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The Effects of Macroeconomic Factors on the Shares of Automotive Manufacturers in the USA, Asia, and Europe in the Short and Long Run

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Abstract

This study aims to broaden the remits of the relatively scant hitherto literature focused on the impact of the changes in macroeconomic indicators on automotive stock returns. Since a considerable fraction of previous empirical research covered multiple industries, historical results may not be directly transferable for the purposes of the analysis of the automotive industry. This article posits that on average in the Panel VAR analysis the Broad Effective Exchange Rate (BEER) and inflation were the most significant factors, which influence the automotive industry. In other words, the positive coefficient of BEER signalled that the more a currency of a country appreciated (on average), the more car stock returns gained, and the negative parameter related to inflation indicated that on a global level automotive stocks suffer in a highly inflationary environment. The study follows up by identifying the most significant in terms of their influence short- and long-run macroeconomic factors on car stock returns on a regional basis. Market benchmark indices, automotive benchmark indices, Brent crude oil, and semiconductor indices exhibited the strongest correlations with automotive stock returns in the regional samples covering the US, Germany, Italy, France, China, Japan, and South Korea.

Keywords: macroeconomic factors, stock returns, VAR, ARDL

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1. Introduction

The relationship between the automotive industry and developments on the macroeconomic frontier stems from the profound cyclicality of the industry – after all, customers may postpone the purchase of a new vehicle amid uncertain or degrading macroeconomic circumstances (e.g. projected by some sort of a consumer confidence indicator). Say, customers may reconsider their purchase intention if the availability of credit financing has worsened since the volume of auto loans is believed to enjoy a spike in periods of economic expansion, and correspondingly - low interest rates. Furthermore, companies generating a significant percentage of their revenues from exports suffer from a stronger domestic currency. For example, Ford, whose overseas revenues account for almost a half of its total top line, had its sales negatively affected by a stronger dollar as its purchasing power as an importer diminished in such a case (Pereira, 2017). Not less important is the influence of commodities – as Pereira (2017) reported the drop in steel price from 15.2 EUR per metric ton in 2008 to 4.8 EUR per metric ton in 2013 boosted manufacturers' gross margins by 2%, ceteris paribus. Broadly speaking, some of the most essential materials underpinning car construction are steel, aluminium, plastic, and glass, which jointly constitute 47% of total costs of car production (Pereira, 2017).

The research question of this article concerns the implications of macroeconomic variables movements on auto manufacturers' stock returns. The selection of variables will be contingent on prior empirical studies and data considerations owing to the broad nature of the study and the resulting difficulty in obtaining consistent data for all seven countries. We were able to quantify significant relationships for all of the reviewed variables either in the short-run or in the long-run or in both.

A quick overview of the chief macroeconomic dynamics within the automotive industry may prove fruitful at this point. Lis et al. (2012) made some general remarks that stock prices of car companies are more likely to be eroded by oil shocks than energy shares are since the price elasticity of energy stock is lower – after all, vehicles are not a complete must-buy (the demand for them can be curtailed if expected costs are projected to rise exorbitantly) and their consumption/purchases can be confined. Preceding research by Hamilton (1985) claimed that exogenous variables within the petroleum industry affect oil prices on top of endogenous factors such as interest rates, inflation, exchange rates, and default spreads. In his study with quarterly data between 1948 and 2005, Sill (2007) posited that lagged oil prices are significant predictor of GDP movement in the US economy. From a European perspective, El Khoury (2019) hypothesised on the basis of existent literature that inflation, for which the change in the consumer price index (CPI) stood as a proxy, impacted car stocks adversely due to heightened interest rates, which dampen customers' purchasing power and harm company earnings. El Khoury (2019) also hypothesised that money supply which is generally considered a boost for stock prices (due to their enhancement feature on company profits, depreciating domestic currency, which cascades into strengthened competitiveness and greater exports, and accompanying lowered interest rates during periods of increased money supply), unemployment (negative influence), industrial production (a trigger for higher stock prices), and Euribor (discretionary policies to lower interest rates will free pent up demand). Despite El Khoury's (2019) preliminary hypothesis about the negative ramifications of CPI on automotive stock prices, historically the role of inflation has not been so clear-cut. Two schools of thought were promulgated with regards to inflation – Keynesian economics suggests that an expanded monetary supply triggers rising inflation and rising interest rates, which are harmful for stock prices (Abbas et al, 2018). Conversely, real activity advocates claim that expansionary economic policies such as boosted monetary supply led to a higher demand for money and correspondingly an upsurge in economic activity. This economic revival is auspicious for company profitability, ultimately resulting in blossoming stock prices (Abbas et al, 2018).

The motivation derived to compose this thesis stems from the relative scarcity of empirical research focused on the effects of macroeconomic factors on the automotive industry. Even though some quality research has been conducted pertaining to the US and Germany, and some key auto-manufacturing outsourcing hubs (such as Turkey), very few of the previous journal articles encompass as broad an investable universe as the current study, which covers stock prices of US, German, Chinese, Japanese, South Korean, French, and Italian carmakers. The selection period covered January 2007 – December 2021 and it was intended to encompass several periods of economic distress. The full effect of the global financial crunch became incontestably visible in Q1 2008, was further aggravated by the Russian oil crisis in the latter half of 2009, and admittedly the pandemic marred global supply chains from Q1 to the end of the sample period. As evinced by Celebi and Hönig (2019), asset managers should prioritise their focus on macroeconomic fundamentals, bond yields, and leading indicators during crises periods. The unique analytical edge of this study, besides the sheer breadth of its panel data format and multiple countries covered, is the incorporation of semiconductor indices proxies. The relevant themes in the industry since 2020 have been chip shortage, exacerbated competition with consumer electronics and smartphones for more and more advanced chips, and relocation of automotive plants to chip facilities – a comeback to just-in-time manufacturing, which used to be prevalent in Japan.

