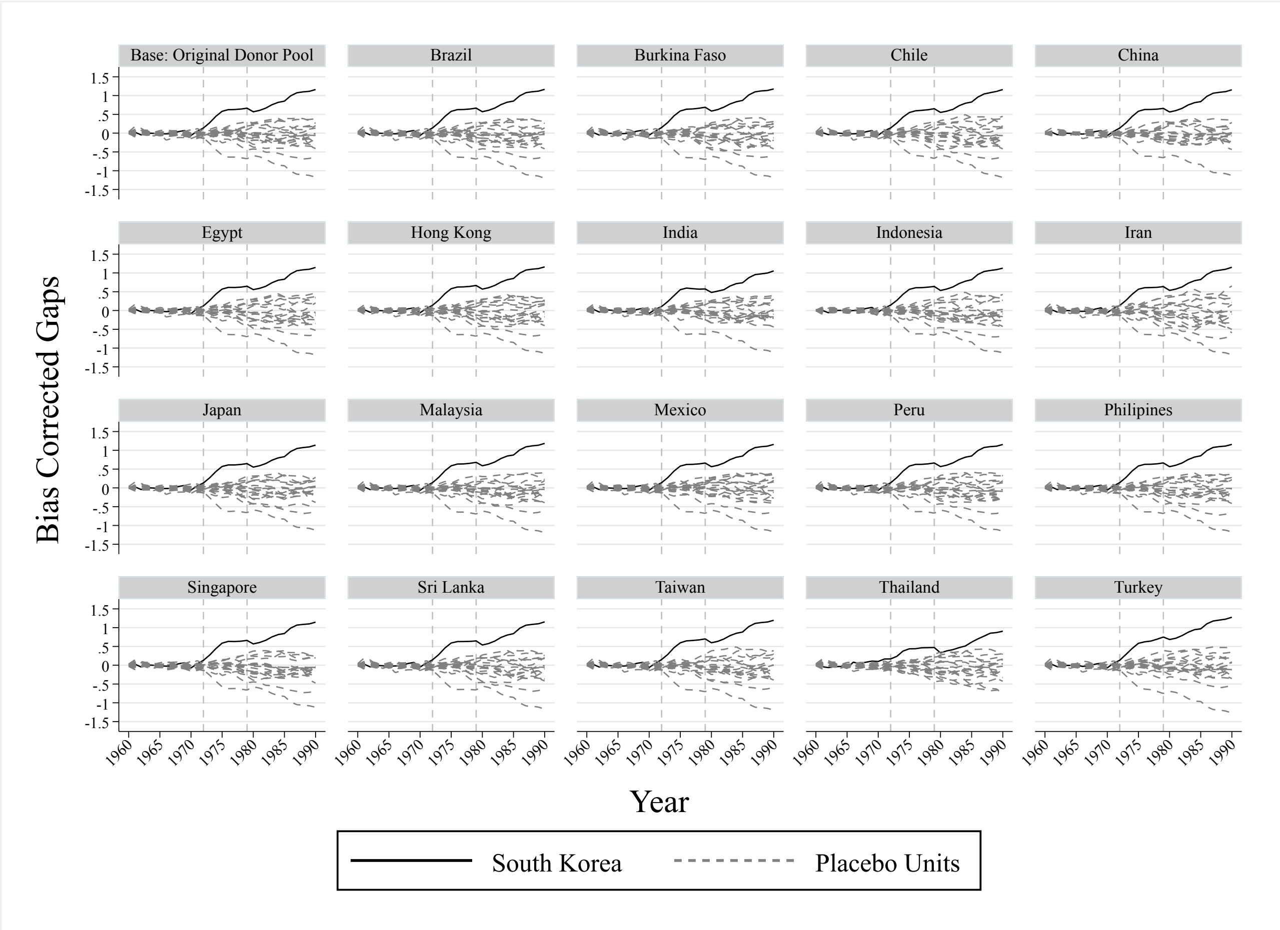
Temporal placebo tests were also conducted to evaluate if the observed treatment effect could be attributed to random chance. Temporal placebo tests shifted the treatment period to 1967 and 1977, testing whether significant divergence occurred outside the actual intervention period. These tests show no substantial statistically significant pre- or post-treatment divergence, affirming that the observed effects post-1973 are uniquely attributable to the HCI drive[14]. Placebo tests (Figures 2b and 2c) validate these findings.

