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MSc International Economics

The Macroeconomics of the Obesity Pandemic in Latin America and the Caribbean

An Error Correction Model Approach

by

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Abstract

Obesity prevalence in Latin America and the Caribbean has grown substantially over the past decades. The aim of this paper is to examine the long-run causal relationship between macroeconomic factors and the development of the obesity pandemic in the region during the years 2000 to 2016. A one-step error correction model is applied to a panel of 14 countries in a multivariate framework with second-order dynamics. Empirical results imply that error correction takes place, although at a low speed. Evidence is found that, in the long run, a 10% increase in GDP per capita is related with a 1.5% increase in obesity prevalence. This is supported by the theory that GDP growth increases obesity prevalence through over-consumption. Further research should uncover the specific components of GDP and consumption that cointegrate with obesity. The study concludes that policy makers must reconsider the purpose of the food system and reorient towards a system dominantly based on health rather than profit. The most impactful policy will not lie in supporting individuals to counteract their environments, but to implement structural changes that make environments less obesogenic.

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1. Introduction

The growth in worldwide obesity prevalence has broadly been described by literature as a recently emerged pandemic (Bühler, 2019; Malik, Willett, & Hu, 2013; Popkin & Gordon-Larsen, 2004; Swinburn, et al., 2011). Being first observed on an increased scale in the United States in the 1970s, obesity spread around the world in the succeeding decades resulting in high prevalence in people of all ages. The World Health Organization (WHO) classified more than a billion people obese in 2016. As obesity causes cardiometabolic diseases, osteoarthritis, dementia, depression and some types of cancers, it can lead to premature disabilities as well as death. In 2015, high body mass index (BMI) was estimated to account for 4 million deaths globally (The GBD 2015 Obesity Collaborators, 2017). Globalization and pandemics have been closely intertwined throughout the past. The sudden rise and direct impacts of recent pandemics have created massive awareness and deep sense of urgency to control spreads. However, the pandemic of obesity seems blatantly visible yet broadly neglected. The alarming death toll has not resulted in effective adjustments among people and policy makers, as prevalence keeps rising.

The risen obesity prevalence has mainly been attributed to the food system globalization (Chooi, Ding, & Magkos, 2019; The GBD 2015 Obesity Collaborators, 2017; Malik et al., 2013; Popkin, Adair, & Ng, 2011; Popkin & Reardon, 2018; Swinburn, et al., 2011). Although the emergence of the global food system might have led to economic development, lower food prices, increased food security, and more product diversity, it has also come with negative effects. It has created structural economic, social, cultural and environmental changes that have negatively impacted the quality of people's diet over the past decades. As a result, global diets have become dominated by ultra-processed obesogenic foods that made BMI rise (Monteiro, Moubarac, Cannon, Ng, & Popkin, 2013). Measuring the exact impact of the global food system on obesity prevalence is hardly possible, because it results from a complex interaction between different macroeconomic and macrostructural factors.

As the driving factors behind the global food system might have positive as well as negative effects on society, public health policy makers face a dual challenge. On the one hand, globalization should be promoted to advance technology and improve living standards; on the other hand, it must be closely regulated in order to control the negative effects it creates. The implementation of obesity reversing policies requires deep understanding of the underlying driving factors of the pandemic. Therefore, a thorough investigation of the long-run relation between obesity prevalence and its structural drivers is essential to design carefully tailored policies.

This study examines the relationship between obesity prevalence and its macroeconomic drivers in Latin America and the Caribbean (LAC) in the period 2000 to 2016. This is employed by performing a test of cointegration through a one-step second-order error correction model (ECM) in an autoregressive distributed lag model of the second order [ADL(2,2)]. The ECM combines a long-term relationship with short-run adjustments in one equation, which allows for a long run gravitation towards the equilibrium after the occurrence of random shocks. We find proof that obesity prevalence and its macroeconomic drivers are cointegrated and error correction takes place. The econometric results suggest that the leading macroeconomic force of the obesity epidemic is the growth of per capita gross domestic product (GDP).

Latin America and the Caribbean (LAC) are a pertinent case for studying the link between obesity and macroeconomics, because the region's economies have developed and globalized over the past decades, while obesity rates exploded. Deaths as well as disability-adjusted life years in LAC are now relatively higher than worldwide averages and those of other developing regions, such as East Asia & the Pacific, South Asia, and Sub-Saharan Africa (Global Burden of Disease Collaborative Network, 2018). Simultaneously, large shares of children are malnourished from poor alimentation in their first years. This double burden of obesity and malnutrition emphasizes the complexity of obesity development in the region. Uncovering the mechanisms behind obesity development can help countries to set policies that dampen future obesity rates.

This study is a first step in measuring the long-run relation between macroeconomic factors and obesity prevalence. Obesity research covering LAC is available, although it often does not incorporate recent trends, such as the emergence of the internet. There are some tests of cointegration for countries in LAC, but these generally incorporate a single aspect related to the macroeconomics of obesity. For instance, Hojjat and Ruiz (2019) relate it to income inequality and poverty among Peruvian women. Some systematic reviews of literature about the region are present, such as Popkin and Reardon (2018) and Kain, Vio, & Albala (2003). However, the focus is not always economic. Also, the speed of development of globalization and technology quickly turn findings irrelevant for future policies. Therefore, researchers have not come to a general consensus about the most dominant drivers of the obesity pandemic in the region and results remain suggestive rather than conclusive. Thorough study of the cointegration of macroeconomics and obesity is required in order to design effective policies. The long-run coefficients of the macroeconomic drivers indicate how obesity prevalence might develop in the future. Policy makers have an interest in these estimations in order to design policies that reverse the obesity pandemic and improve public health.

The paper proceeds as follows. Section 2 provides an explanation and a critical analysis of the current state of knowledge in the field. Section 3 elaborates on the data gathering, the variable construction, the motivation behind it and the descriptive statistics. Section 4 explains the empirical model and Section 5 presents the regression results. These results are interpreted and discussed in Section 6. The paper is then finished in Section 7 by concluding the research and considering opportunities for further research.

2. Theoretical Analysis

2.1 Obesity Prevalence

Obesity is defined as abnormal or excessive fat accumulation that presents a risk to health, often measured by a BMI of minimally 30 kg/m^2 (World Health Organization, 2020). An increase in BMI represents weight gain, caused by a positive energy imbalance that results when an individual's intake of calories exceeds their expenditure of energy. Rising BMI can result from a complex interaction between changes in food environment, physical activity, socioeconomic, environmental and genetic factors (Chooi et al., 2019). Although BMI highly correlates with the percentage of body fat, this correlation may depend on genetics and ethnicity. Evidence of Flegal, et al. (2009) suggests that ethnicity has an effect on the correlation between BMI and body fatness.

BMI levels have increased worldwide and obesity has taken pandemic proportions (Bühler, 2019; Malik et al., 2013; Popkin & Gordon-Larsen, 2004; Swinburn, et al., 2011). The substantial increase in overweight and obesity prevalence was first visible around the 1970s in the United States, when dietary quality was worsening and physical activity quickly started declining (Popkin et al., 2011). The magnitude of the problem became acknowledged in the late 1980s, when the epidemic had already spread towards parts of Europe and the world's richest nations. Rapid globalization transmitted the rise of obesity to all parts of the world and the WHO formally recognized the global effect of the obesity epidemic in 1997. The prevalence of obesity tripled worldwide since 1975, and has continued to grow at a pandemic rate (Bühler, 2019; World Health Organization, 2020).

The Global Burden of Disease Study (2017) estimated that 39% of the world population was either overweight or obese in 2015, while 12% of the total population was estimated to be obese. Although there is some variability between countries and regions, trends were relatively uniform worldwide. Several researchers estimate these trends will continue to spread in the foreseeable future (Chooi et al., 2019; Flegal, Carroll, Kit, & Ogden, 2012; Kelly, Yang, Chen, Reynolds, & He, 2008; Prentice, 2006). Kelly, et al. (2008) approximate that, if current trends continue, 58% of the global population can either be overweight or obese in 2030. Other research highlights that future trends in the development of the pandemic are very hard to estimate. This is partly because little is known about the precise causes of the previously observed trends (Flegal, Carroll, Kit, & Ogden, 2012).

Obesity and overweight were once considered high-income country (HIC) problems exclusively. However, past years' rates have risen most in low and middle-income countries (LMCs) and they probably will follow this trend in the coming years. Although obesity rates in these countries have been rising for decades, it took some time before the obesity epidemic was noticed in LMCs, as attention was mainly given to established problems with malnutrition and hunger (Popkin et al., 2011; Prentice, 2006). Obesity rates grew while malnutrition persisted, which has created a "double burden of disease" at national, community and household levels. Kelly et al. projected in 2008 that population growth and aging, urbanization and changes in lifestyle would result in a disproportionally large increase in the number of obese individuals in LMCs.

Most Latin American and Caribbean countries in the sample are considered Low- and Middle-Income Countries (LMCs), as classified by The World Bank (2020). Exceptions are Chile and Uruguay, who both became high income countries 2012. The region's population faces a serious diet-related health problem accompanied by enormous socioeconomic costs (Popkin & Reardon, 2018). The share of deaths attributed to obesity in LAC, is with 14.1% almost as high as the 14.3% in the United States. This percentage is higher than it is for LMC, HIC and world aggregates (Global Burden of Disease Collaborative Network, 2018).

2.2 Obesity Drivers

There is a general consensus among researchers about the macro mechanism of the obesity pandemic. The dominant systemic force is shaped by the policies and economic systems people live in. These systems promote globalization, economic growth and consumption. This drives environmental change, by increasing food supply and promoting high energy intake. Obesity is a consequence of people responding naturally to these obesogenic environments. Their behavioral patterns are increasingly characterized by high energy food consumption and low physical activity. As a result, an energy imbalance takes place, and obesity levels rise.

