Structural Time Series Models and Synthetic Controls — Assessing the impact of the Chilean Liberalisation on the 1982 Latin American debt crisis.

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Abstract

The 1982 Latin American debt crisis ushered in a decade of weak to negative economic growth known as the "lost decade." However, Chile recovered from the crisis significantly more quickly than its Latin American counterparts. The sweeping economic liberalizations of the mid-1970s are often cited as the reason for the rapid recovery. In this paper I review the events surrounding Chile's liberalization and the debt crisis. It then estimates the effect of liberalization using the classical data-driven synthetic control method and a more recently introduced time series-driven synthetic control by Harvey and Thiele (2021). It is estimated that as a result of liberalization, GDP per capita in Chile increased by 56.0% to 65.7% in 15 years. Furthermore, the gains of using the time series driven model will be discussed using two other prominent examples from the literature.

Keywords: economic liberalisation; debt crisis; Chile; intervention analyses; synthetic control; model-based estimation; stationary tests; placebo tests.

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1 Introduction

A dangerous cocktail of global economic stagnation in the 1970s and early 1980s combined with excessive borrowing by the largest Latin American economies boiled over when the Mexican Finance Minister Jesús Silva-Herzog told the US Federal Reserve that his country could no longer pay off its $80 billion debt (FIDC, 1997). After the announcement in August 1982, lenders realize that virtually all countries in Latin America, led by Brazil, Chile, Argentina and Mexico, are unable to meet their loan obligations. The ensuing debt crisis would lead to years of falling wages, weak to even negative economic growth, skyrocketing unemployment, severe austerity measures and political instability that would come to be known as "La Década Perdida" (the lost decade) in Latin America.

The time it took Latin American countries to recover from the debt crisis varied greatly from country to country. Although Chile was initially hit hardest by the crisis, it recovered much faster than its neighbors (The World Bank, 2020). Which is surprising given that conditions prior to the crisis were very similar throughout Latin America: appreciation of real exchange rates, current account deficits, inflation, high external debt, and authoritarian military dictatorships ruling over more than two-thirds of the Latin American population (Remmer, 1992). The crucial aspect that distinguished Chile from its peers was its liberalized economy. Chile had already implemented structural reforms as early as the 1970s, whereas other Latin American countries did not until the mid-1980s, which was strongly encouraged by the International Monetary Fund (IMF). Bergoeing et al. (2002) argue that these early reforms were critical to Chile's successful recovery.

1.1 Research Objectives and Relevance

Chile's reforms, ten years earlier than its Latin American peers, made it the only liberalized country during the 1982 debt crisis in Latin America. Therefore, Chile lends itself particularly well to using synthetic controls to analyze and compare how a liberalized country performs during a debt crisis compared to a non-liberalized control country. The main objective of this research is therefore to estimate the economic impact of Chile's economic liberalization in the 1970s and to assess the country's performance during the 1982 debt crisis, with the following research question:

> How successful was the Chilean economic liberalisation in combating the 1982 Latin American debt crisis?

Some literature on Chile's liberalization note its remarkable performance, but no paper has attempted to quantify the success of liberalization. In this paper, I have estimated the impact of Chilean liberalisation on GDP per capita using data from 1960 to 2020 and found that in 15 years Chile's GDP per capita had increased between 56.0% and 65.7% due to its liberalisation reforms. Therefore, contributing to the specific Chilean liberalization literature, the liberalization literature in general, the literature on liberalization in the context of a crisis, and through the methods applied in this paper to the synthetic control literature.

The paper is structured as follows. In the upcoming section, I describe the context and process of economic liberalization in Chile. Subsequently, this paper will provide the theoretical basis for my empirical research by elaborating on the relevant literature in Section 2. Following that, section 3 will discuss the empirical methodology and econometric approach of my research. Followed by an overview of the data and determined treatment periods in Section 4. Then, the results are presented in Section 5. Next, chapter 6 contains several tests to check the robustness of my results. Finally, Chapters 7 and 8 will conclude with my conclusions, summarizing the results and offering some suggestions for future research.

1.2 Chilean Economic Liberalisation

1.2.1 A Closed Economy

The collapse of the world economy in the 1930s during the Great Depression marked the beginning of a five-decade period in which Latin American policymakers employed a strategy of Import Substitution Industrialization (ISI). Latin America's terms of trade deteriorated as a result of the crisis, causing major problems for their balance of payments (Diaz and Carlos, 1984). GDP per capita fell by almost 30%, reducing confidence in the laissez-faire policies that had dominated Latin American economies in the decades before (Meller, 2000). ISI promised to reduce vulnerability to extreme external shocks, such as those of the Great Depression, and aimed to catch up with developed countries through state-led industrialization.(Cardoso and Helwege, 2018).

Initially, the Great Depression ushered in a more national-populist period in Chile, which allowed for greater government intervention to restore social stability, economic growth and employment. This resulted in heavy deficit spending, large government projects, and tariff protection for producers of primary goods, such as mining companies and landowners (Silva, 2007). By the 1950s and 1960s, Chile's ISI strategy had shifted toward the Prebisch-Singer hypotheses, arguing that the terms of trade for commodity-based economies will deteriorate over time (De Piñeres and Ferrantino, 1997). Therefore, to transition the economy away from the agricultural and mining sectors, the Corporación de Fomento de la Producción (CORFO) was established. The CORFO established a number of heavy industries by establishing public companies and protecting them through tariffs and preferential exchange rates (Silva, 2007). By the end of the 1950s and throughout the 1960s, there appeared to be several problems with the ISI strategy. First, it was clear that large government expenditures on industrial policy and social welfare programs led to severe inflation. Second, Chile was struggling financially because much of the ISI strategy was paid for by the mining sector, which had stagnated as attention shifted to other industries. Third, the prolonged neglect of the agricultural sector fueled social and political unrest (silva, 2007).

These troubles led to the election of the first Marxist president in Latin America and marked the beginning of the end of the ISI strategy in Chile. The election of President Allende in 1971 promoted a strategy of large-scale nationalization and expropriation of Chilean and foreign, often preceded by long strikes and the exclusion of owners. (Faundez, 1980; Silva, 1996). Inflation skyrocketed due to large budget deficits, increasing from 3% of total GDP in 1970 to 24% in 1973 (Silva, 2007). This led to growing social and political tensions, which would lead to the downfall of democracy in Chile and the establishment of a military regime, supported by the US government.

1.2.2 Early Reformers

Under Pinochet's military regime, following the 1973 coup, Chile pioneered economic liberalization in Latin America. These liberalizations reflected the principles of laissez-faire and monetarism advocated by an influential group of Chilean policymakers educated at the University of Chicago and known as the "Chicago boys". The Allende government had subjected Chile's foreign trade to strict government control, with tariffs that varied by 750 percentage points and averaged 94%, non-tariff barriers that affected more than 60% of total imports, and a complex exchange rate system with eight different rates that varied by more than 1,000 percentage points (Agosin and Ffrench-Davis, 1995). Pinochet's regime wanted to simplify tariffs significantly and reduce them to a uniform maximum of 10%. In 1976, average tariffs were reduced to 33% and would continue to fall to an average of 13.6%, ranging only 6 percentage points in 1979 (Edwards and Lederman, 1998). Further liberalization measures included the privatization of the CORFO portfolio, the creation of private credit institutions, the liberalization of domestic prices, and the downsizing of the government through large layoffs of civil servants. The government deficit was reduced from 22.5% of GDP to only 0.4% in 1975 (Caputo and Saravia, 2018). A main pillar of the liberalization was controlled inflation, however, after the abolition of the domestic price in 1974, inflation reached 700% (Caputo and Saravia, 2018). But after gradually reducing the money supply in combination with fiscal tightening, inflation was finally reduced to 9.9% in 1981 (De Piñeres and Ferrantino, 1997). After a substantial maxi-devaluation in 1974 to counteract the deterioration in the terms of trade resulting from the dismantling of trade barriers, an active exchange rate system was introduced to maintain a competitive exchange rate. The Chilean peso was devalued on average twice a month until mid-1976, after which a crawling exchange rate was maintained. In 1978, a controversial anti-free market decision was made to peg the exchange rate to the US dollar as an anti-inflationary measure, effectively setting a ceiling on inflation (Margitich, 1999).

Chile experienced a severe economic contraction in 1975 with a 12.9% drop in GDP, caused by an external shock that deteriorated Chile's terms of trade, when copper prices halved as a result of a recession triggered by the creation of OPEC, quadrupling oil prices. To make matters worse, restrictive fiscal policies had reduced the government deficit to 0.4%, leading to a 15.6% drop in real wages and a decline in domestic aggregate demand (Labin and Larrain, 1995). In the years following this economic recession, Chile experienced several years of strong consistent growth, averaging 7.5% per year. Some resistance to the regime, due to high unemployment rates, was suppressed, underlining the unique situation in which these reforms took place.

1.3 "Lost" and "Found" Decade

1.3.1 1982 Debt Crisis

In the years leading up to the crisis, oil shocks, such as the one in 1975, led to current account deficits throughout Latin America as a result of increased oil prices combined with decreased commodity prices. Simultaneously, these oil crises generated current account surpluses in oil-exporting countries. US banks began to act as intermediaries between these countries accelerating Latin American debt expansion. They provided relatively cheap and readily available loans to Latin American countries to finance their deficits, while at the same time providing exporting countries with a safe, liquid place for their funds by lending them to Latin America. Total outstanding Latin American debt rose from just $29 billion in 1970 to $159 billion in 1978 and exploded to $327 billion in 1982, 80% was public debt (FIDC, 1997). Chile was no exception to this heavy borrowing, yet liberalization had shifted the country's reliance toward private debt instead of public debt. Public foreign debt, as a percentage of GDP, had fallen from 54.3% in 1975 to less than 27% in 1982, while private debt had soared from 10.5% to 41.8% (Caputo and Saravia, 2018). Most of the loans were used to cover accrued interest on existing debt or maintain consumption levels, rather than using these loans for productive investment. Adding that Two-thirds of Latin American debt contracts incorporated a floating LIBOR rate, which exploded to record highs between 1978 and 1982, from an average of only 6.2% to an average of 15.8%, tripling interest payments from $15.8 billion to $41.1 billion. Together with the appreciation of the dollar in 1981-82, made it increasingly more difficult for Latin American countries to service their dollar-denominated debts (FIDC, 1997). The reduction of capital inflows following Mexico's announcement that it could no longer repay its $80 billion debt was the final devastating blow that ushered in the 1982 debt crisis that would affect Latin America for the next decade.

The impact of the crisis was immensely devastating, with a 9% contraction in Latin America's GDP. However, Chile was most severely affected, with a 14% drop in GDP, which was partly caused by the pegging of the exchange rate to the dollar in 1978 (McKinney, 2021). Chile's economy boomed in 1979 thanks to a large influx of commercial capital, as investors bought the strong peso that resulted from the pegging of the exchange rate to a depreciating dollar. This caused the Chilean economy to collapse even harder, as capital flight ensued from an appreciating dollar after the election of US President Reagan in 1980, who was determined to keep the dollar strong. Chilean banks were pushed to the brink of insolvency as businesses went bankrupt under mountains of bad debt. Chile, further, faced over $18 billion of foreign debt, soaring inflation and employment rising to 22% in Satiago and 30% in the countryside (Margitich, 1999).

1.3.2 Reversal between 1982-85

To combat the 1982 debt crisis, the Pinochet regime asked the IMF for assistance in servicing its foreign debt. The IMF, in conjunction with the World Bank, provided vast loans for Chile's financial recovery on the condition that it would restructure its financial system. In 1982, Pinochet finally gave in and abolished the fixed exchange rate under pressure from the IMF; in the following three months, the exchange rate of the peso devalued from 39 pesos to 63 pesos per US dollar (Mckinney, 2021). The Chilean central bank was forced to absorb the debts of private banks, which went against their ideas of liberalization. To avoid insolvency, 14 of 26 commercial banks and 8 of 17 financial institutions were nationalized by the end of 1985. The program covered 30% of all outstanding debt, equal to 25% of GDP (Margitich, 1999; Caputo and Saravia, 2018). In addition, import tariffs were raised from 10% to 35%, but these increases were short-lived and returned to 15% in 1985 (Edwards and Lederman, 1998). In general, the fundamental features of the liberalizations kept in place or revitalized in the years following the crisis.

1.3.3 Washington Consensus

The IMF, the World Bank, and the US Treasury believed that the current policies, based on industrialization and large government involvement, had led to inflation, debt, and crisis in Latin America and needed to be replaced. Therefore, in their negotiations for reparations with Latin American countries, they imposed a package of policies modeled after the Chilean liberalization that came to be known as the "Washington Consensus," named after the location of the three organizations. This resulted in a wave of liberalizations in the late 1980s that marked the beginning of the end of the "lost decade" in Latin America, which recovered to 1982 levels in 1994. Chile had experienced a "found decade" and recovered in 1988 (McKinney, 2021), thanks to the liberalizing reforms of the 1970s (Bergoeing et al., 2002). Pinochet's military regime would eventually be replaced by a democracy in 1988 after losing the plebiscite, bringing President Aylwin to power who continued the neoliberalist approach.