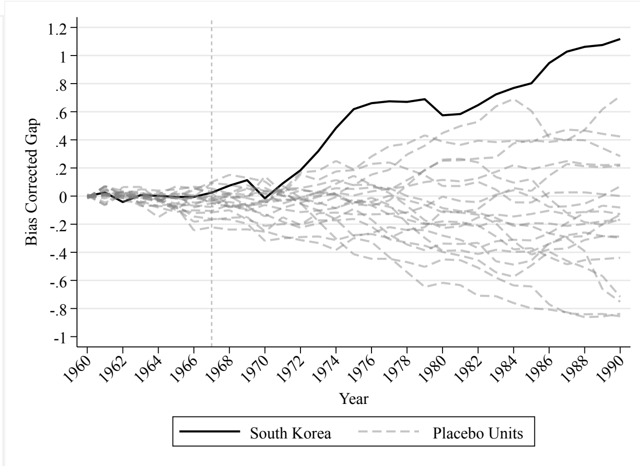
Sensitivity Analysis

Sensitivity analysis addresses potential violations of the Stable Unit Treatment Value Assumption (SUTVA), particularly concerning Singapore and Taiwan. These countries which share significant economic interaction with South Korea, thus raising concerns about spillover effects. However, their relatively low weights in the synthetic control (4.4% and 0.02%, respectively) mitigate the risk of any substantial influence. Furthermore a more diverse donor pool reduces the likelihood of biases stemming from regional dynamics, as argued by Abadie et al. (2010), thus I have chosen to keep them in the donor pool.

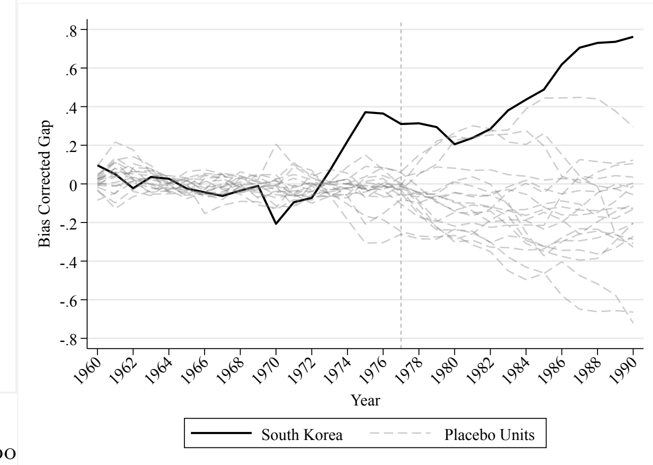
[14] Figure 5 in the appendix shows the p-values for the Temporal placebo test.

Figure 3: (a) Leave-One-Out test BC-SCM. (b) and (c) Bias-Corrected Temporal Placebo Tests





(b) Temporal Placebo Test - 1967



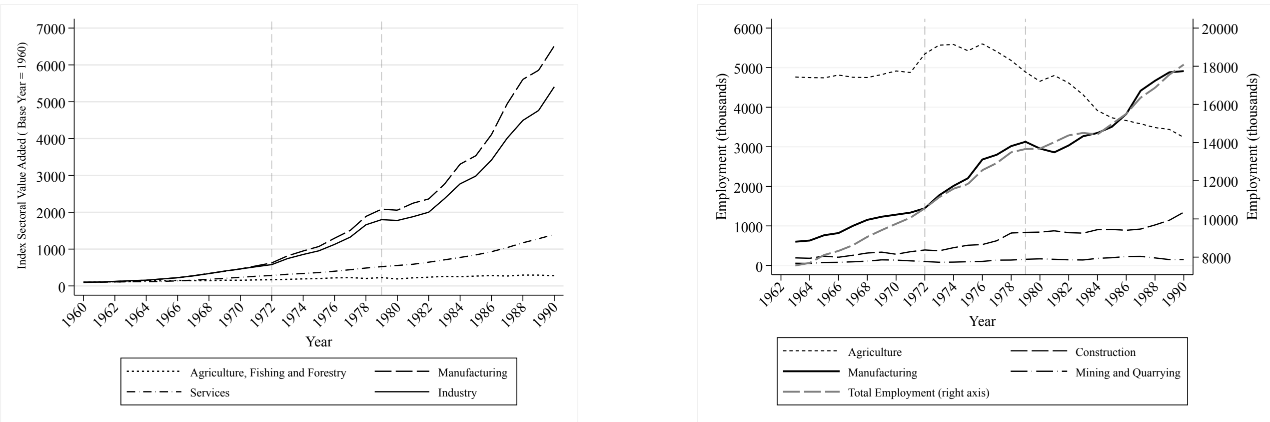
(c) Temporal Placebo Test - 1977

Note: The Leave-One-Out test iteratively excludes donor countries to evaluate robustness. Bias-corrected placebo tests assign treatment dates to pre-1972 periods to verify that observed effects are specific to the HCI-drive's implementation.