Globalization, a result of systemic policies and economic systems, has changed environments in a way that people employ more sedentary lifestyles and consume more calories. These environmental changes decrease physical activity requirements in work, home production, recreation and transportation, which has led to diminished human energy expenditure. An even more powerful impact of globalization on obesity prevalence can likely be attributed to a risen energy intake rather than a fallen energy expenditure. Globalized food environments have changed the structure and composition of diet and the relationships people have with food. People are increasingly reliant on processed foods, away-from-home food intake, edible oil use, and sugar-sweetened beverage consumption. The global food system is considered the dominant driver of the obesity pandemic and improving it is the most promising way to dampen obesity prevalence (Chooi et al., 2019; The GBD 2015 Obesity Collaborators, 2017; Malik et al., 2013; Popkin et al., 2011; Popkin & Reardon, 2018; Swinburn, et al., 2011).

Researchers identify different macroeconomic factors through which the globalization of the food system might have increased obesity prevalence. Finkelstein, Ruhm, and Kosa (2005) conclude that technology advancement is the dominant force behind the obesity pandemic, which expressed itself most in food price reductions. Malik et al., (2013) attribute it to trade liberalization, economic growth and fast urbanization. Hruby and Hu (2015) add industrialization and the rise of mechanized transport as crucial determinants. Kearney (2010) even extends this list further, with income rise, socioeconomic status (SES), the emerge of transnational food corporations (TFCs), the growth of the retail sector, food industry marketing, and changed consumer attitudes. However, most importance should not be attributed to the number of factors, but rather to which ones are most crucial in producing today's global obesity prevalence.

LMCs are particularly affected by globalization, as many of them are in a developing phase and becoming increasingly urbanized (Malik et al., 2013). These countries have been mimicking globalization dynamics of HICs, and they are expected to converge towards them in the future. Researchers observe that lifestyles in LMCs have quickly and vastly converged to the so called "Western diet", which is disproportionally composed of refined carbohydrates, added sugars, fats and foods from animal source (Malik et al., 2013; Popkin et al., 2011; Prentice, 2006). This is a transformation imposed by local producers as well as TFCs penetrating LMC markets. These TFCs have now reached a level of penetration in LMC food markets comparable to HIC markets (Stuckler, McKee, Ebrahim, & Basu, 2012). Consequently, they have become responsible for the major share of certain categories of foods sold in LMCs, such as sugar sweetened beverages and refined oils (Popkin et al., 2011). Measuring the exact impact of global firms on local food environments is complex. In higher-income countries, where governance is relatively open, observing direct impact might be possible. However, accurate information about the roles of these companies in LMCs is generally not publicly obtainable. Besides, there are indirect unobservable effects TFCs have on the way foods are produced, processed and distributed in local environments. Therefore, estimations of the roles of these firms on the globalized food systems will likely be inaccurate.

LAC's food system evolved from a local and fragmented structure in the 1950s to the modern character it has today. Underlying causes of rising obesity seem in line with conclusions from research conducted in Western countries, as diet transformations in LAC have occurred in parallel with the evolution of the global food system. Popkin and Reardon (2018) define five interdependent meta-conditioners that facilitated the food system and diet transformation in LAC: the growth of income, urbanization, the liberalization of policies, the development of infrastructure, and the rise of rural nonfarm employment. They describe that privatization and liberalization in the 1980s and 1990s in LAC initiated rapid investment by foreign as well as domestic private sector firms. In combination with infrastructure improvement, global as well as local players have been increasingly able to distribute their foods across regions.

Although this study investigates the macroeconomics of obesity, one should not forget that these coexist with microeconomic and behavioral economic dynamics. From a microeconomic perspective, the obesity pandemic could result from a shift on the demand side, the supply side or on the treatment side of obesity that distorts the original equilibrium relationship. On the demand side, one could argue that the preferences of individuals have converged towards obesogenic diets, although healthier alternatives are widely available. It could also imply that people have chosen to adopt sedentary lifestyles, although there have been plenty of options to maintain an active life. On the supply side, one could argue that a diminished availability of non-obesogenic foods has resulted in consumers having less opportunity to maintain a healthy diet. This could be enforced by the fact that obesogenic foods are often more profitable to produce than healthier alternatives. It could also be attributed to decreased availabilities for people to burn the calories they consume, for example due to changing work requirements. The obesity pandemic could theoretically have arisen due to diminished success of treating the disease. However, considering the overall economic growth and advancements in technology and science, a drop in ability to effectively treat the obesity is not obvious. The behavioral field of economics relates obesity to heavy discounting of the future (Chavas, 2013; Smith, Bogin, & Bishai, 2005). This implies that individuals give substantially more weight to short-run reward of the food they consume in relation to the long-run health effect. The obesity pandemic results from a complex interaction between countless factors on both the demand and supply side, as well as the behavioral economic perspective. The following subsections proposes a systemic perspective, by focusing on six macroeconomic drivers, as identified by relevant literature. They identify the conceptual foundations for the long run relationship between these factors and obesity, as well as their dynamics.

2.2.1 Growth

Market based economies in modern societies are centered around the objective of economic growth. As it is often associated with progress and improved living standards, the pursue of economic growth has brought health advances to society (Deininger & Squire, 1996; Mayer, 2001; Swinburn, et al., 2011). Increase in annual GDP per capita, an indicator of economic growth, is the most commonly used measure of national progress. Consumption is a relatively easily modifiable determinant of economic growth. Therefore, boosting consumption has become a major political objective. Companies contribute to economic growth by becoming more effective at selling their products. Therefore, their volume driven behavior fits perfectly well in the modern market based economy. Beyond a point, however, the marginal benefits of GDP per capita might decline as the marginal costs start rising (Egger, Swinburn, & Amirul Islam, 2012). Obesity prevalence is a theoretical example of these marginal costs. The constant drive to increase consumer spending can enforce the over-consumption of food energy, which makes obesity rates rise. In this light, the obesity pandemic could be seen as the unavoidable consequence of an unregulated capitalist food system, in which firms compete with each other to tempt consumers to eat or drink more of their product (Malik et al., 2013). Egger et al. (2012) observe a positive relationship between GDP and BMI for a GDP per capita up to $US3,000 and $US5,000 respectively. For a GDP per capita above this level, they observe an almost flat relation. Egger et al. (2012) therefore conclude that some degree of economic prosperity impacts obesity prevalence, but they do not identify it as a major driver in more affluent countries.

Although economic growth might have a positive impact on obesity prevalence, there is also a case for causality running the other way. Obesity is related to negative effects on disability-free life-years, quality-of-life, and productivity. This is often caused by diseases such as diabetes, cardiovascular conditions, cancer, osteoarthritis and depression. Prevalence of these diseases adversely impacts public health costs and productivity. The economic burden of an obese population is substantial and has a protracted time course (Wang, PcPherson, Marsh, Gortmaker, & Brown, 2011). There is a general consensus in research that the societal and public health care costs associated with overweight and obesity are significant, although researchers have not been conclusive about the scale of this impact. This is partly attributable to the substantial discrepancies in methodology and data. Research often estimates the correlation between obesity and medical care costs, but solely measuring correlation is limited by endogeneity issues and does not cover indirect societal costs. Very likely is that the correlation becomes an underestimate of the true causal effect of obesity on public health costs. This arises when those with less access to care, for example attributable to low SES, are more likely to be obese. Measuring correlation between obesity prevalence and public health costs might illustrate the illusion that these people need less medical care than they actually do, because they cannot access all the care they need. However, the negative impact on their productivity, quality-of-life, and disability-free life-years persists and might even be enhanced due to the absence of medical care. Finkelstein, Fiebelkorn, and Wang (2003) limit the issue of endogeneity by incorporating SES and medical insurance controls when performing research for the United States. They estimated that overweight- and obesity-attributable medical spending covered about 9.1% of the country's total medical expenditures in 1998. Cawley and Meyerhoefer (2012) address the endogeneity issue between obesity and health costs by applying a method of instrumental variables (IV) to United States data between 2000 and 2005. People with obesity were estimated to incur an additional $US2,741 per year in medical costs compared to people without obesity. Aggregating this to a national level would result in a $US190 billion per year of extra health care spending in the United States. This suggests that 21% of health care costs were used for treating obesity and obesity related conditions. In their systemic review, Kim and Basu (2016) find significant variations in cost estimates in existing literature. They perform a meta-analysis across twelve studies and estimate that total medical spending attributable to obese individuals in the United States was $US149.4 billion in 2014 values. With a systemic review of 23 studies, Tremmel, Gerdtham, Nilsson, and Saha (2017) concluded that a substantial economic burden of obesity was present in countries of all development levels. However, the variations in methodologies hinder the estimation of the total economic burden of obesity. Studies covering the effect of obesity on economic growth in LAC are scarce. Mayer (2001) studies the role of health in economic growth in an analysis of 18 Latin American countries over 30 years. He finds evidence for the existence of a long-run conditional Granger causation running from health to income in modern economic development. He suggests that these effects occur through direct productivity, education, female participation, and direct economic burdens of disease.

Note that the two directions of causality are not mutually exclusive. Simultaneously they shape the relationship between economic growth and obesity prevalence. The empirical interest if therefore to observe the relation between these factors in the LAC region. Moreover, only an empirical analysis can provide insights of the short-run and long-run intertwinement of these conceptual explanations.