2 Literature Review

2.1 Lessons of Economic Liberalization and Debt Crisis

The goal of economic liberalization is to achieve economic growth by removing controls, reducing government regulations and restrictions, to allow more efficient allocation of resources by private entities. The remarkable rise of Chile, which implemented extensive reforms in the 1970s, is attributed to liberalization (Bergoeing et al., 2002). Wacziarg and Welch (2008) analyzed over 50 years of data on liberalizations and found evidence that liberalizations are generally beneficial. They found that on average, countries' annual growth increased by 1.5 percentage points after liberalization. Furthermore, Wacziarg and Welch (2008) found that liberalization leads to an average increase in investment rates of 1.5 to 2.0 percentage points and in the trade-to-GDP ratio of 5.0 percentage points. However, they admit that there are large differences between countries. This idea of varying successes in liberalization is endorsed throughout the literature on economic liberalization.

The success of a liberalization program depends on political factors, such as political stability and fatigue. Wacziac and Welch (2008) show that stable governments, such as the authoritarian regime in Chile, have higher growth rates than unstable governments because they can adopt, implement, and sustain unpopular reforms. However, even authoritarian regimes need support for their reforms; for example, firms in Chile were compensated for the negative effects of reforms by cost reductions through labor market reforms and currency depreciation (Edwards and Lederman, 1998). Moreover, political fatigue is a serious aspect to consider when liberalizing the economy because a finite bureaucracy can be overwhelmed by the implementation of a new reform, exacerbated by the added pressure of various groups lobbying for their own benefit. The uniform tariffs introduced during the Chilean reforms were intended to reduce pressure on the bureaucracy and as a front against lobbying (Edwards and Lederman, 1998).

The idea of capital liberalization is that price levels and credit allocation should be determined by market forces. This will improve the productivity of capital as the real interest rate adjusts to the market equilibrium, thus improving the efficiency of investment, saving and credit, ultimately leading to economic growth. Capital liberalization often leads to an inflow of capital, but is often short-lived, as these booms were followed by busts. This short-term increase in capital is also observed in Bekaert et al. (2002), where capital increased by 1.4% annually, but these capital flows declined after three years. Stating that global investors induce a one-time rebalacing of their portfolio after liberalisation. Bekaert et al. (2002) further found that when capital leaves, it leaves faster than it came. Thus, these capital liberalizations expose countries to external economic shocks and make them vulnerable to banking crises resulting from capital flight. In addition, Arestis and Demetriades (1999) found that when capital liberalization is accompanied by large stabilization efforts such as the fixed exchange rate, crisis and instability become increasingly likely. Chile's liberalization efforts provide a perfect example of this phenomenon, as the liberalizations, like cutting tariffs to a uniform 10%, were carried out in conjunction with an anti-inflation policy of a dollar-pegged exchange rate. Consequently, the combination of an appreciating dollar, leading to a nominal appreciation of the peso, and a real depreciation of the exchange rate as a result of the economic reforms led to the worst financial crisis in Chile's history.

2.2 Synthetic Control

The synthetic control method proposed by Abadie and Gardeazabal (2003) and Abadie et al. (2010) is considered the most important innovation in intervention analyses in the last 15 years (Athey and Imbens, 2017). Traditional regression analysis methods are not suitable for estimating infrequent events, such as policy interventions, because they require large samples and many observed instances of the intervention (Abadie, 2021). Therefore, researchers have resorted to comparative case study analyses, where a treated series, exposed to the intervention, is compared to an untreated series. The problem with this method is that, first, the methodology for selecting a comparative untreated series is not formalized and differs among researchers, and second, there are often limited untreated series, increasing the probability that no single untreated series alone can provide a good comparison for the treated series (Abadie, 2021). The synthetic control method improves upon the literature of policy analyses by formalizing the methodology for selecting comparative untreated series. Moreover, it provides a solution for cases where there are limited number of untreated series, since it is based on the idea that a combination of series provide a better comparison than a single series. The synthetic control method has become a heavyweight in policy analysis, one such example being universal health coverage in Thailand (Rieger et al., 2017). Synthetic controls are also applied in other areas of academia, such as social sciences, engineering, and medical sciences, for example, Kikuta's (2020) analyses of the environmental costs of civil war. The method has also found widespread use among think tanks, government agencies, consulting firms, and businesses. For example, the analyses by Gutierrez et al. (2016) on the impact of the Bill Melinda Gates Foundation.

Harvey and Thiele (2021) proposed an alternative method for selecting and weighting comparative donor series based on cointegration in the pre-intervention period. Thus, the method does not rely on covariates describing the series in question, which is the case in the synthetic control proposed by Abadie and Gardeazabal (2003) and Abadie et al. (2010). Dreuw (2022) points out that in several empirical studies the results contradict each other when analyzing the introduction of the euro, suggesting that the synthetic control of Abadie and Gardeazabal (2003) and Abadie et al. (2010) is not robust to the subjective basis of selecting covariates. Dreuw (2022) argues that the synthetic control method of Harvey and Thiele (2021) solves this problem because it uses an objective measure, cointegration, to select donor series.

3 Methodology

This section will describes two main methods to estimate intervention effects. The notations in this section are in line with the those proposed in Harvey and Thiele (2021). First, it will explain what the synthetic control method (SCM) is, how to construct a synthetic control, how to estimate it, and the possible interventions in the model. Second, this section will introduce an alternative to the synthetic control method, namely model-based estimation (MBE), explaining its construction, estimation and possible gains in detail. Finally, this chapter will conclude with a comprehensive method for selecting the correct donor series.

3.1 Synthetic Control Method

The synthetic control method estimates the effect of an intervention based on a so-called synthetic control. A synthetic control is constructed to estimate the effect of an intervention on the target variable y_{0t}. This is done by taking a weighted combination of multiple donor series y_{it}, called donors, that resemble the target series before the intervention. In so doing, a close replica of the target series is constructed, in this paper Chile, and therefore an "alternative universe" is simulated in which the intervention does not take place. This enables one to estimate the effect of the intervention by comparing the target with its synthetic counterpart.

3.1.1 Constructing the synthetic control

A synthetic control will thus be constructed by weighting a combination of contemporaneous control series, so that the resulting synthetic control closely matches the target series. This comes down to the following equation (1).

$$y_t^c = \sum_{i=1}^{N} w_i y_{it} = \mathbf{w}'\mathbf{y}_t, \quad t = 1, \ldots, T \tag{1}$$

The weights of the N donors, w_i for all donors $i = 1, \ldots, N$, in the $N \times 1$ vector $\mathbf{w}$ are estimated in the pre-intervention period $t = 1, \ldots, \tau - 1$. The effect of the intervention after time τ can be estimated by taking the difference between the target series and the constructed synthetic control, $y_{0t} - y_{it}$ for $t = \tau, \ldots, T$. When the target series, y_{0t}, is non-stationary, the synthetic control must consist of a combination of donor series that share a common trend with the target series. In other words, the difference between the target variable and the synthetic control, $y_{0t} - y_{it}$, is stationary in the pre-intervention period ($t = 1, \ldots, \tau - 1$). If the difference between the target series and its synthetic control is non-stationary in the pre-intervention period, an undesirable spurious stochastic trend will develop in the effect of the intervention. A KPSS test on the difference will be performed to verify that the difference is stationary. The mechanism of the KPSS test will be further explained in the donor selection (final) section of the methodology.

Harvey and Thiele (2021) provide an example of the dangers of a model that is too general. The example that they provide is a multivariate local level model that included several common stochastic trends. They explain that there is a significant risk of mistaking in-sample overfitting for common trends, especially when the number of donor series (N) is large compared to the length of the pre-intervention period (τ). Harvey and Thiele (2021) suggest using tighter restrictions on the individual donors, which they explain are also more credible for settings with shorter time series. Therefore, a multivariate balanced growth model will be used in this paper. This restricts the donor series and the target to a single stochastic common trend instead of multiple. The multivariate balanced growth model is defined as follows.

$$
\begin{aligned}
y_{0t} &= \mu_t + \mu_0 + \varepsilon_{0t} \\
\mathbf{y}_t &= \mathbf{1}\mu_t + \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t \\
\mu_t &= \mu_{t-1} + \delta_{t-1} + \eta_t \\
\delta_t &= \delta_{t-1} + \zeta_t
\end{aligned}
\tag{2}
$$

Where the donor series $\mathbf{y}_t$, growth vector $\mathbf{1}$, means $\boldsymbol{\mu}$, and errors $\boldsymbol{\varepsilon}_t$ are $N \times 1$ vectors for $t = 1, \ldots, T$. The $\mathbf{1}$ vector ensures that all the series are on the exact same growth path / common trend, consisting of only ones. The common trend, μ_t, takes the value zero at $t = 0$ with stochastic slope δ_t. Furthermore, the disturbances ε_{0t}, η_t, ζ_t are serially independent and normally distributed with means zero and variances σ_0^2, σ_η^2 and σ_ζ^2. One should note that if one sets the level variance to zero, $\sigma_\eta^2 = 0$, the trend then becomes an integrated random walk. Further are the errors $\boldsymbol{\varepsilon}_t$ also serially independent and have a multivariate normal distribution with mean zero and covariance matrix $\boldsymbol{\Sigma}_\varepsilon$, all disturbances are independent from one and another.

To estimate the intervention effect the synthetic control y_t^c in equation (1) is subtracted from the target y_{0t}, the first equation in (2). Resulting in the following equation.

$$y_{0t} - y_t^c = \mu_0 - \mathbf{w}'\boldsymbol{\mu} + \left(1 - \mathbf{w}'\mathbf{1}\right)\mu_t + \varepsilon_{0t} - \mathbf{w}'\varepsilon_t, \quad t = 1, \ldots, T \tag{3}$$

Where the difference $y_{0t} - y_t^c$ is stationary, as the weights are restricted to sum to one making $(1 - \mathbf{w}')'$ a co-integration vector. The weights, $\mathbf{w}$, of the donor series that together construct the synthetic control are estimated in the pre-intervention period, $t = 1, \ldots, \tau - 1$, by Restricted Least Squares (RLS). The RLS estimates $\mathbf{w}$ by minimizing (4) subject to $\mathbf{w}'\mathbf{1} = 1$.

$$\sum_{t=1}^{\tau-1} \left(y_{0t} - y_t^c\right)^2 = \sum_{t=1}^{\tau-1} \left(y_{0t} - \mathbf{w}'\mathbf{y}_t\right)^2, \tag{4}$$

Resulting in the following restricted least squares estimator $\widehat{\mathbf{w}}_{RLS}$.

$$\widehat{\mathbf{w}}_{RLS} = \mathbf{S}_{\mathbf{yy}}^{-1}\mathbf{s}_y + s\mathbf{S}_{\mathbf{yy}}^{-1}\mathbf{1} = \widehat{\mathbf{w}}_{OLS} + s\mathbf{S}_{\mathbf{yy}}^{-1}\mathbf{1} \tag{5}$$

Where $\mathbf{S}_{\mathbf{yy}} = \sum_{t=1}^{\tau-1} \mathbf{y}_t\mathbf{y}_t'$, $\mathbf{s}_y = \sum_{t=1}^{\tau-1} \mathbf{y}_t y_{0t}$, $\widehat{\mathbf{w}}_{OLS} = \mathbf{S}_{\mathbf{yy}}^{-1}\mathbf{s}_y$ and $s = \left(1 - \mathbf{1}'\widehat{\mathbf{w}}_{OLS}\right)/\mathbf{i}'\mathbf{S}_{\mathbf{yy}}^{-1}\mathbf{i}$. One should notice that the last term in (5) $s\mathbf{S}_{\mathbf{yy}}^{-1}\mathbf{1}$ is a restriction adjustment. The restriction adjustment is the divergence between $\mathbf{1}'\widehat{\mathbf{w}}_{OLS}$ and $\mathbb{E}(\mathbf{1}'\widehat{\mathbf{w}}_{OLS}) = 1$. This results in that the impact of large variance donors will be limited and down weighted. Further, leaves this notation room for the individual weights being negative as well as being greater than one. One could compute $\widehat{\mathbf{w}}$ by OLS regression. Subtracting one of the donor series y_{it} from all other donor series $\mathbf{y}_t^{(-i)}$ and the target series y_{0t}. Hence, regressing the difference $y_{0t} - y_{it}$ on the $N-1$ differences with the remaining donors $y_{0t} - y_{it}$, $j \neq i$. This gives $\widehat{w}_j$ for $j \neq i$ and $\widehat{w}_i = (1 - \sum_{j \neq i} \widehat{w}_j)$ in addition of the corresponding standard errors.

The model proposed in equation (2) could be considered quite constraining. However, real applications often show a balanced growth that suits this model, which combined with its clear interpretation provides important advantages for its use. Furthermore, as mentioned earlier, there are some dangers associated with an overly general model.