Internal Development Indicators - Employment and Value Added

This section contains a brief look at two economic metrics. Employment in sectors and Value added to GDP. In part to reaffirm the results by Lane (2022), who found that the HCI-drive promoted the expansion and dynamic comparative advantages in the targeted industries. For this section two data sources are used: World Bank Group's (WBG) World Development Indicators and from the International Labour Organization's (ILO) Labour Force Surveys. Respectively, the WBG dataset contains value added in constant 2015 USD$ for four sectors: Agriculture, Fishing and Forestry, Industry (including construction), Services and Manufacturing. The dataset from ILO is comprised of employment (in thousands) for: Agriculture, Construction, Mining and Quarrying, and Manufacturing; as well as total employment numbers.

Figure 4: South Korea and Synthetic Control: Observed values and Placebo Test



(a) Index Value Added to GDP(constant 2015 USD$) for Manufacturing and additional sectors

(b) Total Employment in Manufacturing and additional sectors

Note: Panel (a) depicts the indexed value added to GDP (base year = 1960) for various sectors, highlighting the significant growth in manufacturing and industry during the observed period. Panel (b) illustrates the total employment across sectors, with manufacturing employment displaying consistent growth, while agriculture employment declines. The dashed vertical lines mark key economic milestones, including the start of the HCI drive in 1972 and its culmination in the late 1970s. Total employment is plotted against the right axis.

This figure enhances the findings of the analysis by illustrating sectoral shifts in South Korea's economy during - and post - the HCI period. Panel (a) shows a rapid growth in manufacturing- and industry value added post-1972, reflecting the structural transformation driven by industrial policy. By 1973 the index doubled to 200, reaching 1000 in 1980. Manufacturing grew from a base index value of 100 in 1963 to a staggering 6514.128 in 1990, a growth factor of 65.14 times in 27 years. This corresponds to a compound average annual growth rate of 13.92%. per year. Panel (b) complements this, demonstrating consistent increases in manufacturing employment, supporting the earlier findings that South Korea's GDP growth during this period is attributable to industrial policy efforts targeting key sectors. These trends serve to underscore the findings behind the divergence observed between South Korea and its synthetic control.

6 Discussion

This study finds that the Heavy Chemical Industry (HCI) drive of 1972 had a substantial economic impact. By 1990, the divergence between South Korea's actual GDP per capita and its synthetic control had reached 1.16 log points, translating to a staggering 219.18% difference. This is evidence for the transformative ability the HCI-drive had in accelerating the South Korean economy's growth and structural transformations.

Several robustness checks, including leave-one-out (LOO)- and placebo tests, confirm the plausibility of these results. For example, excluding Thailand - which held the highest synthetic control weight - slightly reduced the observed divergence, but still maintained marginal statistical significance; in line with results from other studies using SCM. Temporal placebo tests - assigning alternative treatment dates (e.g., 1967 or 1977) - yielded no statistically significant divergences, further validating the causal relationship between the HCI-drive and South Korea's economic growth.

These results align with broader findings in both literature on state-led industrial policies and economic transformations and on the HCI-drive's role in South Korea economic transformation. Studies such as Coricelli and Campos (2014) utilized Synthetic Control Method to asses the economic impact of joining the European union. Adhikari and Alm (2016) applied SCM to evaluate flat tax reforms, identifying that in 7 out of 8 cases there was a significant positive impact. The magnitude and trajectory of the observed in this study are consistent with these findings, particularly in demonstrating a sometimes delayed but compounding economic impact.

However, South Korea's experience presents some noteworthy circumstances. The HCI-drive's success was in part facilitated by a unique combination of previous institutional reforms, geopolitical interest - and subsequent politically motivated aid - and state-led coordination via a quasi-dictatorship. These factors align with the arguments of Chang (2002), who emphasized the role of developmental states in achieving structural transformations. But the bias-corrected SCM, proposed by Ferman et al. (2020), employed in this study further refines the findings by addressing limitations in pre-treatment fit; as seen in earlier studies such as Abadie et al. (2010) and Jones and Marinescu (2022).