2.2.2 Trade Openness

Traditionally, openness to trade has been assumed a driver of prosperity that could lift developing countries out of poverty. Trade has been closely associated with economic growth by established research (Frankel & Romer, 1999). Also more recent findings, such as Alam and Sumon (2020) identify a positive long run bidirectional causality between economic growth and trade openness. Stuckler et al. (2012) argue that trade openness and growth jointly drive the increase in obesity prevalence. They find that rising income has been strongly associated with increased consumption of obesogenic foods, but generally only when there was also a high level of foreign direct investment (FDI) and presence of free trade agreements (FTAs). Therefore, they conclude that economic growth does not inevitably lead to an increased consumption of unhealthy foods. Also Malik et al. (2013) argue that trade liberalization affects the availability of certain foods by increasing variety, making foreign food distribution more effective and by attracting inward FDI. However, these effects of trade might be unequally distributed and might not always be beneficial.

An unfavorable effect of trade openness on obesity prevalence was identified by Barlow, McKee, and Stuckler (2018) for an FTA between Canada and the United States in combination with coinciding exports to Canada and investments in its food and beverage sector. Barlow et al. (2018) analyzed the impact of these factors on calorie availability in Canada between 1978 and 2006. The researchers estimated that the associated rise in calorie availability accounted for a weight gain for Canadians of 1.8 to 12.2 kilograms, depending on their physical activity and sex. Also Stuckler et al. (2012) find evidence that LMCs entering

FTAs with the United States are linked to a 63.4% increase in soft drink consumption, even after correcting for the level of income per capita and urbanization patterns of the trading partner.

This can largely be attributed to supply of TFCs. Over the past decades, global food supplies have become increasingly dominated by ready-to-consume processed products. There is a small group of companies that supply these goods globally and therefore they have colossal power. The markets for TFCs in developed economies are often already highly saturated, but their opportunities in developing countries are immense (Monteiro & Cannon, 2012). The pace at which consumption of their products in these countries rises is even faster than was initially observed in HICs (Stuckler et al., 2012).

The influence of foreign firms on local markets has often been observed through imports. For example, Mendez Lopez, Loopstra, McKee, and Stuckler (2017) indicate that between 2001 and 2014, about 40% of the observed rise in sales of sugar sweetened beverages in LMCs could be accounted for by additional imports. Giuntella, Rieger, & Rotunno (2020) identify a link between food imports and obesity in Mexico. They isolate for the causality running from imports to obesity, by implementing an instrumental variable. Their findings suggest that exposure to food imports from the United States explain up to 20% of obesity occurrence among women between 1988 and 2012. Pro-obesity effects were mainly driven by unhealthy food imports.

Even a more influential factor than imports might be inward FDI. It has stimulated the global spread of fast food chains and supermarkets, of which the latter is a channel for the sale of packaged foods. Rayner et al. (2006) state that United States food companies sell five times more through FDI sales than through export sales. They find that Latin American inward food industry FDI increased from $US222 million in 1988 to $US3.3 billion in 1997, which was substantially more than domestic agriculture investments. Also compared to other developing regions, LAC have led the way in the emergence of the supermarket sector. In the 1980s supermarkets only served 10-20% of the national food retail sales in the region. However, an FDI-led growth increased this share to 50-60% by 2000 (Reardon, Timmer, Barrett, & Berdegué, 2003).

2.2.3 Food Prices

There is very limited research on the relationship between price shifts and the structure of diets (Popkin et al., 2011). Chou, Grossman, and Saffer (2004) find that the downward trend in

United States food prices account for part of the upward trend in weight outcomes in the 1980s and 1990s. They largely attribute the drop in relative food price to technological innovations and economies of scale.

Increased FDI and import supply in food markets could lower consumer prices by exercising competitive pressure on local food suppliers. Giuntella et al. (2020) find evidence for a negative relationship between exposure to United States foods and the price of unhealthy foods in Mexico. This finding suggests a negative relation between imports and local food prices, which could explain increased consumer demand in foods and higher obesity prevalence. They also find evidence for the concept of habit formation after increased demand caused by a supply driven price drop. Under this concept, a temporary demand shift could lead to the implementation of new food preferences that persist over time. Therefore, a significant price drop today could fundamentally change the local food environment in the long run. As a result, it affects current obesity prevalence, but also future growth. As people's preferences change, demand for imported products might increase. Price enforced habit formation therefore denotes a bidirectional and reenforcing relation between trade and obesity prevalence.

2.2.4 Urbanization

An increasing number of research finds that, within a country, there are significantly higher levels of obesity in urban environments compared to rural ones in developed as well as developing regions (Malik et al., 2013). Jiwani et al. (2019) find that urban residents in LAC had consistently higher BMI than their rural counterparts. Popkin (1999) concludes that urbanization goes hand in hand with lifestyle changes that produce major dietary related problems. Rising obesity rates in cities could be a direct consequence of changes in the built living environment, the growing diversity in food options, and technological advancement. Urbanization is also related with risk factors of obesity such as decrease in sleep duration and increased stress. These factors can be enforced by noise pollution, light pollution, increased occupational demands and decreased societal support.

Not all findings point into the same direction. Hales et al. (2018) observe a reverse effect in a nationally representative survey of adults in the United States. They found that the age-adjusted prevalence of obesity between 2013 and 2016 was significantly higher among adults living in nonmetropolitan areas, compared with adults living in large metropolitan areas. This supports a review of Popkin (2011), who observe that obesity rates in HICs are often higher in rural areas, while for LMCs they are generally lower in these areas. Research of

Stuckler et al. (2012) concludes that urbanization no longer defines consumption of obesity enhancing food products, except for soft drinks.

2.2.5 Screen Media Exposure

Globalization activates technological changes in the macroenvironment. The relation between screen media, food marketing, and obesity prevalence has been largely investigated, although it has traditionally focused on television exposure and children (Andreyeva, Rashad Kelly, & Harris, 2011; Boyce, 2007; Chou, Rashad, & Grossman, 2008). This does not tell, however, what the effects of today's internet and small screen technologies are on the population. Video games and social media exposure related with these technologies are fundamentally different from television, as they are interactive, personalized, and accessible outside the house. This comes with new forms of marketing, such as sponsorships, viral marketing, and product placements. Online food marketing is almost entirely composed of calorie-dense, nutrient-poor products and has harmful effects on children (Harris, Pomeranz, Lobstein, & Brownell, 2009). It can affect consumers in the short-run, by imposing a direct trigger to eat certain foods. Moreover, the full range of marketing also include brand creation and product association in the long-run.

Evidence of Robinson et al. (2017) suggests that screen media exposure of all technologies leads to increased eating through, among others, food marketing and purchase requests. A common assumption used to be that individuals develop skepticism towards marketing as they mature, which would make adults less directly affected than young children. Newer forms of marketing are designed to deactivate this, by circumventing the active processing of advertising information. Current psychological studies identify mechanisms that allow marketing to influence behavior of people of all ages. Vassallo et al. (2018), for instance, conclude that brands use social media with high frequency targeted marketing posts that manipulate the emotions of the viewer.

Social media penetration in Central America and South America were 51% and 59% respectively at the start of 2017. This was substantially higher than the 37% world average (Bailey, Bonifield, & Ariasc, 2018). In 2012, social media users in LAC were wealthier, better educated and more urbanized than people who were not active on these platforms. However, Salzman (2015) expects that the connection between social media use and wealth will decline as tools for accessing the internet become relatively cheaper and more accessible.

Salzman (2015) also concludes that there is a strong relationship between an individual's interest and their social media content. This could create a reinforcing relation between preference for unhealthy foods and related marketing: people more interested in certain products will use platforms to see them and might therefore increase their interest even more. Note that this could also direct consumers towards non-obesogenic topics if this is where their interests lie. Therefore, the relationship between social media marketing and obesity prevalence might depend significantly upon the individual or cultural preferences of the people within a country.

2.2.6 Work and Income

While economies globalized, socioeconomics also underwent structural changes. The LAC region globally saw the largest increases in female labor force participation over the past decades (Novta & Wong, 2017). While this was first observed for females in urban areas, the rise of non-farm employment has caused their rural counterparts to increasingly work outside the home as well. Chou, Grossman, and Saffer (2004) were among the first to investigate the effect of expanded labor market opportunities for women on obesity prevalence. As women increasingly tend to work outside the home, less time and energy remains for household activities such as food preparation. Assuming men do not fully substitute all time lost by women, demand for time-efficient foods increases. Chou et al. (2004) conclude that this demand is generally met by the supply of inexpensive convenience and fast-food goods. Courtemanche (2009) finds similar results. He indicates that the rise in female employment in the United States between 1961 and 2004 accounted for a 2.7% rise in adult obesity. However, a concurrent drop in male employment offset some of its increase. This resulted in a net rise of 1.4% in obesity, accounted for by total changes in work hours. When Lakdawalla and Philipson (2009) explored the same relationship through food prices in the United States, they did not find clear effects. Popkin and Reardon (2018) relate obesity growth in LAC to women increasingly working outside the home. They conclude that female labor force participation correlates directly with their opportunity cost of time, which results in them spending less time in the kitchen.

Not only has obesity been related with labor, it has also been related with income. Although Egger et al. (2012) observed a positive relationship between GDP and BMI, they observed an extra layer of dynamics among wealthier countries. Among the countries with per capita GDP above $US30,000, those with lower income inequalities had had lower mean BMI. Pickett, Kelly, Brunner, Lobstein, and Wilkinson (2005) found results in line with this. Income inequality positively correlated with obesity prevalence among men and women in developed countries when adjusting for gross national per capita income. Also Jones-Smith, Gordon-Larsen, and Siddiqi (2012) support these findings, who found that between 1989 and 2006, low SES has become associated with higher BMI and overweight for women in China. In line with this are the researchers who observe an inverse relationship between obesity and income. In a study across 11 OECD countries, Devaux and Sassi (2011) find that obesity and overweight tend to be more prevalent in less affluent socioeconomic groups. Their evidence suggests presence of large social inequalities in overweight and obesity by household income and education based SES. While these results are not as much observed across LMCs, Hruby and Hu (2015) expect that the poverty-obesity dynamics in LMCs will mimic the ones in HICs as their wealth rises.