3.1.2 Interventions with dynamic response

The constructed synthetic control did not allow for a dynamic response. Often an intervention has a dynamic response with an unknown pattern. The application of this paper, Chile's liberalisation, also suggests a dynamic response. Economic liberalisation is not instantaneous and it takes time to see its full effect. Suppose an intervention occurs at $t = \tau$, the pattern of the response is unknown, but it is assumed that its full effect have been materialized after $m \geq 1$ time periods. To model this response, a series of impulse dummies are added to the first equation in (2). Additionally, a step dummy is also introduced to (2), which measures the permanent effect of the intervention after the full effect has materialized. This results in the following equation.

$$y_{0t} = \mu_t + \mu_0 + \lambda d_t + \sum_{j=1}^{m} \lambda_j d^*_{j,t} + \varepsilon_{0t}, \quad t = 1, \ldots, T \tag{6}$$

Where the permanent shift λ in the level of y_{0t} is captured by the following step dummy divined as,

$$d_t = \begin{cases} 0 \text{ for} & t < \tau + m \\ 1 \text{ for} & t \geq \tau + m \end{cases}, \quad 1 < \tau + m \leq T \tag{7}$$

Further are the intermediate level shifts λ_j captured by the set of m pulse dummies divined as,

$$d^*_{j,t} = \begin{cases} 0 & \text{for} \quad t \neq \tau + j - 1, \\ 1 & \text{for} \quad t = \tau + j - 1 \end{cases}, \quad j = 1, \ldots, m \tag{8}$$

To estimate with synthetic control including dynamic response I subtract y^c_t in equation (1) from equation (6). This results in the following equation.

$$y_{0t} - y^c_t = \mu^c_0 + \lambda d_t + \sum_{j=1}^{m} \lambda_j d^*_{j,t} + \varepsilon^c_t, \quad t = 1, \ldots, T \tag{9}$$

Where $\mu^c_0 = \mu_0 - \mu^c$ and $\varepsilon^c_t = \varepsilon_{0t} - \mathbf{w}'\boldsymbol{\varepsilon}_t$. The pulse and step dummies can be estimated by regressing the difference between the target and the synthetic control on the different dummies. If ε_t is serially correlated, a stationary ARMA process can be used to model it. Note that when there is a hard break present in the data, hence no dynamic response, the obtained step dummy $\hat{\lambda}$ in (6) will be a generalized estimate of the difference of differences (Harvey and Thiele, 2021).

3.1.3 Chow-break test

To select the optimal number of pulse dummies, a Chow break test is performed on the series of differences between the target and the synthetic control. This test was proposed by Chow (1960) and allows one to find structural breaks or so-called break-points, with the following test-statistic.

$$F_{chow} = \frac{(S_t - (S_1 + S_2))/k}{(S_1 + S_2)/(N_1 + N_2 - 2k)} \sim \mathrm{F}(k, N_1 + N_2 - 2k) \tag{10}$$

Where S_t is the sum of squared residuals of the total sample, S_1 and S_2 are the sum of squared residuals of the two sub samples, k is the number of parameters, and N_1 and N_2 are the number of observations in each sub sample. The number of pulse dummies is determined by running a chow test over the complete sample after the intervention ($t = \tau, \ldots, T$) and testing for a break-point. This break-point occurs when the full effect of the intervention has materialized and the difference between the target and the synthetic control stabilizes. The number of periods between the intervention and the break-point dictates the number of pulse dummies. Furthermore, after the break-point a step dummy is introduced to measure the full effect of the intervention.

3.2 Model-Based Estimation

In addition to the synthetic control method, Harvey and Thiele (2021) propose an alternative method for estimating the intervention effect, namely model-based estimation. A key difference between MBE and SCM is that donor series weights are estimated over the entire sample rather than just in the pre-intervention period. Therefore, the weights are not treated as a given, which is the case with the SCM. One other important aspect of the MBE is that the common trend μ_t, with stochastic slope δ_t must be estimated. Furthermore, three different MBE methods are highlighted, namely univariate, bivariate and multivariate. This section will also highlight some efficiency advantages of using MBE over SCM and among the MBE methods.

3.2.1 Estimation by Maximum Likelihood

To estimate the the intervention effect including the dynamic response, one can perform a complete maximum likelihood estimation (MLE) on the target series defined in (6) combined with a pool of donor series $\mathbf{y}_t$ in (2). As mentioned is an important aspect of the MLE the estimation of the common trend μ_t, with its stochastic slope δ_t. This is done using a Kalman filtering ans smoothing, as explained in Durbin and Koopman (2012). One could transform this multivariate system by subtracting one of the donor series, y_{it}, $i = 1, \ldots, N$, from the target variable y_{0t} and the remaining $N - 1$ donor series. The remaining donor series are contained in the vector $\mathbf{y}_t^{(-i)}$, resulting in the following equivalent multivariate system.

$$y_{0t} - y_{it} = \mu + \lambda d_t + \sum_{j=1}^{m} \lambda_j d_{j,t}^* + \varepsilon_t \tag{11}$$

$$y_{it} = \mu_t + \mu_i + \varepsilon_{it} \tag{12}$$

$$\mathbf{y}_t^{(-i)} - \mathbf{1} y_{it} = \boldsymbol{\mu}^{(-i)} + \boldsymbol{\varepsilon}_t^{(-i)} - \mathbf{1}^{(-i)} \varepsilon_{it} \tag{13}$$

Where $\mu = \mu_0 - \mu_i$, $\varepsilon_t = \varepsilon_{ot} - \varepsilon_{it}$ and $\mathbf{1}^{(-i)}$, $\boldsymbol{\mu}^{(-i)}$ and $\boldsymbol{\varepsilon}_t^{(-i)}$ are a $(N-1) \times 1$ vector for $t = 1, \ldots, T$. One could notice that the common trend μ_t is only present in the y_{it} donor series equation, due to subtracting donors y_{it} from the target y_{0t} and the donors $\mathbf{y}_t^{(-i)}$.

Next to the multivariate model, where there are $N+1$ number of equations in the system, one might prefer to construct a bivariate model that only contains two equations. The bivariate model is constructed by again taking the difference between donor series y_{it} with the target series y_{0t} and remaining $N-1$ donor series y_{jt}, $j \neq i$. To create the bivariate system one adds the $N-1$ remaining donor differences, $y_{0t} - y_{it}$, $j \neq i$, to the right-hand side of both equations (11) and (12). This results in the following bivariate system.

$$y_{0t} - y_{it} = \mu + \sum_{j \neq i}^{N} w_j \left(y_{jt} - y_{it} \right) + \lambda d_t + \sum_{j=1}^{m} \lambda_j d_{j,t}^{*} + \varepsilon_t^{\dagger} \tag{14}$$

$$y_{it} = \mu_t + \mu_i^{\dagger} - \sum_{j \neq i}^{N} c_j \left(y_{jt} - y_{it} \right) + \varepsilon_{it}^{\dagger} \tag{15}$$

The disturbances indicated by † are a linear combination of the individual disturbances of the underlying donor series. This is also the case for the constant indicated by †, which is a linear combination of the constants of the underlying series. Furthermore, the coefficients c_j's must be estimated, just like the w_j's. With these estimated w_j's one can calculate w_i and, hence the weights of all donor series that together make the synthetic control.

In addition of the multivariate and bivariate systems one can construct a univariate system containing only a single equation. This is done by estimating equation (14) without equation (15). The univariate system also, like the bivariate system, estimates the w_j's, and by extension w_i. This is in contrast to the multivariate system that estimates the intervention effect conditionally on the weights. Moreover, one might note that the main difference between the univariate and bivariate is the exclusion of the dynamic stochastic trend. The incorporation of such a trend in these models does have implications for the efficiency of the results.

3.3 Efficiency Gains From Model Based Estimation

This section compares the efficiencies of both the SCM and MBE's, see if there are any gains are achievable. The research in this section parallels the research on efficiency gains between models presented in Harvey and Thiele (2021), while adding additional insights in the final part. In this section contains a analyses on efficiency gains when the parameters are known. Moreover, Harvey and Thiele (2021) provided an extensive Monte Carlo simulation study analysing the efficiency gains when the parameters are unknown. This will also be discussed in this section.

3.3.1 Efficiency Gains With Known Parameters

The model based estimation methods allow for some efficiency gains to be made over the synthetic control method. To show these gains, an analyses is done where the initial conditions μ_0 and $\boldsymbol{\mu}$, the post-intervention dummies and the parameters σ_η^2, $\boldsymbol{\sigma}_\varepsilon$ and $\boldsymbol{\Sigma}_\varepsilon$ are known.

In the case of the model based estimation the Kalman filter and smoother, as proposed in Durbin and Koopman (2012), can estimate the common trend $\mu_{t|T}$ for $t = 1, \ldots, T$. One should note that, to estimate this common trend, one uses all T observations from the donor series and only the first $\tau - 1$ from the target series. Hence, $|T$ indicates that the estimate is obtained given the full sample $t = 1, \ldots, T$. This results in the following post-intervention period estimator of the target series $y_{0t|T}$. The estimator can be rewritten by plugging in $\varepsilon_{0t|T} = \boldsymbol{\beta}' \varepsilon_{t|T}$, with $\boldsymbol{\beta} = \boldsymbol{\Sigma}_\varepsilon^{-1} \boldsymbol{\sigma}_\varepsilon$ and $\varepsilon_{t|T} = \mathbf{y}_t - \boldsymbol{\mu} - \mathbf{i}\mu_{t|T}$.

$$\begin{aligned} y_{0t|T} &= \mu_0 + \mu_{t|T} + \varepsilon_{0t|T} \\ &= \mu_0 + \mu_{t|T} + \boldsymbol{\beta}' \left(\mathbf{y}_t - \boldsymbol{\mu} - \mathbf{1}\mu_{t|T} \right), \end{aligned} \qquad t = \tau, \ldots, T \tag{16}$$

One can estimate the pulses $\tilde{\lambda}_j$ by subtracting the previous derived estimator $y_{0t|T}$, from the target series y_{0t}, $\tilde{\lambda}_j = y_{0t} - y_{0t|T}$ for $t = 1, \ldots T - \tau + 1$. This results in the following $\tilde{\lambda}_j$ estimator for $j = 1, \ldots, T - \tau + 1$ and related variance.

$$\tilde{\lambda}_j = \left(1 - \boldsymbol{\beta}'\mathbf{1}\right) \left(\mu_t - \mu_{t|T}\right) + \varepsilon_{0t} - \boldsymbol{\beta}' \varepsilon_t \tag{17}$$

$$\operatorname{Var}\left(\widetilde{\lambda}_j\right) \simeq \left(1 - \boldsymbol{\beta}'\mathbf{1}\right)^2 \operatorname{Var}\left(\mu_t - \mu_{t|T}\right) + \sigma_0^2 - \boldsymbol{\beta}' \boldsymbol{\sigma}_\varepsilon \tag{18}$$

The variance is an approximate, because the small cross term $(\mu_t - \mu_{t|T})(\varepsilon_{0t} - \boldsymbol{\beta}'\boldsymbol{\sigma}_\varepsilon)$ is left out, but is however dominated by the terms left in the equation. In addition, as the Kalman estimated $\mu_{T|T}$ at the end of the sample results in the variance becoming an upper bound it can then be shown that the cross term is zero in which case the equation becomes exact.

The variance of the pulses λ_j^c using the synthetic control method, involving y_{0t}^c, is shown in Harvey and Thiele (2021), and can be written as follows.

$$\operatorname{Var}\left(\lambda_j^c\right) = \frac{\left(1 - \boldsymbol{\beta}'\mathbf{1}\right)^2}{\mathbf{1}'\boldsymbol{\Sigma}_\varepsilon^{-1}\mathbf{1}} + \sigma_0^2 - \boldsymbol{\beta}'\boldsymbol{\sigma}_\varepsilon \tag{19}$$

Harvey (1990, P 119) shows that $Var(\mu_T - \mu_{T|T}) = \bar{\sigma}_\varepsilon^2 p$, where $\bar{\sigma}_\varepsilon^2 = 1/(\mathbf{1}'\boldsymbol{\Sigma}_\varepsilon^{-1}\mathbf{1})$ and $p = (-q + \sqrt{q^2 + 4q})/2$, with q being the signal-noise ratio $\sigma_\eta^2/\bar{\sigma}_\varepsilon^2$ which is ≥ 0. To see the gain in efficiency one might subtract $\operatorname{Var}\left(\widetilde{\lambda}_j\right)$ from $\operatorname{Var}\left(\lambda_j^c\right)$, illustrated below.

$$
\begin{aligned}
\operatorname{Var}\left(\lambda_j^c\right)-\operatorname{Var}\left(\widetilde{\lambda}_j\right) &= \frac{\left(1-\boldsymbol{\beta}'\mathbf{1}\right)^2}{\mathbf{1}'\boldsymbol{\Sigma}_{\varepsilon}^{-1}\mathbf{1}}-\left(1-\boldsymbol{\beta}'\mathbf{1}\right)^2\operatorname{Var}\left(\mu_t-\mu_{t|T}\right)\\
&=(1-p)\frac{\left(1-\boldsymbol{\beta}'\mathbf{1}\right)^2}{\mathbf{1}'\boldsymbol{\Sigma}_{\varepsilon}^{-1}\mathbf{1}}\\
&\geq 0
\end{aligned}
\tag{20}
$$

The difference in (21) is strictly non-negative, because $\left(1-\boldsymbol{\beta}'\mathbf{1}\right)^2/\mathbf{1}'\boldsymbol{\Sigma}_{\varepsilon}^{-1}\mathbf{1}\geq 0$ and $0<(1-p)\leq 1$, as $q\to\infty$, $p\to 1$. Therefore, is the SCM never superior over MBE in terms of efficiency, especially in cases where the signal-noise (q) ratio is small. One might notice that a special case could arise when $\boldsymbol{\beta}'\mathbf{1}=1$ then SCM and MBE are equal in the sense that y_{0t}^c and $y_{0t|T}$ are equal, and thus no efficiency gains can be made.