Limitations

Despite the robustness of it's findings, this study has several limitations. First, potential violations of the Stable Unit Treatment Value Assumption (SUTVA) may arise due to South Korea's economic interactions with donor countries such as Singapore and Taiwan. Though their weights are minimal (e.g., 4.4 % and 0.2 %) these interactions could still introduce biases. Second, the analysis focuses on a selected post treatment period from 1972 to 1990. This excludes potential long-term impacts or disruptions cause by subsequent events - such as the 1997 Asian Financial Crisis. Extending the analysis to incorporate these effects could potentially provide a more comprehensive understanding of the HCI-drive's legacy.

However, the analysis also identifies key limitations, such as potential violations of the Stable Unit Treatment Value Assumption (SUTVA) due to regional economic interactions, and the exclusion of post-1990 effects, such as those related to the 1997 Asian Financial Crisis. These limitations suggest avenues for further research, such as exploring the long-term legacy of the HCI drive or comparing South Korea's trajectory with other industrialized nations.

Finally, the reliance on the Penn World Tables dataset - and isolated use of data from WBG and ILO - while a standard in macroeconomic research, introduces potential measurement errors, particularly in historical data for developing countries. Future research could address said limitations by integrating alternative datasets or utilizing complementary methods.

Future Research

This study contributes to the broader literature on the effects of targeted industrial policy on economic development. Reaffirming the role of state-led interventions in sustaining structural transformation, the HCI-drive is an example of how strategic coordination and investment in key industries at the right time can help overcome market failures and accelerate development.

Future research could explore the long-term effects of the HCI-drive, including delving further into its implications for income distribution, regional disparities, and environmental sustainability. Comparative analysis with other Asian Tigers - Taiwan, Singapore and Hong Kong - could provide further insight into what conditions facilitate successful economic transformations. Additionally, future advances in Synthetic Control Methods could be a reason for re-examining the results of this study.

7 Conclusion

The study evaluated the economic impact of South Korea's Heavy Chemical Industry (HCI) drive using the Bias-Corrected Synthetic Control Method (BC-SCM). By constructing a synthetic counterfactual of South Korea's GDP per capita trajectory, the analysis provides robust evidence of the policy's positive transformative effects on economic growth. The findings indicate that by 1990, South Korea's GDP per capita was 1.16 log points higher than its synthetic counterpart; equivalent to a 219.18% increase, implying South's GDP per capita was more than 3 times as high as it would have been without the HCI-drive. The divergence began shortly before the policy's implementation in 1972, subsequently widening - underscoring the HCI drive's cumulative, sustained and significant impact.

These results align with the broader literature on industrial policy and economic development, highlighting the vital role of state-led coordination in driving structural transformations. The HCI drive not only accelerated South Korea's industrialization but also laid the foundation for its emergence as a global economic powerhouse. Its success illustrates how targeted investments in strategic sectors, supported by export-oriented growth strategies and institutional reforms can help produce long-term productivity gains and global competitiveness.

The findings of this study have implications for policymakers in emerging economies. But for any country seeking to replicate the transformation of South Korea, it should be noted that it isn't so straightforward. While the HCI-drive demonstrates that *targeted or strategic industrial policies* in South Korea helped produce accelerated economic growth, it is vital to also grasp the context of the time period. In the late 20th century, the global market was in part marked by the emergence of the relatively new, and rapidly expanding, electronics industry. South Korea's focus in this industry allowed for new players - backed by state-driven industrial policies and new technological advancements - to gain a considerable market share in a sector with fewer established competitors.

Additionally the geopolitical landscape carried major implications. With it's communist neighbour to the north, capitalist South Korea enjoyed massive financial and military support from the United States and other western countries. These effects should not be underestimated, in their role in supporting the HCI-drive's transformative capabilities. Should any policy makers seek to recreate the so called "Miracle on the Han river" using the same strategies, they must ensure complementary institutional reforms and adapt strategies that conform to their unique economic and political landscape - nationally, regionally and globally.

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9 Appendix

Arguments for Assumptions of Synthetic Control Method

Convex Combination Assumption

- South Korea's economic structure was broadly comparable to other industrializing economies in the donor pool.
- Pre-treatment RMSPE shows a strong match, indicating the synthetic control closely approximates South Korea's pre-treatment trajectory.
- The donor pool was diverse enough to construct a plausible synthetic control.