When comparing obesity rates from national surveys conducted in Brazil in 1975, 1989, and 2003, Monteiro, Conde, and Popkin (2007) conclude that within the country, the burden of obesity is shifting towards the individuals in lower income groups. Also in a cross-sectional series analysis of obesity prevalence among 13 LAC countries, Jiwani, et al. (2019) find a shifting burden across SES from the higher to the lower groups.

The review of this literature could suggests that low SES promotes the chance of developing obesity. However, there is also a case of causality running the other way, when low SES is a cost of obesity. In this case, someone's state of obesity partly determines their SES, by lowering their chances of getting and maintaining a job, being productive and building a career.

3. Data and Descriptive Statistics

The empirical study is based on a sample of 14 Latin American and Caribbean countries, with annual data from 2000 until 2016. Countries were eligible for inclusion if they were included in the United Nations M49 area code 419 (United Nations Statistics Division, 1999), had a population of over three million, a per capita GDP of more than $US3,000 in 2016, and available data on the indicators of GDP per capita, price levels, urbanization, inward FDI stock, internet adoption, and female labor force participation over the indicated time period. The final sample consists of the following 14 remaining LAC countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Guatemala, Mexico, Peru, Paraguay, El Salvador, and Uruguay.

Annual age-standardized obesity prevalence data from people of both sexes over eighteen years old were retrieved per country from the World Health Organization (2020). The data were part of a pooled set of yearly worldwide population based surveys that measured height and weight of individuals. Obesity prevalence was indicated as the defined population with a BMI of 30 kg/m^2 or higher. As the data were age-standardized, all groups in the sample were given the same age distribution structure. Descriptive statistics of obesity prevalence per country are presented in Appendix A.

The inclusion of independent variables was determined based upon data availability regarding the most prominent indicators as identified by the literature review. This resulted in a final set of six variables related to growth, price levels, FDI, urbanization, and demographics. Per capita gross domestic product is applied as an indicator of growth. Countries' annual GDP per capita data were retrieved from The World Bank (2020). Figures are reported in constant 2010 $US in order to measure true growth of the series, adjusting for the effects of price inflation. General consumer price indices (CPI) and food consumer price indices, with 2015 as base year, were retrieved from the Food and Agriculture Organization of the United Nations (2020). The food CPI was divided by the general CPI to obtain a relative food price. Inward FDI stocks as a percentage of GDP, retrieved from the United Nations Conference on Trade and Development (2020), were incorporated to indicate the level of establishment of foreign firms in the domestic economy. Accumulation was defined by the net inflows of foreign investment to acquire at least 10% of voting stock in the host economy. Data on individuals using the internet as a percentage of the total population was retrieved from The World Bank (2020). It was incorporated as an indicator of people's exposure to small screens and food marketing. Female labor force participation, also retrieved from The World Bank (2020), was used to indicate for the time women spend working out of the home rather than doing house work.

Table 3.1 provides descriptive statistics of the variables in level forms, while Table 3.2 describes the corresponding annual growth rates. Graphs of the development of all variables over the indicated time period are provided in Appendix B.

Table 3.1: Descriptive Statistics of Variable Levels

Variable name	Observations	Mean	Std. Dev.	Minimum	Maximum
Obesity Prevalence	238	19.9	4.1	12.3	28.9
GDP per Capita	238	6607	3433	1598	14777
Relative Food Price	238	0.91	0.10	0.64	1.55
Inward FDI Stock	238	31.2	17.2	7.0	99.8
Rural Population	238	26.9	12.9	4.9	54.7
Female Share Labor Force	238	39.9	3.4	32.6	46.2
Internet Adoption	238	26.6	19.2	0.7	83.6

Table 3.2: Descriptive Statistics of Variable Growth Rates

Variable name	Observations	Mean	Std. Dev.	Minimum	Maximum
Obesity Prevalence	224	0.0259	0.0061	0.0144	0.0428
GDP per Capita	224	0.0228	0.0303	-0.1262	0.0921
Relative Food Price	224	0.0087	0.0508	-0.5254	0.1313
Inward FDI Stock	224	0.0377	0.1431	-0.4712	0.6720
Rural Population	224	-0.0174	0.0114	-0.0451	-0.0037
Female Share Labor Force	224	0.0046	0.0154	-0.0512	0.0583
Internet Adoption	224	0.1822	0.1596	-0.0668	0.9016

4. Empirical Strategy

The empirical investigation employs a one-step error correction model (ECM) as proposed by Bårdsen (1989) and applied in practice by, among others, Foon Tang (2008). In this mechanism, the long-run relationship between obesity and its drivers as well as their short-run dynamic causal relation are observed by means of Ordinary Least Squares (OLS). If the underlying variables in the equation have a long-run stochastic trend, the mechanism allows for lagged deviations of the equilibrium to have an effect on the short-run dynamics of the relationship. In this relation, the ECM estimates the speed at which the dependent variable returns to its equilibrium after a sudden shock in the independent variables. Also, the coefficients of the long-run relationship can be estimated by simply computing the ratio of two parameters. The fact that Bårdsen (1989) allows for the computation of the long-run coefficients by means of ordinary least squares (OLS) makes the research method particularly efficient.

We apply the model of Bårdsen (1989) in an autoregressive distributed lag model with up to second-order dynamics [ADL (2,2)]. There has been former research applying an error correction model in an ADL(2,2) setting, such as Bond, Elston, Mairesse, and Mulkay (2003). The investigation starts from the assumption that obesity prevalence in the long run depends on the dominant macroeconomic drivers determined by the theoretical analysis. Obesity prevalence is assumed to be correlated with its own value lagged two periods as well as the values of its explanatory variables lagged two periods. We test for serial correlation in the residuals of the regressions. Building upon the assumption of cointegration, the following ADL (2,2) model could be considered:

$$OB_{i,t} = f(OB_{i,t-1}, OB_{i,t-2}, X_{i,t}, X_{i,t-1}, X_{i,t-2}) \text{ ,}$$

Equation 1

where the subscript $i = 1, \dots, N$ stands for each country in the panel, and $t = 1, \dots, T$ refers to each year in the time period. $OB_{i,t}$ is the obesity prevalence in country i in year t. The vector $X_{i,t}$ represents a $K \times 1$ vector of the regressors, where K stands for the number of incorporated drivers. A multiple regression model could estimate the dynamic relationship as follows:

$$\ln OB_{i,t} = \delta + \theta_1 \ln OB_{i,t-1} + \theta_2 \ln OB_{i,t-2} + \delta_0 \ln X_{i,t} + \delta_1 \ln X_{i,t-1} + \delta_2 \ln X_{i,t-2} + \psi_t + v_{i,t} \text{ ,}$$

Equation 2

Where δ represents a constant term, δ_0, δ_1 and δ_2 denote $K \times 1$ vectors of parameters that give the elasticities of the different lags of the explanatory variables. The time-specific effect, denoted by ψ_t for year t, accounts for an assumed time trend. This deterministic trend term eliminates correlation across countries' fixed effects due to common time-related shocks. Assuming fixed effects, the cross section error term $v_{i,t} = \varepsilon_i + u_{i,t}$ contains the unobserved time-invariant, country-specific effect ε_i, and a stochastic error term $u_{i,t}$. Factors such as differences in geography, the size of the country area, fixed cultural effects and historical ethnic make-up of the population are covered by ε_i. The variable $u_{i,t}$ is an unobserved country-specific time varying effect that allows for the heterogeneity of countries. The variables in Equation 2 are said to be cointegrated if $v_{i,t}$ is a stationary process and $\ln OB_{i,t}$ is non-stationary.

Equation 2 implicitly assumes that a country's obesity prevalence in the presence of adjustment costs is proportional to its obesity prevalence in the absence of adjustment costs, and that the long run obesity dynamics are sufficiently stable over the sample period to be estimated by the distributed lags in the regression model. This ADL (2, 2) model can be reparametrized in the error-correction form of a dynamic panel model. This linear transformation of the variables in Equation 2 allows an explicit distinction between the short-run and long-run effects:

$$\Delta \ln OB_{i,t} = (\theta_1 - 1)\,\Delta \ln OB_{i,t-1} + \delta_0\, \Delta \ln X_{i,t} + (\delta_0 + \delta_1)\Delta \ln X_{i,t-1} + \eta\,(\ln OB_{i,t-2} - \beta_1 \ln X_{i,t-2}) + \psi_t + v_{i,t}\ ,$$

Equation 3

where $\eta = (\theta_1 + \theta_2 - 1)$ and $\beta_1 = -\frac{(\delta_0+\delta_1+\delta_2)}{\eta}$. The symbol Δ denotes the first-difference operator. Therefore, this model expresses the growth rate of obesity prevalence as a function of both growth rates and level information. For simplicity, we assume that $\Delta \ln X_{i,t-1}$ is independent of ψ_t and $v_{i,t}$. Expressing the relation in this form is convenient, because η provides a simple t-test of error correcting behavior. The ECM test can be based upon the OLS estimator of the error correction term, coefficient η. For the validity of this test, η is required to be significantly smaller than zero. This allows a mechanism where obesity prevalence above its long-run equilibrium level is associated with a downward correction towards that equilibrium in the future, and vice versa. The relationship between obesity and the macroeconomic indicators then exists in the long run, and the error correcting mechanism induces the obesity adjustments to close the gap with respect to the long-run relationship between obesity and the identified macroeconomic drivers. The presence of the described relationship is identified based on the test of the following hypotheses:

$$H_0: \eta = 0$$
$$H_1: \eta < 0.$$

The symbol η indicates the speed at which the mechanism corrects towards the equilibrium relationship after a sudden shock. If $\eta < 0$, this implies that $\ln OB_{i,t}$ and $\ln X_{i,t}$ are cointegrated and error correction takes place. Under rejection of H_0, obesity prevalence could deviate from the long run equilibrium relationship due to short-run shocks, but eventually will converge towards the equilibrium as long as no other shocks occur. Therefore, long-run obesity prevalence will be determined by both the changes in the determinants as well as the stable nature of the long run equilibrium. On the other hand, if $\eta = 0$, there is no cointegration and therefore no error correction takes place.