3.3.2 Efficiency Gains With Unknown Parameters

In the previous section, it was shown that the efficiency of SCM is not superior to that of MBE when the parameters are unknown. However, Harvey and Thiele (2021) conducted an extensive Monte Carlo simulation study to verify whether this result is true in practice and to analyze whether this is the case when the parameters are unknown. Indeed, Harvey and Thiele (2021) find that when the parameters are known, MBE is more efficient than SCM. This is also true when the parameters are not known, with MBE performing better when (q) becomes smaller. However, they found a special case where SCM is slightly more efficient than MBE. This occurred when the signal-noise ratio (q) was relatively large. When Harvey and Thiele (2021) introduced correlation between the donors, MBE always outperformed SCM.

3.4 Selecting Donor Series

The synthetic control should match as closely as possible the observations of the target series in the pre-intervention period. In the case of non-stationarity, the individual donor series must be on the same growth path as the target series. One can perform three separate tests to determine whether both are on the same growth path. First, a test to see if the donor or target is integrated of order zero ($I(0)$). Second, a test to see if the donor or target is integrated of order one ($I(1)$), if both tests are rejected then the series is integrated of order two or higher. One requires the donor and target series to be on the same order of integration, which is necessary for co-integration. Finally, a third test will be performed if the donor and target series are indeed co-integrated, testing for stationarity of the difference between the target and donor series. The NM and KPSS tests proposed by Nyblom and Makelainen (1983) and Kwiatkowski et al. (1992) are well suited for these tasks and will be explained in further detail in the next section.

After performing the three tests, a selection of potential donor series remain. The weights of the donors included in a synthetic control can be obtained by RLS. However, it should be noted that donors with large variances when differenced with the target series are severely down weighted, as shown in (5). Hence, these donors are dropped from the donor pool. Furthermore, one does not want to include donors where the same intervention occurs shortly after the target intervention event, as this would mitigate the intervention effect. This particular point is especially challenging in the case of Chile, considering that many countries were liberalized right after Chile[1]. In order to estimate the intervention effect over a significant period of time and to have sufficient appropriate donors, countries that were liberalized within 12 years are excluded. Furthermore, donor series that undergo a donor-specific shock, such as wars or natural disasters, are also excluded, as this also obstructs the accurate estimation of the intervention effect. One can do this by researching the donors or by graphically examining the donor series. Haiti, for example, is excluded due to the 1991 coup, which led to foreign intervention in 1993, severely affecting GDP per capita. Finally, a sanity check can be performed on the difference between the constructed synthetic control series and the target series, by testing for stationarity in the pre-intervention period.

3.4.1 NM and KPSS tests

The Kwiatkowski-Phillips-Schmidt-Shin test (KPSS), introduced in Kwiatkowski et al. (1992), can be used to test whether a time series is stationary around a level or a linear trend. The null hypothesis is that the series is stationary; rejection would mean non-stationarity. Since the observations in the pre-intervention period are often small, a Monte Carlo simulation study similar to that in Harvey and Thiele (2021) is conducted to assess the size and power of the NM and KPSS tests. This study assumes a pre-intervention period of $T = 20$ periods, which corresponds to the length of the pre-intervention period of Chile and the two case studies in the Appendix. The KPSS test depends on lag l, where the special case $l = 0$ yields the NM test. An optimal number of lags is determined using this simulation study. The model proposed in Kwiatkowski et al. (1992) is simulated in Monte Carlo study, presented below.

$$
\begin{aligned}
y_t &= \mu_t + \varepsilon_t \\
\mu_t &= \mu_{t-1} + \eta_t \\
\varepsilon_t &= \phi \varepsilon_{t-1} + \xi_t
\end{aligned}
\tag{21}
$$

[1]Most liberalizations in Latin America took place after 1988, 12 years later than in Chile.

In this model are η_t and ξ_t mutually independent and generated following two normal distributions, namely $\eta_t \sim N(0, q)$ and $\xi_t \sim N\left(0, 1-\phi^2\right)$. Following Harvey and Thiele (2021), the parameters $\phi \in \{0, 0.5\}$ and $q \in \{0, 0.1, 0.5\}$ are set, maintaining a significance level of 10%, which has a critical value of 0.347. For each time difference l, 15,000 simulations are used to calculate the rejection rates, which is an increase of 5,000 compared to Harvey and Thiele (2021) to obtain more consistent results. Table 1 below shows the results.

Table 1: Results Monte Carlo simulation.

ϕ	q	$l=0$	$l=1$	$l=2$	$l=3$	$l=5$	$l=7$
0	0	0.104	0.102	0.097	0.097	0.098	0.117
	0.1	0.166	0.156	0.149	0.143	0.137	0.156
	0.5	0.596	0.534	0.490	0.450	0.382	0.329
0.5	0	0.244	0.201	0.168	0.142	0.126	0.119
	0.1	0.203	0.177	0.163	0.162	0.168	0.169
	0.5	0.666	0.590	0.537	0.488	0.405	0.344

Note: Number of runs are 15000, significance 10% with P-value 0.347 and T = 20

When $\phi = 0$, no auto correlation in the transistory component η_t, the tests have good size. However, this changes when auto-correlation is introduced, then the rejection rates shoot up. The rejection rates also increase significantly when the level variance q increases. One might note that it is beneficial to add up to 5 lags, after which adding lags negatively impacts the size of the tests. Regarding the lower lags l, however, there is a trade-off between size and power. Kwiatkowski et al. (1992) propose a formula to be used in selecting the lag $l = 4 * (T/100)^{1/4}$, this results in a lag value of 2.675 for $T = 20$. One can see from Table XX that a lag, $l = 2$, indeed strikes a good balance between size and power.

4 Data

This section explains the data settings used for the analyses of Chile's liberalization and the two additional case studies of Germany's reunification and policy implementation in California. It includes the source of the datasets, the choice of the studied variable, data removal, data transformation, and the selection of the pre-intervention period.

4.1 Chile

For the analysis regarding the impact of the 1976 liberalization on the Chilean economy, GDP per capita is the variable of intrest. Gross domestic product (GDP) is the total value of goods produced and services provided in a country in a given year. It is therefore generally used as a measure of the performance of a country's economy. GDP per capita divides a country's economic output by its total population, allowing for a more accurate comparison between large and small countries. In addition, the natural logarithm is taken of GDP per capita, which converts the data into growth rates. This also removes the exponential trend in the data.

The dataset used for this analysis is from the Federal Reserve Bank of St. Louis and contains annual per capita GDP data, measured in 2015 US dollars, for 265 countries and regions from around the world, including Chile, for the period 1960-2020. All regions were removed, so that only countries remained. For example, "European Union" and "North America" were excluded. Furthermore, countries for which data were missing in the 1960-2000 period were removed, as these observations were essential for the construction of the synthetic control and the estimation of the intervention effect. In addition, countries were removed when more than 5% of the data were missing. In total, 101 countries remain in the potential donor pool. Two additional constraints are imposed on potential donors when selecting donor series based on cointegration. First, a country is excluded if it has suffered a severe country-specific shock, such as a war or natural disaster. Second, countries that have no liberalization date[2] or were liberalized before 1988[3] are excluded. This is necessary to create a synthetic control that allows estimating the intervention effect over a significant period of time. The dates of liberalization are determined using a binary indicator developed by Sachs and Werner (1995) which was later revised by Wacziarg and Welch (2008). A country is considered liberalized if none of the following five conditions are met: (i) the country has a socialist economic system, (ii) a large part of its exports are controlled by state monopolies, (iii) average tariffs exceed 40%, (iv) non-tariff barriers cover more than 40% of imports, and (v) black market premiums on exchange rates exceed 20%. The pre-treatment period is between 1960-1975, with $T = 16$ time periods.

4.2 Germany

For the analysis of the reunification of West and East Germany in 1990 and its impact on the GDP of West German states, GDP per capita is again the variable of interest. The data is transformed by taking the natural logarithm. The dataset can be obtained from the article by Abadie et al. (2015) where the application first appeared. The dataset contains annual GDP levels for the period 1971-2003, including 16 OECD countries and West Germany. No countries were excluded for this analysis. The pre-intervention period falls between 1971-1989, with $T = 19$ time periods. This is in contrast to the pre-intervention period used in Harvey and Thiele (2021), where they choose a pre-intervention period between 1971-1990, with $T = 20$ time periods. Reunification takes place in early October 1990, leaving enough time in that year for the intervention effect to take place. Therefore, 1990 is not included in the pre-intervention period.

[2]This does not refer to countries that are not liberalized as of today.

[3]Within 12 years of the liberalisation of Chile in 1976

4.3 California

For the analysis of the 1990 policy change, Proposition 99, in California, the variable of interest is annual cigarette sales. For the selection of donors, the data is transformed by taking the natural logarithm, but for the eventual estimation of the intervention effect, the original non-logarithm data is used[4]. The dataset can be obtained from the article by Abadie et al. (2010) in which the application was first examined. The dataset includes annual cigarette sales for 1970-2000 in 39 US states, excluding states where smoking regulation was already in place or introduced shortly after 1989. The pre-intervention period is between 1970-1988, with $T = 19$ time periods.

5 Results

This section estimates the intervention effect, the 1976 liberalization of Chile, and discusses the results. Starting with donor selection, it continues with the estimation of the effect and ends this section with a robustness check of the results. Two additional cases where the intervention effect is estimated are shown in the appendix. The first case involves the reunification of West and East Germany in 1990 and the second the introduction of stricter smoking regulations in California in 1989, both well studied in the synthetic control literature. These two cases are replicated from Harvey and Thiele (2021) and demonstrate the validity of the methodology in this paper.

5.1 Selecting Donors

Balanced growth, i.e., co-integration, in the pre-intervention period between the target (Chile) and its donors is a key assumption necessary to construct the synthetic control according to the method outlined in this paper. Table 1 presents three tests to verify that the donor and the target are co-integrated. The first two columns are two KPSS tests to determine the order of integration. The column I(0) gives the P-values for the test of whether the series shows a deterministic trend versus a stochastic trend, with a threshold value of 0.146. Furthermore, the column I(1) gives the P-values for the test of the order of integration, I(1) versus I(2), with a threshold of 5% of 0.463. In theory, one requires the donor series to have the same integration order as the target series, as this is usually a condition for co-integration. The third column is also a KPSS test to verify that the donor series is indeed co-integrated with the target, with a threshold value of 5% of 0.463.

The total donor pool consisted of 101 countries from all over the world; when testing the hypothesis of balanced growth and equal integration order, 15 countries remained as potentially suitable donors for Chile's synthetic control. However, many of these countries had problems such as a country-specific

[4]Following Harvey and Thiele (2021), to obtain similar results.

shock, the liberalization date preceded 1988, or the liberalization date could not be determined at all[5]. Table 1 therefore shows a selection of countries with a liberalization date after 1988 and without significant country-specific shocks. Interestingly, the list of potential donors was predominantly from Latin America.

Table 2: KPSS tests for integration level and co-integration.

	I(0)	I(1)	Coint.	Var	Lib. year
Trend	Yes	No	No		
Chile	0.150**	0.418	-	-	1976
Guyana	0.085	0.167	0.174	0.076	1988
Peru	0.115	0.186	0.174	0.127	1991
Honduras	0.144	0.211	0.182	0.111	1991
Ecuador	0.156**	0.404	0.187	0.091	1991
Philippines	0.132	0.169	0.213	0.079	1988
Uruguay	0.151**	0.289	0.296	0.039	1990
Nicaragua	0.145	0.303	0.331	0.376	1991
Argentina	0.095	0.119	0.393	0.119	1991
El Salvador	0.149**	0.345	0.318	0.154	1989
Guatemala	0.151**	0.160	0.441	0.107	1988
South Africa	0.169**	0.429	0.448	0.177	1991
Brazil	0.163**	0.327	0.470**	0.080	1991

Note: 5% significance is indicated with **, test statistics are 0.146 for I(0), 0.463 for I(1) and Coint. The table is ordered on the co-integration test. Furthermore, this a small selection of the 101 countries analysed.