Abadie et al. (2010); Wiltshire (2024)

No Spillover Effects

- South Korea's industrial policies primarily targeted domestic industries, with limited direct effects on donor pool countries.
- The synthetic weight construction excluded close trading partners (e.g., Japan) thus minimizing indirect spillovers.

Wiltshire (2024); Abadie (2021)

Predictor Balance

- Key predictors such as trade openness, pre-treatment GDP, and industrialization levels were included.
- Visual and statistical evidence (e.g., low RMSPE) confirms a strong pre-treatment fit.
- Sensitivity analyses demonstrate robustness to variations in predictors.

Abadie et al. (2010); Wiltshire (2024)

Parallel Trends in Absence of Treatment

- Historical data indicate that South Korea and its donor pool followed similar growth trajectories before the intervention.
- Pre-treatment fit suggests parallel trends would have persisted in the absence of treatment.
- Placebo tests conducted on other donor pool countries confirm the validity of parallel trends.

Abadie et al. (2010); Firpo and Possebom (2018)

Unconfoundedness

- Relevant covariates (e.g., pre-treatment GDP) were included to reduce confounding risks.
- Bias correction techniques adjust for any remaining discrepancies in predictors between South Korea and the synthetic control.
- Limitations are acknowledged, but robustness checks suggest minimal impact of unobserved confounding.

Ben-Michael et al. (2021); Wiltshire (2024)

Table 6: SUTVA Concerns and Reasons Inclusion for Each Donor Countries

Country	**SUTVA Concern**	**Justification**	**Reason for Inclusion**
Japan (JPN)	High	Significant economic ties, including trade and financial assistance post-1965 normalization treaty.	Geographical proximity and similar rapid industrialization trajectory. (Abbott, 2007)
Singapore (SGP)	Medium	Shared regional development dynamics; limited direct competition in industrial exports during the 1970s.	Comparable economic development as a "Tiger Economy.". (Cho, 2015)
Indonesia (IDN)	Low	Limited interactions during the 1970s; minimal competition in export markets during the HCI era.	Emerging economy in Southeast Asia with industrial growth. (Kim & Park, 2020)
Hong Kong (HKG)	Medium	Similarities as a "Tiger Economy" with overlapping export markets; reliance on finance reduces direct spillover risk.	Rapid economic growth and industrialization in the same period. (Cho, 2015)
Malaysia (MYS)	Low	Focused on resource extraction; little direct economic or industrial policy competition.	Developing economy with industrial policy initiatives. (Kim & Park, 2020)
Philippines (PHL)	Low	Industrial base lagged behind South Korea; unlikely spillover effects.	Southeast Asian country with industrialization efforts. (Kim & Park, 2020)
Taiwan (TWN)	High	Direct competitor in key export industries, including electronics and machinery.	Similar economic structure and industrial policies. (Abbott, 2007)
Brazil (BRA)	Low	Geographical distance and specialization in agricultural exports reduce spillover risk.	Large developing economy with industrialization programs.(Ahn & Kim, 2023)
Mexico (MEX)	Low	Similar to Brazil; geographic and economic distance reduces likelihood of spillover.	Emerging market with industrial growth during the period. (Ahn & Kim, 2023)
Burkina Faso (BFA)	Very Low	No significant economic or structural interaction with South Korea.	Included as a control due to differing economic structure. (Ahn & Kim, 2023)
China (CHN)	Medium	Limited trade until the 1990s; regional dynamics could imply indirect influences.	Regional proximity and later rapid industrialization. (C. W. Lee, 2020)
India (IND)	Low	Import-substitution industrial policies make it structurally distinct, reducing spillover risks.	Large developing economy with significant industrial sector. (C. W. Lee, 2020)
Sri Lanka (LKA)	Low	Limited industrial development during the treatment period; no significant economic interaction.	South Asian country with developing industrial policies.(S. H. Lee, 2020)
Thailand (THA)	Low	South Korea's import restrictions during the HCI period minimized potential spillover effects.	Geographical proximity and similar economic development stage. (Kim & Park, 2020)
Chile (CHL)	Low	Limited industrial overlap; focus on agricultural and mineral exports.	Developing economy with industrial policy initiatives. (Park, 2023)
Peru (PER)	Low	Similar to Chile; limited industrial overlap or trade interaction.	Emerging economy with industrialization efforts. (Park, 2023)
Egypt (EGY)	Very Low	No significant economic or industrial interaction with South Korea.	Included as a control due to differing economic structure. (Kang, 2015)
Iran (IRN)	Low	Oil-exporting economy with limited structural similarity to South Korea.	Developing country with industrialization programs. (Kang, 2015)
Turkey (TUR)	Low	Focused on agriculture and light manufacturing; minimal overlap in industrial policies.	Emerging economy with industrial growth during the period. (Park, 2023)