If obesity prevalence and the macroeconomic drivers are cointegrated, a long run relationship exists that can be described as:

$$\ln OB_{i,t} = \beta_0 + \Psi_t + \beta_1 \ln X_{i,t},$$

Equation 4

where the constant $\beta_0 = -\frac{\delta}{\eta}$, the long-run elasticity estimate of obesity $\beta_1 = -\frac{(\delta_0+\delta_1+\delta_2)}{\eta}$ and the time trend $\Psi_t = -\frac{\psi_t}{\eta}$.

5. Results

We performed the ECM test on four different variable combinations. Table 5.1 presents Model 1 and Model 2, while Table 5.2 presents Model 3 and Model 4. All variables were incorporated in Model 1. In the succeeding models, variables were removed one by one. Model 2 excluded the relative food price; Model 3 also excluded the FDI variable; Model 4 additionally excluded the internet variable. In order for the results to be valid indicators of cointegration, we assumed no autocorrelation in the residuals. The test results that present evidence of no serial correlation up to the fifth order are to be found in Appendix C.

We found that the coefficient of $\ln OB_{i,t-2}$ is significant on the 1% level in all models, so we reject the null hypothesis of no cointegration. This implies that error correction takes place in the long run relation between obesity prevalence and the macroeconomic variables and a sudden shock in the current period will be corrected for in the future. Therefore, the relationship between obesity prevalence and the macroeconomic indicators will eventually converge towards a long-run equilibrium. The coefficient η of the error correction term ranges from -0.0492 in Model 2 to -0.0526 in Model 3. Since η is close to zero, error correction towards the equilibrium occurs at a very slow pace. Ceteris paribus, the half-life period of a deviation from the long-run equilibrium could be estimated as $\frac{ln(0.5)}{ln(1-0.05)} \approx 13.5$ years.

We also found that the lagged first-difference of the dependent variable has a negative coefficient that is significant at the 1% level. This indicates a negative relationship between the change in obesity prevalence in the current period and the change in obesity in the previous period. It suggests that a 10% drop (rise) in the growth of obesity prevalence in the previous period is related with approximately a 4.9% rise (drop) in the growth of obesity prevalence in the current period.

In the short-run, the change in GDP per capita is positively related with the change of obesity prevalence at significance levels of 5% and 10%. This implies that a rise (drop) in per capita GDP change of 10% is associated with a rise (drop) in the change in obesity prevalence of 0.12% to 0.18% in the same period. However, the one period growth rate lag of per capita GDP shows no significant influence on the obesity growth rate in the current period.

Table 5.1: Fixed effects panel ordinary least squares regression results with a time trend for the relationship between macroeconomic factors and obesity prevalence over the period 2000-2016

	Model 1		Model 2	
	$\boldsymbol{\beta}$	$\boldsymbol{SE}$	$\boldsymbol{\beta}$	$\boldsymbol{SE}$
$\ln OB_{i,t-2}$	-0.0504***	(0.0088)	-0.0492***	(0.0083)
$\Delta \ln OB_{i,t-1}$	-0.4784***	(0.0665)	-0.4840***	(0.0657)
$\Delta\ln GDP_{i,t}$	0.0176**	(0.0072)	0.0169**	(0.0071)
$\Delta \ln GDP_{i,t-1}$	-0.0006	(0.0070)	0.0003	(0.0069)
$\ln GDP_{i,t-2}$	0.0077**	(0.0034)	0.0076**	(0.0034)
$\Delta\ln RURAL_{i,t}$	-0.0518	(0.0991)	-0.0483	(0.0978)
$\Delta \ln RURAL_{i,t-1}$	-0.0652	(0.0891)	-0.0596	(0.0872)
$\ln RURAL_{i,t-2}$	0.0021	(0.0045)	0.0033	(0.0041)
$\Delta\ln FEMALE_{i,t}$	0.0105	(0.0111)	0.0108	(0.0110)
$\Delta \ln FEMALE_{i,t-1}$	-0.0094	(0.0119)	-0.0105	(0.0116)
$\ln FEMALE_{i,t-2}$	-0.0156*	(0.0081)	-0.0160**	(0.0080)
$\Delta\ln INTERNET_{i,t}$	-0.0024*	(0.0015)	-0.0023	(0.0014)
$\Delta \ln INTERNET_{i,t-1}$	-0.001	(0.0013)	-0.0008	(0.0013)
$\ln INTERNET_{i,t-2}$	-0.0015*	(0.0008)	-0.0015*	(0.0008)
$\Delta\ln FDI_{i,t}$	0.0014	(0.0013)	0.0012	(0.0013)
$\Delta \ln FDI_{i,t-1}$	-0.0007	(0.0014)	-0.0008	(0.0014)
$\ln FDI_{i,t-2}$	-0.0006	(0.0007)	-0.0006	(0.0007)
$\Delta\ln PRICE_{i,t}$	-0.0022	(0.0052)		
$\Delta \ln PRICE_{i,t-1}$	0.0043	(0.0048)		
$\ln PRICE_{i,t-2}$	0.0025	(0.0040)		
$Constant$	0.1704***	(0.0532)	0.1657***	(0.0524)
R^2	0.6671		0.6646	
N	210		210	

Note. Standard errors are in parentheses; the dependent and independent variables are in natural logs; * p<0.10, ** p<0.05, *** p<0.01.

Table 5.3 reports the long-run estimates of Models 1 to 4. We found significance for the long-run coefficients of $\ln GDP_{i,t}$ with respect to $\ln OB_{i,t}$. This implies that a 10% increase in GDP per capita is associated with approximately a 1.3% to 1.5% increase in obesity prevalence in the long run. Also some evidence was found for the long-run relation of $\ln FEMALE_{i,t}$ with respect to $\ln OB_{i,t}$. Following this evidence, a 10% rise in female labor force participation would be related to a 2.3% to 3.7% drop in obesity prevalence. Some weak evidence is found for $\ln INTERNET_{i,t}$ with respect to $\ln OB_{i,t}$. The results entail that a doubling of the share of people using the internet would result in a 3% decline in obesity prevalence in the long run.

Table 5.2: Fixed effects panel ordinary least squares regression results with a time trend for the relationship between macroeconomic factors and obesity prevalence over the period 2000-2016

	Model 3		**Model 4**	
	$\boldsymbol{\beta}$	$\boldsymbol{SE}$	$\boldsymbol{\beta}$	$\boldsymbol{SE}$
$\ln OB_{i,t-2}$	-0.0482***	(0.0081)	-0.0535***	(0.0074)
$\Delta \ln OB_{i,t-1}$	-0.4921***	(0.0652)	-0.4865***	(0.0653)
$\Delta\ln GDP_{i,t}$	0.0138**	(0.0068)	0.0116*	(0.0067)
$\Delta \ln GDP_{i,t-1}$	0.0001	(0.0067)	-0.0014	(0.0066)
$\ln GDP_{i,t-2}$	0.0069**	(0.0033)	0.0071**	(0.0033)
$\Delta\ln RURAL_{i,t}$	-0.031	(0.0957)	-0.0249	(0.0958)
$\Delta \ln RURAL_{i,t-1}$	-0.0656	(0.0860)	-0.0654	(0.0862)
$\ln RURAL_{i,t-2}$	0.005	(0.0037)	0.0029	(0.0036)
$\Delta\ln FEMALE_{i,t}$	0.0092	(0.0109)	0.0087	(0.0106)
$\Delta \ln FEMALE_{i,t-1}$	-0.0127	(0.0115)	-0.0121	(0.0112)
$\ln FEMALE_{i,t-2}$	-0.0178**	(0.0078)	-0.0125*	(0.0070)
$\Delta\ln INTERNET_{i,t}$	-0.0022	(0.0014)		
$\Delta \ln INTERNET_{i,t-1}$	-0.0007	(0.0013)		
$\ln INTERNET_{i,t-2}$	-0.0014*	(0.0008)		
$Constant$	0.1674***	(0.0516)	0.1651***	(0.0515)
R^2	0.6596		0.6509	
N	210		210	

Note. Standard errors are in parentheses; the dependent and independent variables are in natural logs; * p<0.10, ** p<0.05, *** p<0.01.

Table 5.3: Panel long-run estimates between macroeconomic factors and obesity prevalence over the period 2000-2016

	Variable					
Model	$\ln GDP_{i,t}$	$\ln RURAL_{i,t}$	$\ln FEMALE_{i,t}$	$\ln INTERNET_{i,t}$	$\ln FDI_{i,t}$	$\ln PRICE_{i,t}$
1	0.1528**	0.0417	-0.3095*	-0.0298*	-0.0119	0.0496
2	0.1508**	0.0671	-0.3252**	-0.0305*	-0.0122	
3	0.1432**	0.1037	-0.3693**	-0.0290*		
4	0.1327*	0.1626	-0.2336*			

Note. The variables are in natural logs; * p<0.10, ** p<0.05, *** p<0.01.