Table 2 shows that Chile rejects the null for the I(0) test and does not reject the null for the I(1) test, both at a 5% significance level, and thus can be modeled by an I(1) process. A suitable donor is likewise first-order integrated, and can therefore be modeled by an I(1) process. Furthermore, a suitable donor is co-integrated with Chile and the combination of these three tests results in five countries that qualify as suitable donors. Interestingly, South Africa is part of a list overwhelmingly dominated by Latin American countries. No other country was eligible in the entire dataset based on the previously mentioned criteria. It is not really a surprise that the suitable donor pool is made up of 80% Latin American countries. Considering that these countries are very similar to Chile culturally, geographically and economically, the likelihood of co-integration is greater. If we include the countries that were not suitable donors, it is interesting to note that the co-integration test still selects 81,8% Latin American countries, with the Philiphines also being co-integrated. However, none of these countries were at the same order of integration and were therefore excluded from the pool of suitable donors. Furthermore, Brazil is interesting because it is at the same order of integration (I(1)) with Chile, but narrowly rejects the co-integration test, so it is excluded from the suitable donor pool.

[5]The list of countries that were selected as suitable donors based on co-integration in the pre-intervention period, but were excluded for these listed reasons, can be found in table 8, Appendix B.

One could conduct a graphical analysis of the suitable donors to see if there are potential crises or general trends that should be accounted for. Figure 1 plots all the differences between Chile and the five suitable donors for analysis.

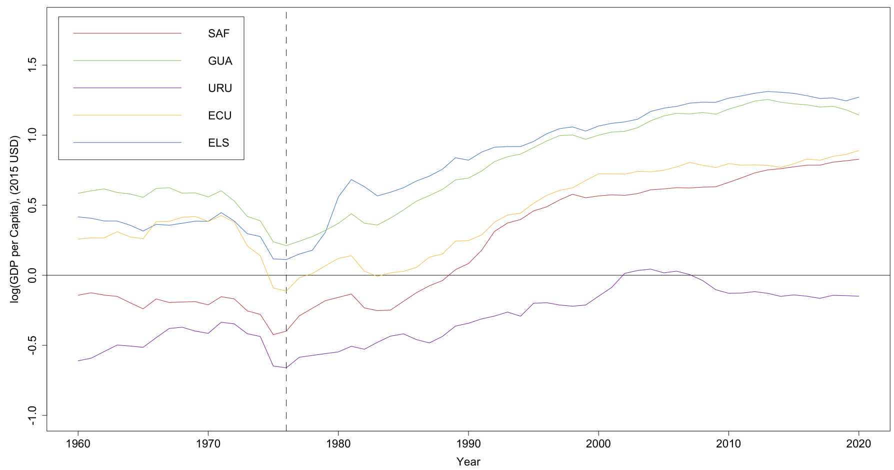

Figure 1: The diffrences between Chile's and its suitable donor's GDP per capita.

Figure 1 confirms the results of column 3 in Table 2, namely that the appropriate donors are all relatively stationary in the pre-intervention period, though it is worth noting the strong negative shock around 1973. This shock occurs in all differences, suggesting that it occurred only in Chile. This is correct because it coincides with the 1973 Pinochet coup, which dealt a severe blow to the Chilean economy. From the time of the intervention in 1976, one can see that all the differences are trending upward. This suggests that liberalization has indeed made the Chilean economy grow faster in comparison to its peers. This is also shown by the fact that Chile started in the middle of the group[6], with a GDP per capita lower than that of South Africa and Uruguay and higher than that of Guatemala, El Salvador and Ecuador. And then ended just below Uruguay, to surpass South Africa in 1988 and even Uruguay for a brief period from 2001 to 2007[7]. The differences initially grow rapidly and then slow down around the start of the 1990s, this coincides with the liberalization wave of the suitable donors, who also begin to grow faster as a result of their liberalization, which stabilizes the difference. Apart from these anticipated observations, there are no surprising trends or crises that need to be accounted for.

Donors with relatively high variance tend to be down-weighted significantly. Therefore, donors with the relatively high variance of the individual donor's differences with Chile are removed from the donor

[6]The X axis (y = 0), can be interpreted as the difference between Chile and Chile, and thus remains zero.

[7]None of the differences, $y_{jt} - y_{it}$, is negative during this period, hence Chile's GDP per capita was the highest.

pool. Consequently, South Africa (0.177) and El Salvador (0.154) are dropped in favor of Guatemala (0.107), Ecuador (0.091), and Uruguay (0.039).

5.2 Estimation Intervention Effect

Using the donors Guatemala, Ecuador and Uruguay, obtained from the KPSS analyses, the intervention effect of the 1976 liberalization can be estimated. This intervention effect is measured using four different models, the synthetic control method, the univariate model estimation, bivariate model estimation and the multivariate model estimation. The weights of the donors in the synthetic control are estimated by performing a restricted least squares regression (RLS) by regressing the difference between Chile and Ecuador on the difference between Guatemala and Ecuador and between Uruguay and Ecuador with no intercept, so that the weights add up to one. This will allow negative weights to be obtained and absolute weights to be greater than one. The RLS performed yielded the following weights: 1.386 for Guatemala, -1.232 for Ecuador, and 0.846 for Uruguay. The implementation of these weights in a single synthetic control results in Figure 2. First, a KPSS test for co-integration (without trend) is applied to the difference between Chile and its synthetic control to verify that our SC is indeed co-integrated with the target before the intervention. This sanity check is satisfied with a test statistic of 0.431 and a P-value of 0.064, so that the null of co-integration is not rejected at a level of 5%.

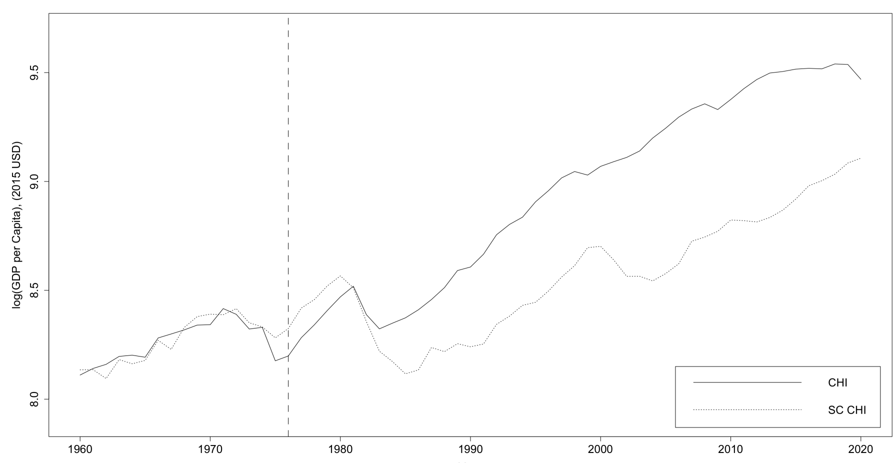

Figure 2: Chile's and synthetic Chile's GDP per capita between 1960-2020

The findings of the pre-intervention KPSS test on co-integration are noticeable above in Figure 2, as the synthetic control closely follows its target Chile. However, an undesirable deviation from the synthetic control just before the intervention in 1976 stands out. The sudden drop in GDP prior to liberalization can be attributed to Pinochet's 1973 coup, which is a country-specific shock and makes it difficult for donor countries to replicate it because they did not experience it. This results in a difficult pre-treatment fit for the synthetic control. In turn, this leads to an underestimation of the fall in GDP caused by the coup. However, one could argue that the liberalization in the years immediately following the 1976 intervention until 1980 produced a relatively quick recovery from the coup, so that GDP growth in Chile followed a similar trend as if there had been no coup. The 1982 debt crisis is very noticeable in both Chile and Chile's synthetic control, both of which show significant declines during this period. Interestingly, Chile began to recover in 1983, two years earlier than its synthetic control which exhibited very low levels of growth until 1991. The "lost decade" is evident as GDP did not return to pre-crisis levels until 1994, while Chile recovered to pre-crisis levels as early as 1988.

One can further see in Figure 2 that the GDP growth of the synthetic control at the turn of the century to the 1990s shows a similar trend to that of Chile, this coincides with the wave of liberalization sweeping across Latin America and especially the donor countries, with Guatemala and Ecuador liberalizing in 1988 and Uruguay in 1991. By which they accelerated their GDP growth to the same rate as that of Chile. Furthermore, an interesting shock can be seen in the synthetic control around 2000, caused by a banking crisis that broke out in Argentina at that time. This crisis affected most of Latin America, but the impact was relatively more pronounced for Uruguay than for its neighbors (Rojas-Suarez, 2004).This caused its GDP to slow significantly, which is visible in the synthetic control. In figure 3 the difference between the GDP of Chile versus its synthetic control is shown.

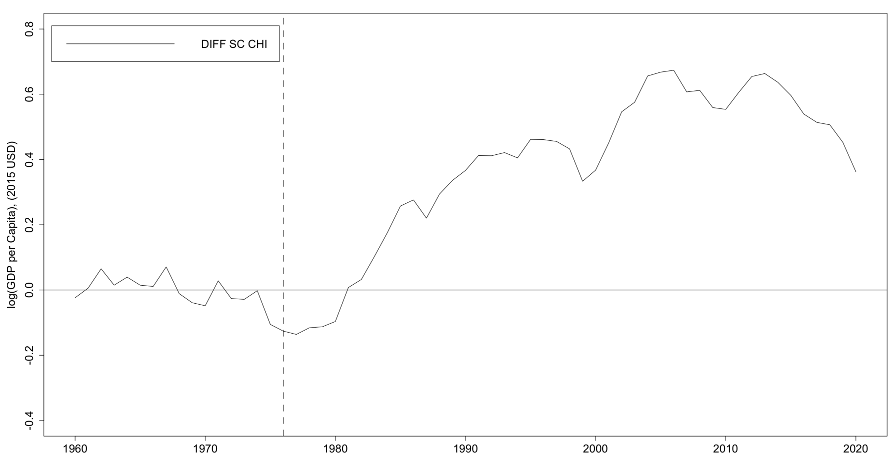

Figure 3: The diffrence between Chile and synthetic Chile between 1960-2020

Again, it can be noted that the difference between Chile and its synthetic control is small in the pre-intervention period, with a small deviation after Pinochet's coup. Starting in 1980, Chile's GDP grows much faster than that of the synthetic control, surpassing it in 1982 and then leveling off around 1991.

After 1991, there is some volatility, but there does not appear to be any significant growth, indicating that the intervention effect has completely materialized.

In order to estimate the full intervention effect, a dynamic response must be taken into account, as it takes some time for the Chilean liberalization to take full effect. Therefore, a number of pulse dummies should be included for the period when the effect has not yet fully materialized. The choice of the number of pulse dummies is determined by the level break after which the difference between Chile and its synthetic control has stabilized and the full effect has materialized. One could perform a Chow (1960) break test on a level break over the full sample, and the test confirmed that there was indeed a level break at 1991 with an F-statistic of 9.241 and a P-value of 3.342×10^{-4} strongly rejecting the null of no structural break. As a result, a total of 15 pulse dummies are used for the period from 1976 to 1990 and a permanent dummy from 1991 onward to measure the effect of the intervention. As a sanity check, a stationarity test is again performed on the difference between Chile and its synthetic control for the period after 1991. The KPSS test without trend indicated that there was indeed stationarity after 1991 with a test statistic of 0.414 not rejecting the null of stationarity at a level of 5%.

After establishing the number of pulse dummies, one could now estimate the intervention effect using OLS and model-based estimates. To estimate the effect using the synthetic control method, one regresses the difference between Chile and its synthetic control on the pulse and permanent dummy including an intercept. Equation (14) is used for univariate model estimation over the full sample. This results in the estimated weights Guatemala 0.899 (0.173) and Uruguay 0.937 (0.097) obtained from the model and the resulting weight of Ecuador, -0.836 (0.206), can be calculated, with standard errors in parentheses. The bivariate model is estimated using both equations (13) and (14), the standard deviation of the slope, $\hat{\delta}_t$, for the stochastic trend is 0.223×10^{-3}. The bivariate model estimates the following two weights Guatemala 0.928 (0.175) and Uruguay 0.969 (0.097) and allows one to calculate the weight of Ecuador, -0.895 (0.211). Lastly, for the multivariate model, equations (10), (11) and (12) are estimated for the full sample. This resulted in a standard deviation of 0.236×10^{-3} for $\hat{\delta}_t$, the slope of the stochastic trend. The estimated irregular covariance matrix is obtained from the differences series (with Ecuador) and can be transformed to obtain following covariance matrix using the transformation procedure listed in the appendix.

$$\widetilde{\boldsymbol{\Sigma}}_\varepsilon = \begin{bmatrix} 0.338 & -0.151 & 0.325 \\ -0.151 & 0.085 & -0.098 \\ 0.325 & -0.098 & 2.465 \end{bmatrix} \times 10^{-2}, \;\; \widetilde{\sigma}_\varepsilon = \begin{bmatrix} -0.067 \\ 0.179 \\ 2.067 \end{bmatrix} \times 10^{-2} \quad \text{and} \quad \widetilde{\sigma}_0^2 = 2.805 \times 10^{-2},$$

Using $\widetilde{\mathbf{\Sigma}}_\varepsilon$ and $\widetilde{\sigma}_\varepsilon$ I am able to compute the $\widetilde{\boldsymbol{\beta}}$. $\widetilde{\boldsymbol{\beta}}' = \widetilde{\sigma}'_\varepsilon \widetilde{\mathbf{\Sigma}}_\varepsilon^{-1} = \begin{pmatrix} 1.892 & 6.486 & 0.847 \end{pmatrix}$ and $\mathbf{i}'\widetilde{\boldsymbol{\beta}} = 9.225$, which can be inserted in the formula (5) to obtain the estimated weights. The estimated weights for Ecuador, Guatemala and Uruguay respectively are $\widetilde{\mathbf{w}} = \begin{pmatrix} -0.894 & 0.925 & 0.969 \end{pmatrix}'$. One could note that the weights from all four models are rather close to one each other, this makes perfect sense and suggests that all estimations went as expected. The complete estimation of the intervention effects and their standard errors by the three models are presented in table 3 below.