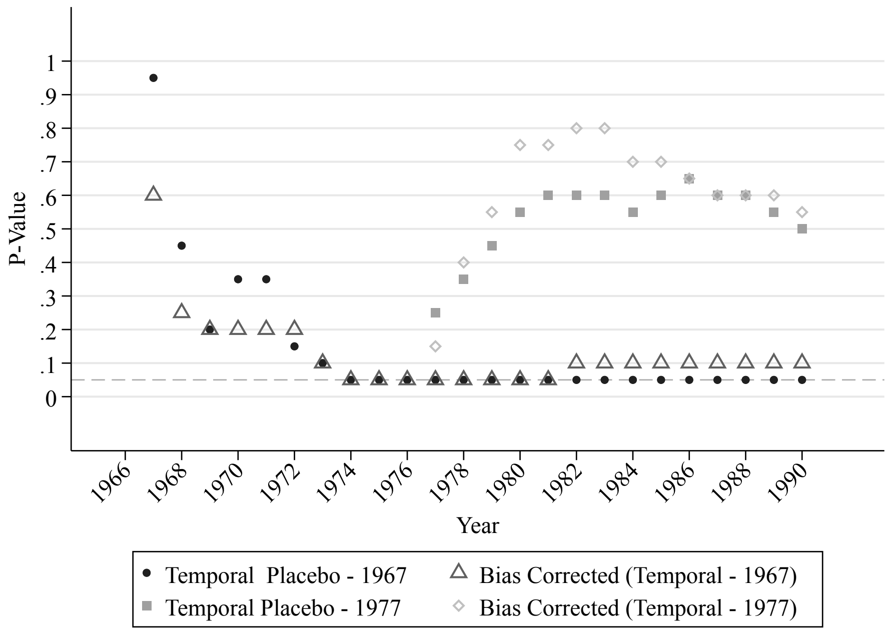
10 Additional Tables and Figures

Table 7: Leave One Out -Thailand - Bias Corrected Synthetic Control Method Results

Statistic	**Pre-treatment Period**	**Post-treatment Period**	**Overall**	**RMSPE-Ratio**
MSPE (Mean Square Prediction Error)	0.0045421	0.719106	0.4425006	12.5826
Bias-Corrected MSPE:	0.0066228	0.3144376	0.1952835	6.8905
Placebo Test Results				
Average MSPE of Donor Units	0.0070388	0.197945	0.1377462	5.567
Bias-Corrected Average of Donor	0.0032318	0.0662012	0.041826	4.526
P-value from Placebo Test		0.0526 From 1972-1980		
Country	**Synthetic Control Weight**	**Country**	**Synthetic Control Weight**	
Burkina Faso (BFA)	-	Brazil (BRA)	-	
Chile (CHL)	-	China (CHN)	-	
Egypt (EGY)	0.455	Hong Kong (HGK)	-	
Indonesia (IDN)	-	India (IND)	0.271	
Iran (IRN)	0.045	Japan (JPN)	-	
Sri Lanka (LKA)	-	Mexico (MEX)	-	
Malaysia (MYS)	-	Peru (PER)	-	
Philipines (PHL)	-	Singapore (SGP)	0.229	
Thailand (THA)	(Omitted)	Turkey (TUR)	-	
Taiwan (TWN)	-			

Notes: The table shows the results from the Leave One Out (Thailand) Robustness test for South Korea's Synthetic Control Method (SCM) output. MSPE values indicate the model fit, with lower values representing better fit. The weights of control units represent their contribution to the synthetic control. Placebo tests compare the treated unit's RMSPE to those of the donor pool units to assess significance. A higher RMSPE-Ratio value indicates a stronger divergence, thus stronger evidence of treatment significance.

Figure 5: P-Values for Temporal Placebo Test: 1967 and 1977



Note: This figure presents p-values from the temporal placebo tests. Two hypothetical treatment years, 1967 and 1977, are tested to evaluate the robustness of the observed treatment effect of the HCI-drive in 1972. Bias-corrected p-values are represented by triangles (1967) and diamonds (1977), while uncorrected p-values are shown as circles (1967) and squares (1977). The horizontal line at 5% marks threshold of statistical significance at a 5%. Observed p-values during the HCI intervention period (1973–1979) fall marginally within the threshold.