6. Discussion

Before discussing the findings, the data limitations of the study should be highlighted. Although comprehensive sources of data are used, quality might differ between countries. This limits the generalizability of the study. There is no direct reason to suspect that measurement error in BMI would vary systematically with the other variables, as BMI data are not self-reported, but measured by surveyors. Yet, there might be a measurement error in diagnosing obesity. The definition of obesity in this sample is based on BMI and not on body fatness per se. However, obesity is defined as abnormal or excessive fat accumulation that presents a risk to one's health. As noted in Section 2.1, the correlation between BMI and body fatness may depend on ethnicity. As ethnic make-up differs per country, obesity prevalence defined by BMI does not fully reflect differences in body fatness between countries. Another measurement error might have occurred when retrieving data on internet adoption. The data used for this indicator describe the individuals using the internet as a share of the total population. However, this does not denote how often these people use the internet. Therefore, it might not be an accurate indicator of people's exposure to small screen media and food marketing. It is very probable that not only the share of people using the internet has increased, but also the time individuals spend using this service. Hence, the impact of internet exposure on obesity prevalence might be underestimated.

Also, multicollinearity between the explanatory variables could be present, which affects the calculations regarding the coefficients of the individual factors. For instance, literature suggests that trade openness and economic growth could be cointegrated. As suggested in Section 2.2.3, inward FDI could have a substantial effect on food price levels. Besides, one could argue that individuals in urban areas are more exposed to trade and the internet than their rural counterparts, which suggests some cointegration between these factors. Since we do not expect this to be perfect multicollinearity, we assume the underlying assumptions of OLS are not violated.

Another limitation is caused by a potentially omitted variable. As described in Section 2.2.6, income inequality within a country is an often identified factor of influence on the prevalence of obesity. Unfortunately, no complete datasets for the defined countries over the indicated time period were encountered on this topic. This constraints the study by potentially omitting a crucial variable. We might therefore underestimate the long-run cointegration level.

Finally, although causality is mainly expected to run from the macroeconomic factors towards obesity prevalence, Section 2.2 suggests some potential reverse causality. May this be present, OLS will not give us an unbiased estimate of the causal effect of the macroeconomic factors on obesity prevalence.

The results indicate a short-run and long-run positive relationship between GDP per capita and obesity prevalence. This supports the theory described in Section 2.2.1 that GDP growth increases obesity levels through over-consumption. The evidence does not support the theory that obesity leads to a decline in GDP due to public health costs. Hence, we conclude that, for this sample, the positive relation running from GDP to obesity is more dominant than the negative relation running vice versa. However, the potential negative reverse causality implies that the effect of GDP on obesity prevalence might be slightly overestimated.

One could argue that, in the light of the obesity pandemic, economic growth leads to diminishing returns in human wellbeing. It is very probable that this is a consequence of the over-consumption that has arisen from nations' pursuit of consumption-driven growth. Consumption is the fundamental instrument in the modern capitalist model to achieve national prosperity. Therefore, consumption patterns leading to public health issues implies there is a failure of the model. This calls for alternative approaches to attain sustainable prosperity. There is no well-defined model for achieving economic stability without growth in consumption. However, an increasing number of researchers propose sustainable macro-economic models, such as the concept of "prosperity without growth" by Jackson (2009). The transition towards an alternative model will be extremely costly and time-consuming, while results are insecure. Hence, it seems unlikely that policy makers will completely halt consumption-driven growth in the coming decades. This makes the obesity pandemic particularly complex to reverse.

However, a more attainable solution lies in regulating the specific components of GDP growth that result in obesity. A deeper analysis of consumption behavior could uncover the specific mechanism through which this occurs. Subsequently, policies could be designed in order to improve consumption patterns. This could be the start of reorientation towards a purposeful food system that is based on health and development, rather than growth and profit.

The results also indicate a negative relationship of internet adoption and female labor force participation with obesity prevalence, respectively. The negative coefficients observed in the long-run estimations of these factors contradict established observations in literature. As described in Section 2.2.5 and Section 2.2.6 respectively, increase in female labor force participation and internet adoption are generally associated with an increase in obesity prevalence. Possibly, there is an omitted variable negatively (positively) related to these indicators, while affecting the dependent variable positively (negatively). For instance, the rise in female labor force participation may have caused a decline in male labor force participation. Men might consequently have substituted the time they originally spent working by healthier alternatives that dampened total obesity prevalence. Another potential explanation could be that the jobs females in LAC generally employ when entering the labor market require more physical effort than the work they used to do in the house. It could also be that there is less opportunity for food consumption at work than there is in the house, which reduces snacking behavior. Hence, the preceding two suggestions could enforce a negative energy imbalance which implies weight loss among females.

The observed negative relation between internet adoption and obesity prevalence could be motivated by several concepts. As noted in Section 2.2.5, the relation of social media marketing with obesity depends on the individual and cultural preferences of the user. Hence, the adoption of internet might have enforced some favorable habits in LAC rather than the adverse ones observed in the United States. As denoted in Section 2.2.5, Salzman (2015) argues that social media users in LAC were wealthier, better educated and more urbanized than the people who were not active on these platforms. The adoption of the internet by these people over the studied time period might have resulted in obesity dampening habits. Contrary to other studied regions, social media use in LAC could have increased body awareness or interest in the fitness community. Moreover, the adoption of internet could have made it easier for individuals to localize and gain access to non-obesogenic foods. These are potential mechanisms through which internet adoption might have dampened the overall growth in obesity prevalence.

We found a strong negative relation between the obesity growth rate in the current period and the obesity growth rate in the previous period. This suggests that a relatively high growth in the previous year results in a relatively slow growth in the current year, and vice versa. It remains unclear what the force behind this pattern is, although it could indicate an observational error. For instance, obesity data could be collected once every two years and extrapolated in between. However, the metadata of the World Health Organization (2020) do not contain information in support of this conjecture.

7. Conclusion

The aim of this paper was to study a long-run relationship between obesity prevalence and macroeconomic indicators in Latin America and the Caribbean (LAC) between 2000 and 2016. We applied a one-step error correction model to a sample of 14 countries in a multivariate framework with second-order dynamics. The empirical results implied that the variables were cointegrated and error correction took place at a slow rate. The evidence suggested that, in the long run, a 10% increase in GDP per capita was related with approximately a 1.5% increase in obesity prevalence. We attributed this to the consumption patterns that have arisen from consumption-driven growth. The results also indicated a long-run negative relationship between obesity and the explanatory variables female labor force participation and internet adoption. As this contradicts common academic theories, there might be an omitted variable affecting these indicators as well as the dependent variable.

Current interventions have not led to a reversal of the obesity pandemic. The evidence of macroeconomic integration implies that governmental leadership is necessary to employ structural changes that can improve public health. Although supporting individuals to counteract their obesogenic environments might partly help, real improvements can only be enforced by changing systemic patterns. We conclude that reversing the obesity pandemic requires a more controlled form of capitalism that optimizes rather than maximizes consumption. Policy makers should focus on the construction of a purposeful food system that is centered around health and development.

This study contributed to the literature by identifying a cointegration relationship between obesity and macroeconomics in the LAC region with the most recent data. The identification of this relationship underscored the systemic dynamics of the pandemic. The macroeconomic character of this study highlighted that the problem of the obesity pandemic does not lie in the misbehavior of individuals, but in the design of the food system. The evidence should therefore motivate researchers to base future studies on the reversal of obesogenic environments. For governments, this implies that the most impactful policy will not involve supporting individuals to counteract the environment, but instead it suggests a reconsideration of the purpose of the food system.

Further research could investigate the directions of causality to acquire a deeper understanding of the different relationships shaping the macroeconomics of obesity. Also, an instrumental variable approach could be employed in order to eliminate potential reverse causality running from obesity prevalence towards the determinants. Besides, one could apply tests to determine appropriate lag lengths, or employ the most recent error correction techniques in order to investigate the robustness of the results. Finally, shorter time spans incorporating only the most recent data could be investigated. These shorter time frames will then be able to include the latest data sources applicable to very recent developments.

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Appendix A: Descriptive Statistics of Obesity Prevalence per Country

Table A.1: Descriptive statistics of obesity prevalence of 18+ individuals per country over the period 2000-2016 in percentages

Country	Observations	Mean	Std. Dev.	Minimum	Maximum
Argentina	17	24.4	2.3894	20.7	28.3
Bolivia	17	16.6	2.2151	13.2	20.2
Brazil	17	18.3	2.3767	14.5	22.1
Chile	17	24.2	2.3334	20.6	28.0
Colombia	17	18.7	2.1920	15.4	22.3
Costa Rica	17	20.1	3.4754	14.8	25.7
Dominican Republic	17	21.6	3.7138	16.0	27.6
Ecuador	17	16.5	2.0938	13.2	19.9
Guatemala	17	16.9	2.6020	12.9	21.2
Mexico	17	24.8	2.5349	20.8	28.9
Peru	17	16.5	1.9647	13.5	19.7
Paraguay	17	16.2	2.5117	12.3	20.3
El Salvador	17	20.0	2.8222	15.6	24.6
Uruguay	17	24.2	2.3287	20.6	27.9

Appendix B: Graphs of Variable Levels over Time

B.1 Legend

- Argentina
- Bolivia
- Brazil
- Chile
- Colombia
- Costa Rica
- Dominican Republic
- Ecuador
- Guatemala
- Mexico
- Peru
- Paraguay
- El Salvador
- Uruguay