Table 3: Estimates of the intervention effect.

	SCM		Univariate		Bivariate		Multivariate	
Year	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
1976	-0.124	0.091	-0.141*	0.076	-0.124**	0.053	-0.126**	0.051
1977	-0.134	0.091	-0.122	0.074	-0.112*	0.060	-0.112**	0.056
1978	-0.114	0.091	-0.104	0.074	-0.095	0.059	-0.096*	0.056
1979	-0.111	0.091	-0.100	0.073	-0.081	0.058	-0.082	0.056
1980	-0.094	0.091	-0.086	0.073	-0.093	0.058	-0.091	0.056
1981	0.010	0.091	-0.004	0.073	-0.072	0.059	-0.072	0.056
1982	0.035	0.091	0.008	0.076	0.035	0.061	0.034	0.056
1983	0.105	0.091	0.074	0.079	0.151**	0.065	0.149***	0.056
1984	0.178**	0.091	0.138*	0.081	0.136**	0.068	0.134**	0.056
1985	0.259***	0.091	0.197**	0.084	0.198***	0.070	0.197***	0.056
1986	0.278***	0.091	0.192**	0.084	0.217***	0.070	0.215***	0.056
1987	0.222**	0.091	0.144*	0.080	0.187***	0.068	0.187***	0.056
1988	0.296***	0.091	0.261***	0.082	0.179***	0.068	0.177***	0.056
1989	0.338***	0.091	0.289***	0.080	0.274***	0.066	0.273***	0.056
1990	0.369***	0.091	0.289***	0.081	0.347***	0.061	0.346***	0.052
1991	0.522***	0.027	0.453***	0.032	0.454***	0.033	0.452***	0.022

Note: Significance level is indicated by * $P \leq 0.1$, ** $P \leq 0.05$ and *** $P \leq 0.01$.

Table 3 clearly shows that the univariate model is more efficient than the synthetic control method. The bivariate is more efficient than the univariate and the multivariate model is the most efficient with the smallest standard errors of all four methods. However, one should keep in mind that the univariate and bivariate models take into account the variability of the weights in the estimation, while the multivariate model estimates the effect conditionally on the weights. The smaller standard errors of the bivariate and multivariate can be largely attributed to the incorporation of a dynamic stochastic trend. This gain is most accurately identified by comparing the bivariate and univariate models, as the main difference between these models is the incorporation of this dynamic stochastic trend in the bivariate model. The synthetic control method closely follows the other models but estimates the intervention effects slightly larger. One might also note that the difference between the Chilean synthetic control method estimates compared to the model estimation methods is larger than that in both cases included in Appendix A. This is because the synthetic control method weights are calculated in the period before the intervention and taken as given, while the other weights are estimated using MLE over the full period. The larger difference in the Chilean case is probably due to the significant event just before the intervention, Pinochet's coup in 1973, which takes place in the period in which the synthetic control method estimates its weights and is therefore more dependent on this period compared to the other two models that estimate over the full sample. Thus, the model-based estimation methods are more robust to significant events in the pre-intervention period. Table 3 shows a significant effect of the intervention in Chile, with the total effect estimated at 0.522 for the synthetic control method and about 0.453 for the model-based estimates. This means that GDP per capita in Chile is between 57.3%[8] and 68.5%[9] higher than it would have been had the country not been liberalized in 1976.

6 Robustness Check

In this section, the robustess of the results are tested. One could imagine that the SCM and MBE are highly dependent on key assumptions made throughout the process, for example the chosen donors could impact the results immensely. Therefore, robustness checks are performed using three placebo tests proposed by Abadie et al. (2015). Namely, a so-called "in-time" placebo test, a so-called "in-space" placebo test and a "leave-one-out" test.

6.1 In-time Placebo

First, the in-time placebo test, which checks the robustness of the intervention date. One sets the intervention date before or after the actual intervention date. This allows one to determine whether the intervention effect is still present after the date is shifted. In the case of Chile, the intervention date is shifted both 5 years backward, to 1971, and 5 years forward, to 1981, using the same donors. In this way, new weights need to be estimated since the SCM determines the weights in the pre-intervention period. The resulting weights for the 1971 synthetic control are (1.013, 0.735, -0.748) for Guatemala, Uruguay, and Ecuador, respectively. The weights for the 1981 synthetic control are (1.735, 0.935, -1.671) for Guatemala, Uruguay, and Ecuador, respectively. Despite the large differences in weights, the resulting synthetic controls are remarkably similar, as shown in Figure 4.

[8] 0.453 is the log effect, so $e^{0.453} = 1.573$, which means GDP per capita is 57.3% higher.

[9] 0.522 is the log effect, so $e^{0.522} = 1.685$, which means GDP per capita is 68.5% higher.

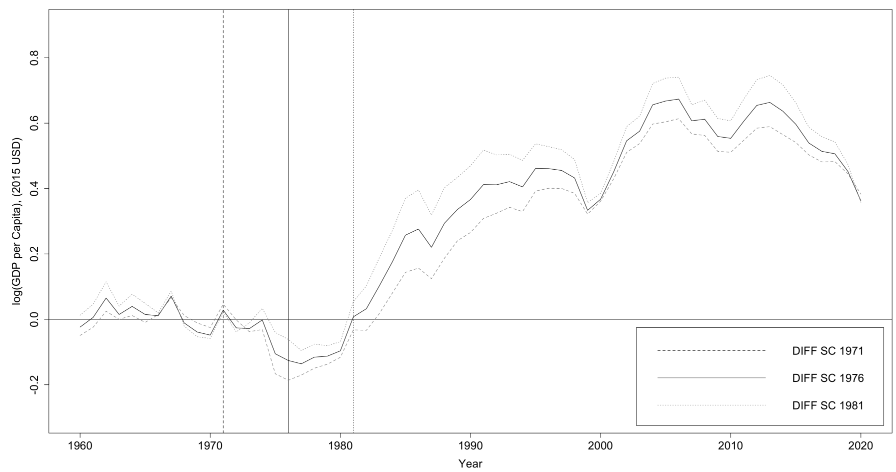

Figure 4: The in-time placebo test, including the intervention dates 1971, 1976 and 1981.

In Figure 4, the in-time placebo test shows that the findings in this paper are quite robust to a shift in the intervention date. The differences between the target series Chile and the different synthetic controls are very close. All synthetic controls underestimate Pinochet's 1973 coup and estimate the overall permanent effect around the same level. One might be suspicious of the results due to a country-specific shock, Pinochet's coup, occurring just before the intervention date, but shifting the date further away or even before the event does not greatly affect the results.

6.2 In-space Placebo

An important test in the synthetic control literature is the in-space placebo; instead of changing the intervention date as in the in-time placebo test, the intervention effect can be tested to see if it occurred anyway and did not result from the intervention. This is tested by treating each individual donor series as the target series and creating a synthetic control of its own (from a donor pool without the actual target country, Chile). The difference between the actual target series, Chili, and its synthetic control must be large compared to the other differentiated placebo target series for the intervention effect to be true. The in-space placebo test is performed using the same donor selection methodology as outlined in this paper. Only in the case of Guatemala and Ecuador could a in-space placebo be constructed, since there were sufficient amount donors available. However, no valid synthetic control could be constructed for Uruguay, as only Bangladesh was available as a valid donor series. The donors and their weights for Guatemala are -0.367 South Africa, 1.114 El Salvador and 0.253 Ecuador. The donors and their weights for Ecuador are 0.163 Costa Rica, 0.193 South Africa, and 0.644 Guatemala. The differences between the target series and their synthetic control are presented below, with the exception of Uruguay.

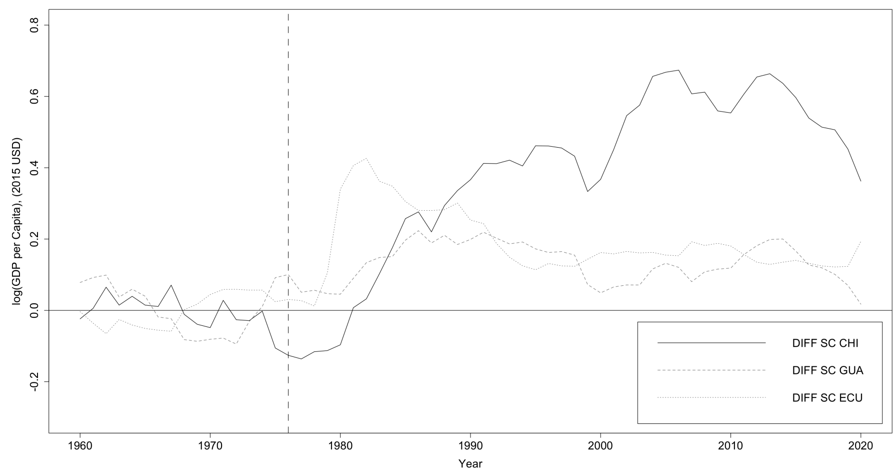

Figure 5: The in-space placebo test, including differences for Chile, Guatemala and Ecuador and their respective SC's

Figure 5 shows that a slight effect is also visible in the two placebo donor series, but not as significant and profound as in Chile. It can therefore be concluded that the intervention in Chile did have a significant effect.

6.3 Leave-one-out

A leave-one-out robustness check can be used to determine whether a single donor country heavily influences the results. Following Abadie et al. (2015), one can iteratively re-estimate the synthetic control by omitting one donor series each time. As shown in Figure 6, the sensitivity test confirms the finding and is robust to changes is the donor composition.

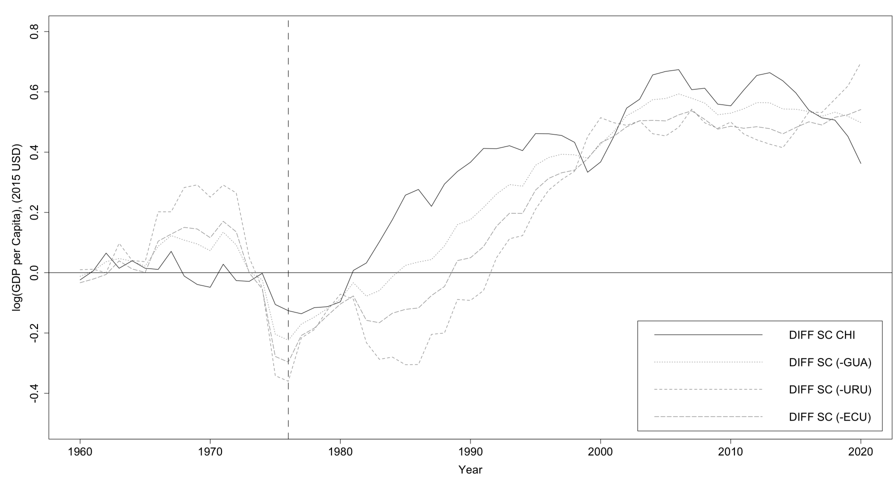

Figure 6: The leave-one-out test, where the name indicates which donor is left out.

The permanent effect of the intervention is very similar between the synthetic controls. However, the synthetic controls that omit one donor have a relatively poor pre-intervention fit and greatly underestimate the Pinochet coup. Furthermore, it can be noted that it takes longer for the intervention effect to reach the final level. Overall, the results are robust against the assumption that a single donor has a large impact on the estimate.

7 Conclusion

Whereas many Latin American countries experienced a "lost decade" due to a slow recovery after the 1982 debt crisis, Chile grew rapidly and became one of the richest countries in Latin America. The literature suggested that Chile's economic liberalization in 1976 played an instrumental role in this rapid recovery. So much so that other countries followed Chile's example and a wave of economic liberalization hit Latin America in the late 1980s, ushering in the end of the lost decade. But, was it actually successful? If so, how successful? This study examines the impact of the 1976 liberalizations on GDP per capita in Chile. In doing so, attempts to answer the research question: *How successful was Chilean economic liberalization in combating the 1982 Latin American debt crisis?*

To answer the research question, a well-known technique in policy analysis is used, namely the construction of a synthetic control. Instead of creating a "classical" synthetic control, as proposed by Abadie and Gardeazabal (2003) and Abadie et al. (2010), this paper opts for the more recent synthetic control introduced by Harvey and Thiele (2021) based on balanced growth . The final dynamic effect is estimated using both OLS and model-based estimates, with different levels of efficiency.

The resulting synthetic control revealed that Chile benefited from its sweeping economic reforms in 1976. It rebounded rapidly from the 1973 crash caused by Pinochet's coup. The liberalizations also limited the damage of the 1982 debt crisis; the country began to recover earlier and grew faster than its synthetic control. However, the intervention effect seemed to have fully materialized around 1991, when other countries also began to liberalize putting the synthetic control on the same growth trajectory.