B.2 Figures

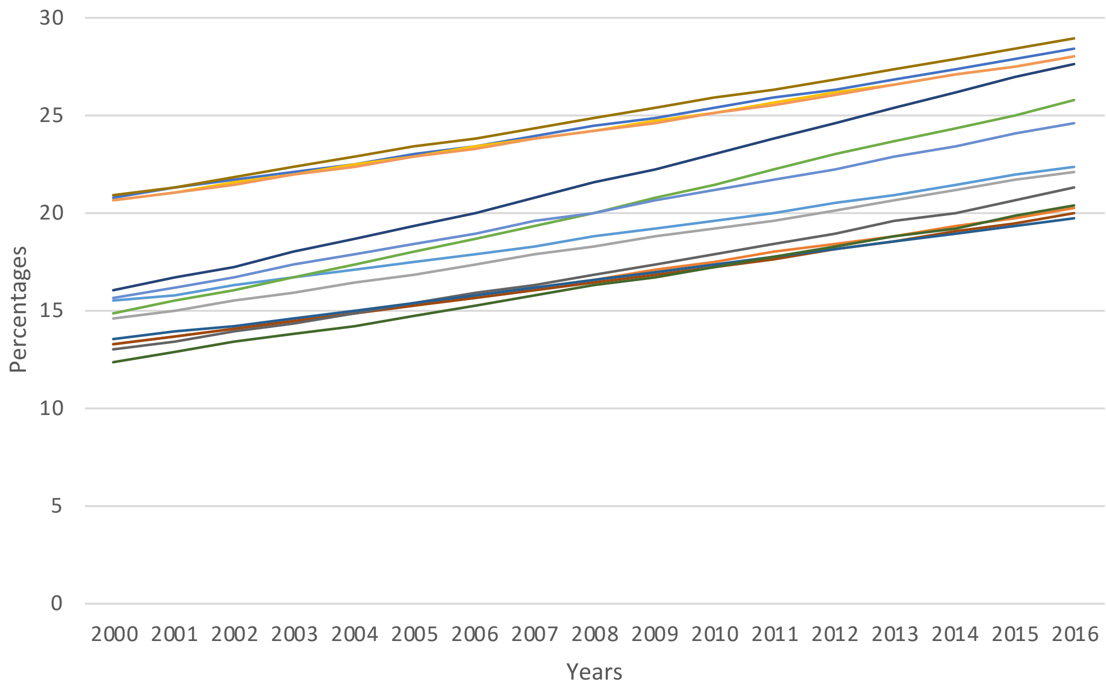

Figure 1: Age adjusted Obesity Prevalence among adults
Adapted source: World Health Organization (2020)

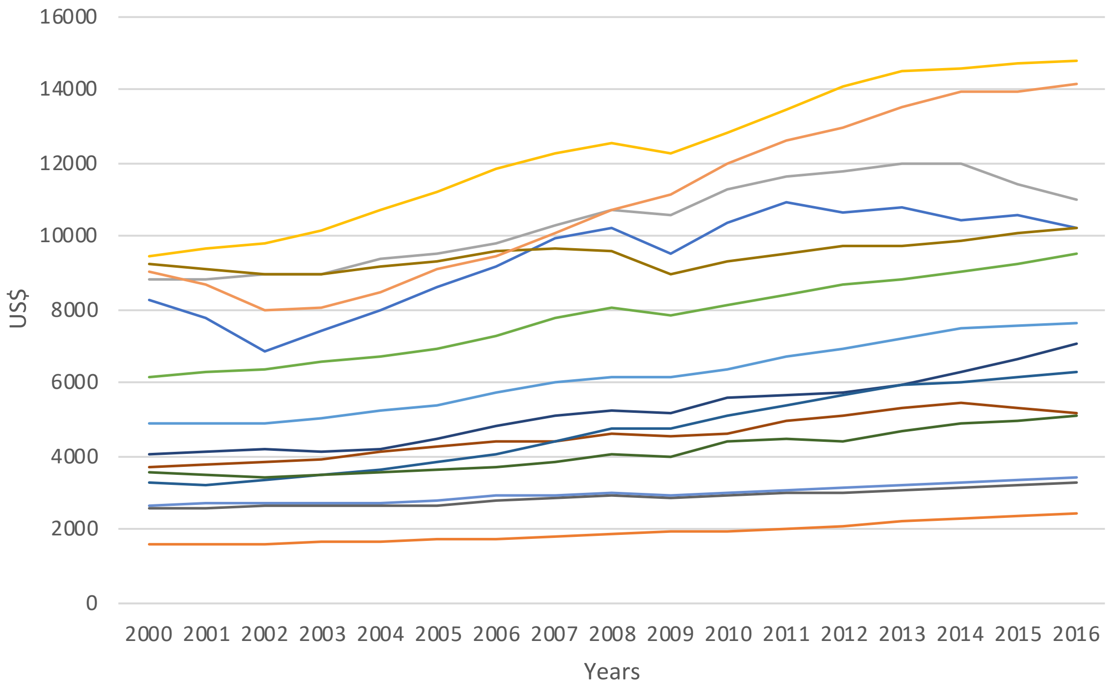

Figure 2: Annual GDP per Capita in Constant 2010 US$
Adapted source: World Bank (2020)

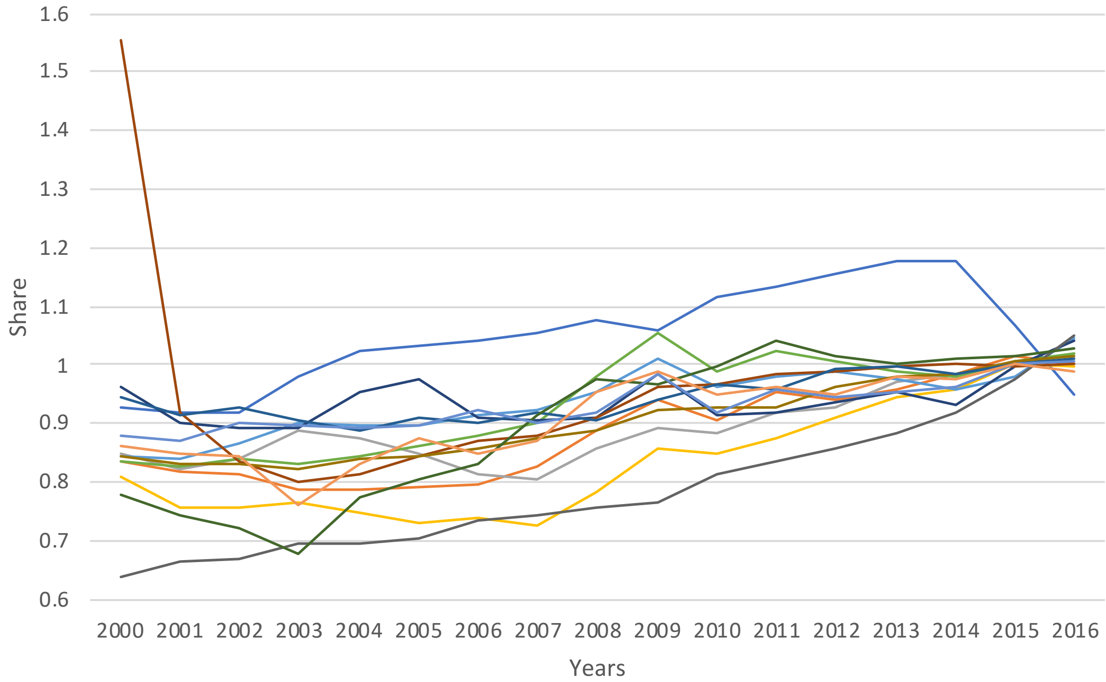

Figure 3: Relative food price as measured by Food CPI divided by general CPI with base year 2015
Adapted source: Food and Agriculture Organization of the United Nations (2020)

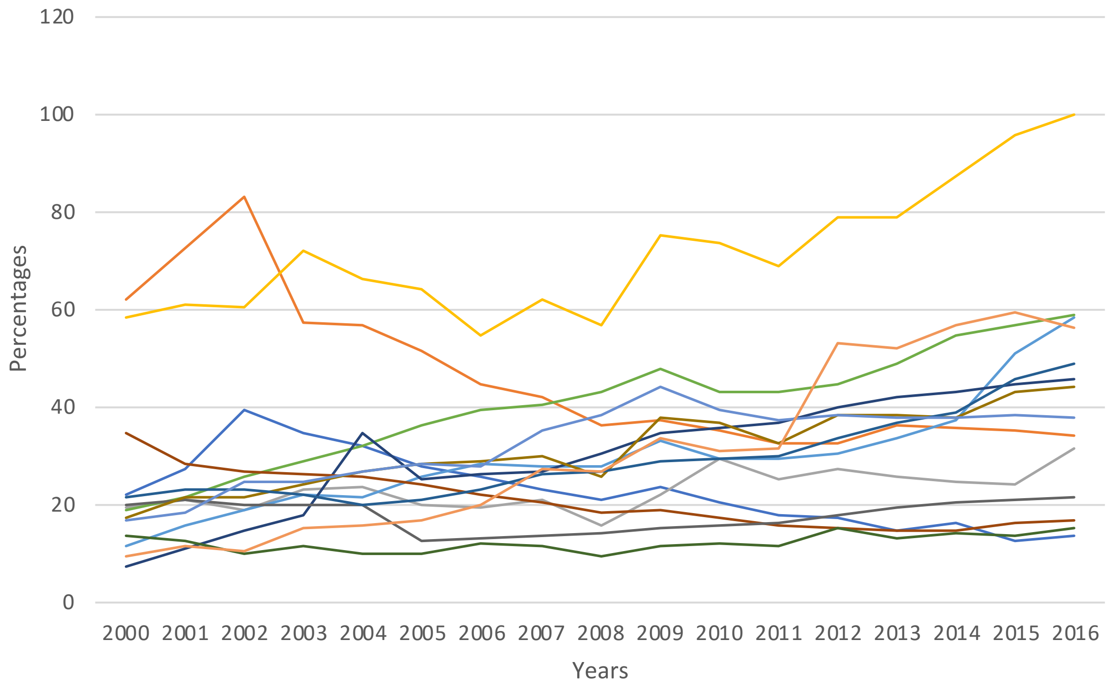

Figure 4: Inward FDI Stock as a percentage of GDP
Adapted source: United Nations Conference on Trade and Development (2020)