In these 15 years from the intervention until other countries followed, Chile made between 56.0% and 65.7% gains over its non-liberalized synthetic control[10]. It can be concluded that the liberalizations were a resounding success for Chile.

[10]These are the extreme values 95% confidence interval of all models.

8 Discussion

The research conducted in this paper has some notable limitations and remaining questions that could be further explored in future research. In this paper, I aimed to analyze the effect of the 1976 liberalization on Chile and concluded that liberalization did indeed have positive effects on GDP per capita. However, the estimated effect is a sum of many overlapping policies and events that befell Chile and its donors during that time. As a result, it is difficult to identify any particular policies that had the greatest impact on this improved GDP per capita. It is most likely the case that some policies imposed as part of the liberalization had no or even adverse effect. But, this precision is not captured by the methods utilized for this research. Future research, therefore, could identify which form of economic liberalization is most beneficial to an economy.

Moreover, the results of this paper did not estimate the actual effect of liberalization on Chile. The effect was measured only within 12 years, because the donor countries were also liberalizing after that time[11]. Thus, the effect of liberalization is most likely much larger and is still increasing to this day. Thus, the results of this paper actually answer the question, "What is the benefit to Chile's GDP per capita of liberalizing twelve years earlier compared to its neighbors?"

It should also be noted that the political situation in Chile was very unusual. Pinochet's military dictatorship made the large-scale liberalization possible. The speed and scope of the reforms would most likely not be possible in a democracy. For example, in Mexico, where the 1986 liberalization efforts were less successful. Wacziarg and Welch (2008) point out that this could be due to the amount of liberalization that took place at any given time. While Chile implemented major liberalizations very quickly, Mexico held on to large government oligopolies that prevented industrial restructuring. Arnold Harberger (1999), one of the figure heads of the Chicago Boys, himself admitted that the political environment played a large part in the success of Chile's reforms:

> "Given that there was a military government, the idea that they were willing to cede economic authority to a group of technocrats made that transition easier than it would have been in a democratic context of the same time and place." (Harberger, 1999)

Indicating that the liberalisation reforms could have been less effective or far reaching as it was under the military regime of Pinochet. It would therefore be interesting to find out which political situation is most favorable for the implementation of large-scale reforms in a country.

[11]Ecuador was the first donor series to liberalize in 1988.

9 Appendix

9.1 Appendix: A

9.1.1 Germany

This section applies the methodology described in this paper to a real-life case study, namely the reunification of East and West Germany in 1990 and its effect on GDP per capita in West Germany. This is a well-known and often cited case study in the synthetic control literature. This case study is also discussed on Harvey and Thiele (2021), the paper that first proposed the idea of selecting donors based on balanced growth. This chapter will use the methodology of Harvey and Thiele (2021) and replicate it on the case study, there are some critical points where this paper differs from the choices made in Harvey and Thiele (2021). The dataset includes the target variable West Germany and a set of industrialized donor countries for the period 1971-2003. In this section, I will use a significance level of 10%, which is consistent with what the authors of Harvey and Thiele (2021) use in their paper. The authors of Harvey and Thiele (2021) determined the pre-intervention period to be 1971-1990, with T = 20. Presumably because reunification did not occur until fairly late in 1990 (October 3), they opted to include 1990 in the pre-intervention period. However, in an earlier working version of the paper, written in 2018, they choose the pre-intervention period 1971-1989, with T = 19. I will also use this shorter pre-intervention period, since the intervention takes place three months before the end of 1990, and thus it is still relevant to exclude 1990 in the pre-intervention period, since a significant part of the effect could lie in these first three months. There are some errors in the results of Harvey and Thiele (2021) and the 2018 working paper. In both papers they have selected Austria as a donor, but this country is not integrated with West Germany having a KPSS(2) statistic of 0.484, at either the 5% or the 10% level. In the 2021 paper, they seem to have swapped the UK cointegration KPSS statistic with that of Austria, but continue to use a non-cointegrated Austria as the donor. In Harvey and Thiele (2018), the value is wrong outright. Further, in the 2018 working paper the standard errors are reported for the wrong pre-intervention period, they report the standard errors for the period 1971-1990 instead of the period 1971-1989 which they should be reporting in that paper. Below are the corrected results of the KPSS(2) tests, with countries in bold that are potential donors.

In Table 4, one may note that Portugal is not considered as a potential donor since one requires the donor to be at the same level of integration as the target. This is not the case as Portugal is I(1) and West Germany is I(2). The selected donors are France, Belgium and the US based on their low variance. Spain has more than five times the variance and the UK almost three times the variance of the highest selected donor, the US, so they were not selected because they would be heavily down-weighted. The RLS, without intercept, estimates the following weights: France 0.480, Belgium 0.086,

Table 4: KPSS tests for (co-) integration level.

	I(0)	I(1)	Coint.	Var$\times 10^{-3}$
Trend	Yes	No	No	
West Germany	0.184*	0.445*	-	-
France	0.181*	0.429*	0.056	0.162
Belgium	0.195*	0.445*	0.073	0.294
Portugal	0.130*	0.141	0.140	1.955
USA	0.185*	0.455*	0.166	0.372
UK	0.192*	0.513*	0.191	0.934
Spain	0.177*	0.400*	0.329	1.969
Austria	0.188*	0.512*	0.484*	0.512
Denmark	0.180*	0.512*	0.545*	1.479
Australia	0.176*	0.357*	0.559*	1.639
New Zealand	0.127*	0.302	0.560*	7.717
Greece	0.191*	0.514*	0.582*	3.952
Switzerland	0.125*	0.152	0.582*	5.359
Italy	0.184*	0.416*	0.668*	0.702
Netherlands	0.189*	0.434*	0.664*	1.734
Norway	0.187*	0.480*	0.669*	6.038
Japan	0.170*	0.331	0.701*	2.233

Note: 10% significance is indicated with *, test statistics are 0.119 for I(0), 0.347 for I(1) and Coint. Calculated for the pre-intervention period 1971-1989, T = 19.

and the US 0.434. These estimated weights result in the following synthetic control illustrated in Figure 7, in addition the difference between the target (West Germany) and its synthetic control is also shown in Figure 8.

Figure 7: West Germany's and synthetic West Germany's GDP per capita between 1971-2003

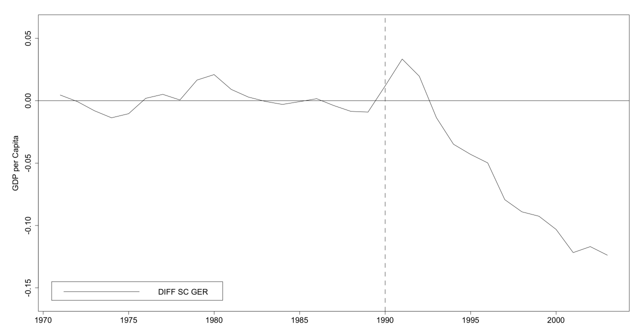

Figure 8: The difference between West Germany and synthetic West Germany 1971-2003

In figure 7 and 8 above one could notice that the synthetic control closely follows the target in the pre-intervention period. This observation is confirmed by a KPSS(2) test for stationarity in the pre-intervention period with a test statistic of 0.131, which does not reject the null of stationarity at 5%

and 10% levels. Immediately after the intervention, there is a slight underperformance of the synthetic control, indicating that West Germany's GDP per capita received a short-lived boost. However, this changes in 1991 and the synthetic control outperforms West Germany by 1993 to continue to outperform and widen the gap. The outperformance of synthetic control appears to slow down around the turn of the millennium. Harvey and Thiele (2021) suspect a level shift in 1999, when the full intervention effect is established. Therefore, a Chow break test is conducted to see if there is a level break in 1999. The Chow break test confirms a level break in 1999 with an F-statistic of 9.076 and a P-value of 8.691×10^{-4}, strongly rejecting the null score of no structural break. This leads to the use of nine impulse dummies and one level dummy to estimate the intervention effect. The intervention effect is estimated using four models: synthetic control method, univariate model, bivariate model and estimation using the multivariate model. The resulting weights of the univariate model-based estimate are 0.410 for the US (0.065) and -0.111 (0.127) for Belgium; the weight of France, 0.701 (0.136), can be calculated using the estimated weights. Finally, for the multivariate model the standard deviation of the slope of the stochastic trend, $\hat{\delta}_t$, is estimated at 0.134×10^{-3}. The transformed covariance matrix obtained from the differences series (with France) is shown below.

$$\widetilde{\boldsymbol{\Sigma}}_\varepsilon = \begin{bmatrix} 0.780 & 1.284 & -0.784 \\ 1.284 & 3.622 & -0.481 \\ -0.784 & -0.481 & 3.318 \end{bmatrix} \times 10^{-4}, \;\; \widetilde{\sigma}_\varepsilon = \begin{bmatrix} -0.289 \\ -0.045 \\ 0.507 \end{bmatrix} \times 10^{-4} \quad \text{and} \quad \widetilde{\sigma}_0^2 = 0.277 \times 10^{-4},$$

Using these matrices $\widetilde{\boldsymbol{\beta}}'$ can be computed. $\widetilde{\boldsymbol{\beta}}' = \begin{pmatrix} -0.853 & 0.289 & -0.007 \end{pmatrix}$ and additionally $\mathbf{i}'\widetilde{\boldsymbol{\beta}} = -0.571$. These can be plugged in to formula (5) to obtain the following weights for France, Belgium and France respectively $\widetilde{\mathbf{w}} = \begin{pmatrix} 0.684 & -0.097 & 0.413 \end{pmatrix}'$. The complete estimation of the intervention effects is shown in table 5 below.

The small differences in the intervention effect estimates compared to the results in Harvey and Thiele (2021) are due to the difference in donor selection, Belgium versus Austria. Furthermore, this paper uses nine pulse dummies and one level dummy, while Harvey and Thiele (2018, 2021) use eight pulse dummies and one level dummy in their papers. Analyzing the standard errors in table 5, one can see that the multivariate model is clearly the most efficient of all four models, slightly outperforming the bivariate model. There is a greater efficiency gain between the univariate and bivariate/multivariate models. This suggests that the incorporation of the dynamic stochastic trend significantly improves the efficiency. Furthermore, the synthetic control method is the least efficient, but its estimates are close to those of the other models. More closely than the difference in the Chilean intervention effects between the models. This is due to the absence of a significant shock in the pre-intervention period.

Table 5: Estimation of the intervention effect.

Year	SCM Estimate ($\times 10^{-1}$)	SCM SE ($\times 10^{-2}$)	Univariate Estimate ($\times 10^{-1}$)	Univariate SE ($\times 10^{-2}$)	Bivariate Estimate ($\times 10^{-1}$)	Bivariate SE ($\times 10^{-2}$)	Multivariate Estimate ($\times 10^{-1}$)	Multivariate SE ($\times 10^{-2}$)
1990	0.115	1.004	0.138***	0.804	0.181***	0.643	0.181***	0.629
1991	0.331**	1.004	0.362***	0.828	0.324***	0.706	0.323***	0.670
1992	0.194*	1.004	0.219***	0.814	0.278***	0.701	0.279***	0.670
1993	-0.138	1.004	-0.106	0.820	-0.171**	0.716	-0.172**	0.671
1994	-0.351**	1.004	-0.294***	0.878	-0.287***	0.762	-0.287***	0.669
1995	-0.432***	1.004	-0.374***	0.877	-0.370***	0.764	-0.370***	0.668
1996	-0.501***	1.004	-0.468***	0.831	-0.498***	0.714	-0.498***	0.667
1997	-0.795***	1.004	-0.794***	0.813	-0.771***	0.694	-0.771***	0.668
1998	-0.893***	1.004	-0.916***	0.826	-0.902***	0.681	-0.901***	0.647
1999	-1.119***	0.492	-1.111***	0.408	-1.115***	0.415	-1.115***	0.394

Note: Significance level is indicated with * $P \leq 0.1$, ** $P \leq 0.05$ and *** $P \leq 0.01$.

The total intervention effect is estimated to be between -1.111×10^{-1} and -1.119×10^{-1}, meaning that West Germany's GDP per capita is between 89.4% and 89.5% of its potential if it would not have reunited with East Germany.

9.1.2 California

This section replicates the second case study from Harvey and Thiele (2021). The case study relates to the introduction of smoking regulation, proposition 99, in California at the end of the 1980s. This is a well-documented case study in the synthetic control literature and was first discussed in Abadie er al. (2010). The dataset includes annual per capita cigarette consumption in 39 US states from 1970 to 2000. Since the intervention takes place in 1990, the pre-intervention period is set to 1970-1988 and includes $T = 19$ time periods.In order to match Harvey and Thiele (2021) results as closely as possible, a significance level of 10% is used. The authors of Harvey and Thiele (2021) select the donors by taking the logarithm of the data to which they apply KPSS tests. After selecting the donors, they estimate the intervention effect using the original, non-logarithmic, data. To replicate their results, this paper also selects the donors using the logarithmic data. However, it should be noted that this could be a poor practice since the synthetic control is constructed using the original data, so a better practice would be to test the original datasets for their properties such as integration order and level of co-integration for donor selection. Since these are the series that are used for the synthetic control. Below in Table 6 are the results of the KPSS(2) tests for the level of integration and co-integration.
In Table 6, one can see that five states remain suitable as donors based on their integration and co-integration order with California during the pre-intervention period. California rejected both the I(0) and I(1) tests and is therefore best modeled as an I(2) process. Of the five remaining states, both North Carolina and Wyoming are omitted because their variance is 6 times or even 18 times greater than

Table 6: KPSS tests for (co-)integration level.