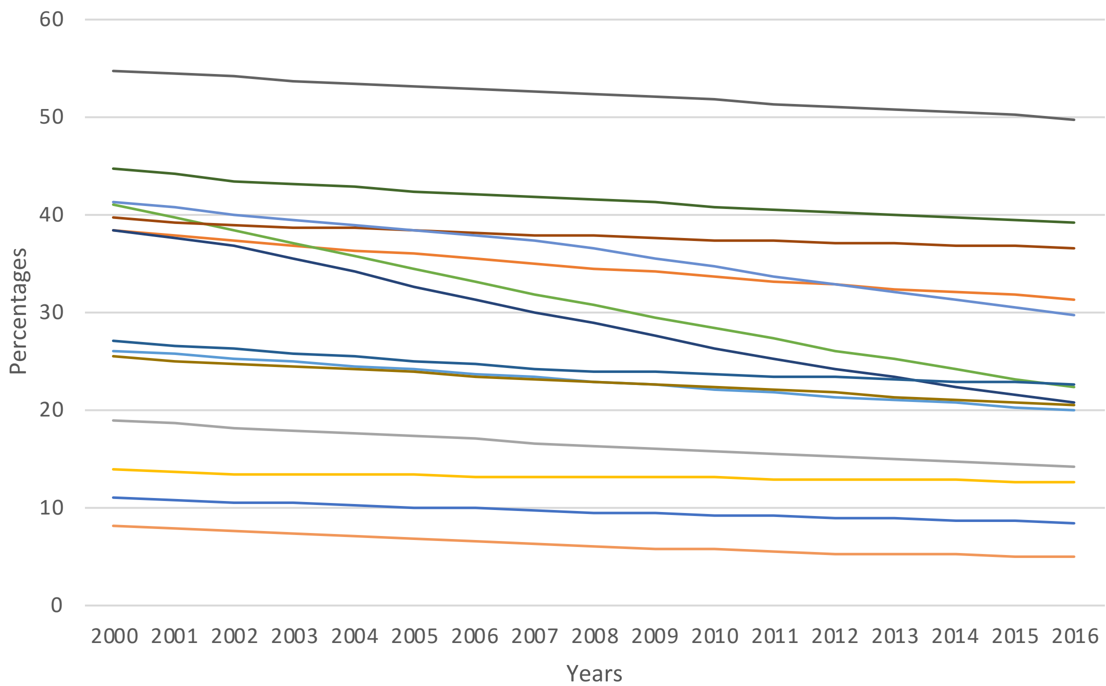

Figure 5: Rural population as a percentage of total population
Adapted source: World Bank (2020)

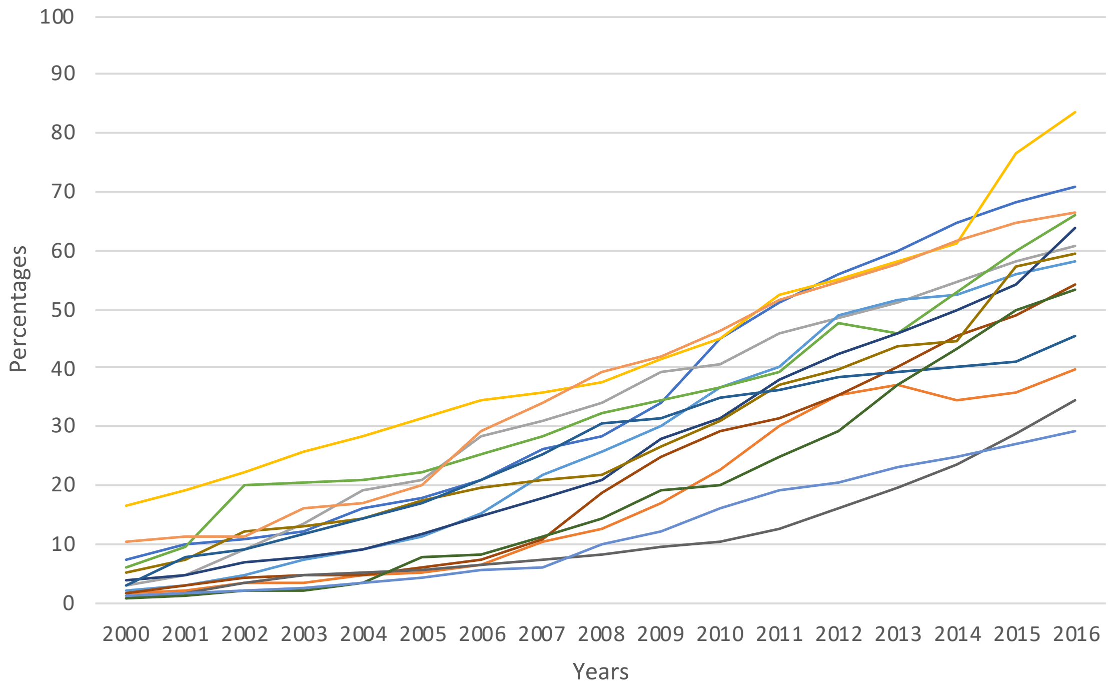

Figure 6: Individuals using the internet as a percentage of total population
Adapted source: World Bank (2020)

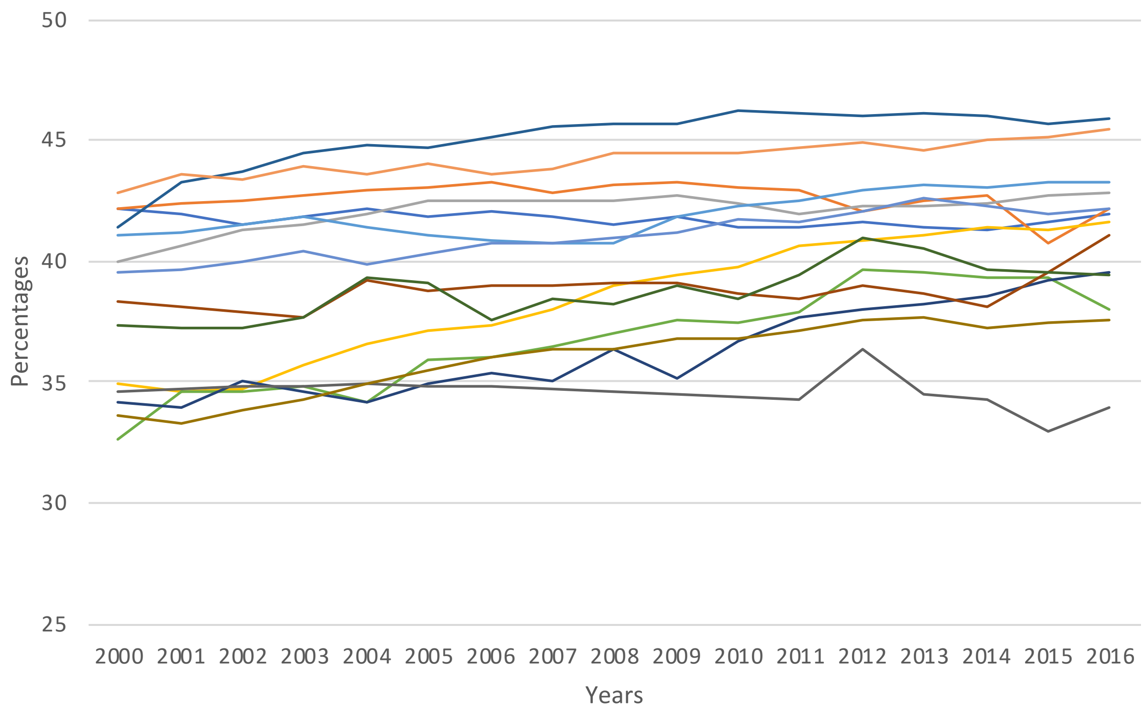

Figure 7: Female labor force as a percentage of total labor force
Adapted source: World Bank (2020)

Appendix C: Tests for Residual Autocorrelation

Table C.1: Ordinary least squares test results of separate regressions of $v_{i,t}$ with its lags up to the fifth order, based on the residuals of Model 1 in Table 5.1

Model 1

	***t*-statistic**	***p*-value**
$v_{i,t-1}$	-1.55	(0.122)
$v_{i,t-2}$	-1.48	(0.142)
$v_{i,t-3}$	0.73	(0.469)
$v_{i,t-4}$	-0.31	(0.760)
$v_{i,t-5}$	-0.60	(0.548)

Table C.2: Ordinary least squares test results of separate regressions of $v_{i,t}$ with its lags up to the fifth order, based on the residuals of Model 2 in Table 5.1

Model 2

	***t*-statistic**	***p*-value**
$v_{i,t-1}$	-1.56	(0.120)
$v_{i,t-2}$	-1.46	(0.147)
$v_{i,t-3}$	0.73	(0.469)
$v_{i,t-4}$	-0.32	(0.748)
$v_{i,t-5}$	-0.56	(0.576)

Table C.3: Ordinary least squares test results of separate regressions of $v_{i,t}$ with its lags up to the fifth order, based on the residuals of Model 3 in Table 5.2

Model 3

	***t*-statistic**	***p*-value**
$v_{i,t-1}$	-1.41	(0.160)
$v_{i,t-2}$	-1.44	(0.151)
$v_{i,t-3}$	1.00	(0.318)
$v_{i,t-4}$	-0.39	(0.700)
$v_{i,t-5}$	-0.65	(0.520)

Table C.4: Ordinary least squares test results of separate regressions of $v_{i,t}$ with its lags up to the fifth order, based on the residuals of Model 4 in Table 5.2

Model 4

	***t*-statistic**	***p*-value**
$v_{i,t-1}$	-1.44	(0.153)
$v_{i,t-2}$	-1.34	(0.183)
$v_{i,t-3}$	1.08	(0.280)
$v_{i,t-4}$	-0.20	(0.842)
$v_{i,t-5}$	-0.45	(0.652)