	I(0)	I(1)	Coint.	Var
Trend	Yes	No	No	
California	0.197*	0.613*	-	-
Idaho	0.192*	0.598*	0.218	24.949
North Carolina	0.158*	0.428*	0.249	364.528
Colorado	0.186*	0.580*	0.286	20.298
Montana	0.196*	0.636*	0.309	19.373
Wyoming	0.191*	0.464*	0.334	129.917
Nevada	0.145*	0.234	0.422*	183.677
Kentucky	0.182*	0.498*	0.506*	375.162
North Dakota	0.194*	0.617*	0.522*	123.404
Delaware	0.129*	0.203	0.531*	55.117
Indiana	0.154*	0.336	0.547*	67.416
Connecticut	0.129*	0.160	0.593*	95.284
Vermont	0.190*	0.522*	0.606*	191.004
Oklahoma	0.197*	0.676*	0.614*	154.016
New Hampshere	0.192*	0.470*	0.624*	589.730

Note: 10% significance is indicated with *, test statistics are 0.119 for I(0), 0.347 for I(1) and Coint. Furthermore, this a small selection of the countries analysed.

that of the other states and thus they would be heavily down-weighted. Three donor series are then left for the construction of the synthetic control, namely Idaho, Colorado, and Montana. Performing the RLS with these three donor series yields the following weights: 0.288 for Idaho, 0.327 for Montana, and 0.385 for Colorado. Using these estimated weights, a synthetic control can be constructed, shown below in Figure 9. In addition, the difference between California and its synthetic control is shown in Figure 10.

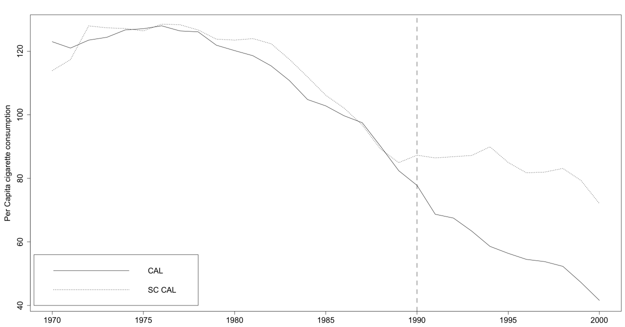

Figure 9: California's and synthetic California's GDP per capita between 1970-2000

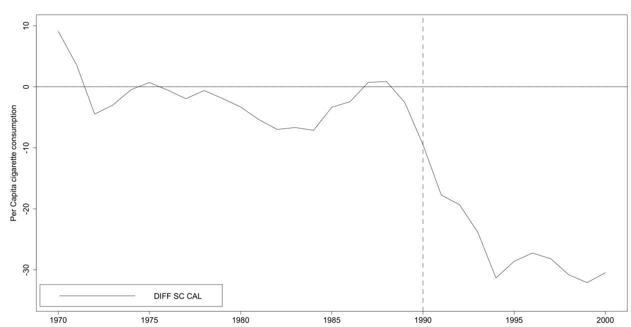

Figure 10: The difference between California and synthetic California 1970-2000

In Figures 9 and 10 it can be seen that the synthetic control follows the target closely in the period before the intervention, around the intervention in 1989 the target, California, seems to continue its trend, where the synthetic control seems to level off. This means that the intervention has indeed reduced annual cigarette consumption in the state of California. As a sanity check, a KPSS(2) test is conducted on the stationary relationship between California and the synthetic control in the pre-intervention period. The test confirms that the synthetic control is indeed cointegrated with the target series with a test statistic of 0.322 failing to reject the null of stationarity at 5% and 10% levels. However, the synthetic control appears to deviate just prior to the 1988 intervention. A Chow break test (1960) on the full sample of the difference between California and its synthetic control confirms that there is indeed a break point in 1988 where the two series diverge. The Chow break test also found a level break in 1994, with an F-statistic of 4.134 and a P-value of 0.027, after which the difference stabilizes and the intervention effect has fully materialized. This means that a total of 6 pulse dummies are introduced from the intervention in 1989 to when the effect materialized in 1994, followed by a step dummy from 1995 onwards that estimates the total effect. The intervention effect is again estimated using the four models based on SCM and MBE. The standard deviation of the stochastic slope delta, *delta*, is estimated to be 2.510 using the multivariate model. The estimated irregular covariance matrix is obtained from the differenced series (with Colorado) and can be transformed into the following covariance matrix using the transformation procedure in Appendix B.

$$\widetilde{\mathbf{\Sigma}}_\varepsilon = \begin{bmatrix} 16.133 & -3.830 & 4.186 \\ -3.830 & 19.530 & 9.784 \\ 4.186 & 9.784 & 30.504 \end{bmatrix}, \quad \widetilde{\sigma}_\varepsilon = \begin{bmatrix} -2.047 \\ -0.258 \\ 4.551 \end{bmatrix} \quad \text{and} \quad \widetilde{\sigma}_0^2 = 1.780,$$

From these results the following can be calculated: $\widetilde{\boldsymbol{\beta}}' = \begin{pmatrix} -0.231 & -0.178 & 0.238 \end{pmatrix}$ and $\mathbf{i}'\widetilde{\boldsymbol{\beta}} = -0.171$, which can be inserted in formula (5) to obtain the estimated weights of the multivariate model. The estimated weights for Colorado, Montana and Idaho respectively are $\widetilde{\mathbf{w}} = \begin{pmatrix} 0.397 & 0.246 & 0.357 \end{pmatrix}'$. For the bivariate model the following weights are obtained $\widehat{\mathbf{w}} = \begin{pmatrix} 0.403 & 0.241 & 0.356 \end{pmatrix}'$, with estimation standard deviations (0.191) and (0.137) for Montana and Idaho. The standard deviation of the stochastic slope delta, δ, is 2.450. One could note that the weights of both multivariate ($\widetilde{\mathbf{w}}$) and bivariate ($\widehat{\mathbf{w}}$) are quite close, as expected. The univariate weights are 0.380, 0.395 and 0.225 for Colorado, Montana and Idaho respectively, with estimation standard deviations (0.232) and (0.165) for Montana and Idaho. The estimation of the intervention effect using the fout models is shown in table 7 below. The estimates of the intervention effect are relatively close in all four models, more so than in the Chile case study, where a significant shock occurred just before the intervention. The incorporation of the stochastic slope in the bivariate and multivariate models makes these models significantly more efficient than the other two. The multivariate model is twice as efficient as the synthetic control method and the univariate model. As for the synthetic control method and the univariate model, it can be

Table 7: Estimation of the intervention effect.

	SCM		Univariate		Bivariate		Multivariate	
Year	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
1989	-0.813	3.676	-1.162	3.520	-3.029**	1.431	-3.006**	1.275
1990	-7.751**	3.676	-7.273*	3.876	-8.398***	2.053	-8.412***	1.711
1991	-15.986***	3.676	-15.668***	3.356	-15.460***	2.235	-15.460***	1.825
1992	-17.580***	3.676	-17.539***	3.624	-16.826***	2.378	-16.869***	1.837
1993	-22.060***	3.676	-21.876***	3.613	-22.191***	2.501	-22.247***	1.784
1994	-29.586***	3.676	-29.154***	4.023	-28.649***	2.718	-28.725***	1.623
1995	-27.822***	1.678	-28.409***	3.406	-27.720***	2.830	-27.759***	1.384

Note: Significance level is indicated with * $P \leq 0.1$, ** $P \leq 0.05$ and *** $P \leq 0.01$.

noted that the efficiency of these models, in this particular case study, are on a similar level. Thus, the synthetic control method is not the worst in terms of efficiency and can compete with model-based estimation without a stochastic trend. The models estimate the total intervention effect between -27.720 and -28.409. The estimates can be easily interpreted because these models are estimated using the untransformed original data. Thus, the implementation of Proposal 99 resulted in Californians smoking about 28 fewer cigarettes in one year.

9.2 Appendix: B

9.2.1 Transformation of the Estimated Irregular Covariance Matrix.

To calculate the variances and covariances between the donors we have to transform the following estimated covariance matrix where the covariances are shown between the differences with donor 1.

$$\begin{bmatrix} \widehat{\sigma}_1^2 & \widehat{\sigma}_{1,2-1} & \widehat{\sigma}_{1,3-1} & \widehat{\sigma}_{1,4-1} \\ \widehat{\sigma}_{1,2-1} & \widehat{\sigma}_{2-1}^2 & \widehat{\sigma}_{2-1,3-1} & \widehat{\sigma}_{2-1,4-1} \\ \widehat{\sigma}_{1,3-1} & \widehat{\sigma}_{2-1,3-1} & \widehat{\sigma}_{3-1}^2 & \widehat{\sigma}_{3-1,4-1} \\ \widehat{\sigma}_{1,4-1} & \widehat{\sigma}_{2-1,4-1} & \widehat{\sigma}_{3-1,4-1} & \widehat{\sigma}_{4-1}^2 \end{bmatrix} \Rightarrow \begin{bmatrix} \widehat{\sigma}_1^2 & \widehat{\sigma}_{1,2} & \widehat{\sigma}_{1,3} & \widehat{\sigma}_{1,4} \\ \widehat{\sigma}_{1,2} & \widehat{\sigma}_2^2 & \widehat{\sigma}_{2,3} & \widehat{\sigma}_{2,4} \\ \widehat{\sigma}_{1,3} & \widehat{\sigma}_{2,3} & \widehat{\sigma}_3^2 & \widehat{\sigma}_{3,4} \\ \widehat{\sigma}_{1,4} & \widehat{\sigma}_{2,4} & \widehat{\sigma}_{3,4} & \widehat{\sigma}_4^2 \end{bmatrix}$$

To obtain $\widehat{\sigma}_{1,2}$ one can use the following equation using estimated $\widehat{\sigma}_{1,2-1}$ and $\widehat{\sigma}_1^2$.

$$\widehat{\sigma}_{1,2-1} = \widehat{\sigma}_{1,2} - \widehat{\sigma}_1^2 \;\Leftrightarrow\; \widehat{\sigma}_{1,2} = \widehat{\sigma}_{1,2-1} + \widehat{\sigma}_1^2$$

Further, to calculate $\widehat{\sigma}_2^2$, one can take the previous calculated $\widehat{\sigma}_{1,2}$ in combination with the estimated $\widehat{\sigma}_{2-1}^2$ and $\widehat{\sigma}_1^2$ by plugging them in the following equation.

$$\widehat{\sigma}_{2-1}^2 = \widehat{\sigma}_1^2 + \widehat{\sigma}_2^2 - 2\widehat{\sigma}_{1,2} \;\Leftrightarrow\; \widehat{\sigma}_2^2 = \widehat{\sigma}_{2-1}^2 - \widehat{\sigma}_1^2 + 2\widehat{\sigma}_{1,2}$$

To calculate $\widehat{\sigma}_{2,3}$, one uses calculated $\widehat{\sigma}_{1,2}$ and $\widehat{\sigma}_{1,3}$ (which is calculated in the same manner as $\widehat{\sigma}_{1,2}$) in combination with estimated $\widehat{\sigma}_{2-1,3-1}$ and $\widehat{\sigma}_1^2$ by plugging them in the following equation.

$$\widehat{\sigma}_{2-1,3-1} = \widehat{\sigma}_1^2 + \widehat{\sigma}_{2,3} - \widehat{\sigma}_{1,2} - \widehat{\sigma}_{1,3} \;\Leftrightarrow\; \widehat{\sigma}_{2,3} = \widehat{\sigma}_{2-1,3-1} - \widehat{\sigma}_1^2 + \widehat{\sigma}_{1,2} + \widehat{\sigma}_{1,3}$$

Using the above methodology all covariance matrix elements can be calculated.

9.2.2 Dropped Donors

Table 8: Reasons for dropping specific donor series.

Country	Reason of exclusion
Indonesia	Liberalised before 1988 in 1970
Congo, Rep.	Country-specific shocks due to political unrest and civil wars after its independence in 1960
Colombia	Liberalised before 1988 in 1986
Haiti	Country-specific shocks due to natural disaster in 1979 and severe political unrest in 1991
Belize	No date of Liberalisation by Sachs and Warner (1995)
Fiji	No date of Liberalisation by Sachs and Warner (1995)
Dominican, Rep.	Country-specific shocks due to political unrest and natural disaster in 1979
Paraguay	Implemented law 550 in 1975, which is a very liberalising policy that had a great impact on Paraguay's GDP per capita. Hence, it is excluded even though Sachs and Warner (1995) date its liberalisation in 1989.
Note:	The countries are ordered on lowest variance with Chile

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