This thesis is structured in the following way: **Section 2** puts forward an overview of the automotive industry by outlining some key facts and figures. **Section 3** shall be constructed in a two-fold manner – initially, previous empirical research will be presented to glean the effects of macroeconomic variables on stock prices across all industries, whilst a standalone paragraph will be allocated to disclosing the impact of macroeconomic factors specifically on automotive stocks. Section 3 is finalised with the null hypotheses derived from the existing empirical research. **Section 4** – "Data and descriptive statistics" is devoted to the presentation of selected macroeconomic variables, outlining null hypotheses about their relationship with automotives stock prices, utilised data sources, and most crucially - a summary of descriptive statistics pertaining to the regressors (i.e., macro factors) in the model. **Section 5** shall serve the purposes of outlining the methodology of the statistical approaches implemented in the study – the Vector autoregressive (VAR) model on a panel data basis, followed by a short-run Autoregressive distributed lag (ARDL) model on a country basis and an error correction model to depict the long-run macroeconomic coefficients whenever a cointegration relationship was identified in the short-run ARDL model for a given market. **Section 6** will review the empirical results from the models presented in the strictly theoretical Section 5. Additionally, Section 6 shall formulate insights on how future studies can be enhanced in light of the study limitations. **Section 7** will describe the model findings by seeking to interpret the coefficient in a theoretical and practical manner, whereas **Section 8** will act as a conclusion, hence solidifying the estimated findings and how they stacked against the preliminary hypotheses.

2. Industry review

A set of reports by Statista (2021) provided a solid overview of the automotive industry. It was projected to rise by 68% from 2017 to 2030. The top 3 most revenue generating producers in 2020 were Volkswagen Group leading by a very slim margin ahead of Toyota Motor, both comfortably ahead of third place Daimler. The EU imported most vehicles in 2020, followed by US and China. Toyota, Volkswagen, and Hyundai account for the three most widely represented automakers with most significant worldwide market share (respectively, 8.5%, 7.8%, and 5.4%). Vehicle production registered growth from 2015 to 2017 but since then the periods 2018-2019 and particularly 2019-2020 were far less successful, with vehicle production considerably shrinking (down by 5.2% and 15.8% respectively). Passenger production unit statistics for 2020 revealed that China held a hegemonic position with 21.39 million produced units, followed by Japan (8.33 million units), and Germany (4.66 million units). The remainder of the scrutinised economies in this thesis – South Korea, US, and France ranked correspondingly 5th, 6th, and 9th. Trends in sales growth replicated the downward trajectory in vehicle manufacturing volume. Vehicle production in the US had its trough in 2009, had its peak in 2016, fell in 2017, remained static in 2018, fell moderately in 2019, and decreased drastically in 2020.

The auto department of PricewaterhouseCoopers assembled a report focused on the "five trends transforming the automotive industry (PricewaterhouseCoopers, 2017). It included the key characteristics of the future vehicle in 2030 were projected to be "electrified, autonomous, shared, connected and yearly updated", or in other words - "EASCY". 55% newly produced in 2030 cars sold in Europe were forecast to be fully electrified (PricewaterhouseCoopers, 2017). Autonomy is driven by advances in Artificial Intelligence, Machine Learning, and neural networks (PricewaterhouseCoopers, 2017). The consulting firm posited that shared mobility will accelerate – people will no longer need to search for themselves a shared vehicle in proximity, but they will be able to order an autonomous shared vehicle directly to the customer's location. Product lifecycles spanning five to eight years will no longer be the industry norm since producers will seek to embed the latest hardware and software advances as promptly as possible (PricewaterhouseCoopers, 2017). The report proceeded by stating that some of the modelling outcomes involve reduced car inventory and yet concurrently rising car sales. Vehicle mileage will surge, mostly due to "empty" mileage by autonomous vehicles. Mileage is forecast to rise by 23% to 5.88 trillion kilometres in Europe, an equal trend is projected to occur in the US where mileage is forecast to pick up by

24% and most evidently in China, where mileage will rise considerably by 183% (PricewaterhouseCoopers, 2017). 55% of new sales on average in the key markets is projected to comprise pure electrified vehicles, around 40% will retain some internal combustion engine (ICE) propulsion in the form of hybrids and plug-in hybrid electric vehicles (PHEVs), whereas traditional ICE vehicles will constitute a single digit share of new car sales (PricewaterhouseCoopers, 2017). According to the experts at the consulting company, the forms of mobility adopted by the 3 divergent types of customers (traditional, transitory, and modern) were self-driven private vehicles, self-driven shared vehicles, autonomous private vehicles, and autonomous shared vehicles. An in-depth persona analysis across the EU, US, and China revealed that the rural part of the population remains highly dependent on personal vehicles, due to relatively insufficient infrastructure (PricewaterhouseCoopers, 2017). The EU stands out with its developed inter-modal transport (car vs. public transport; the so-called Park + Ride in the US) (PricewaterhouseCoopers, 2017). Car-sharing and ride-sharing have blossomed in China through apps such as Didi Chuxing. Car sharing is segmented into station-based (e.g. Flinkster) and free-floating (e.g. DriveNow), the former meaning one should collect their vehicle from a pre-defined station, whereas the latter reflects the business area of the supplier (PricewaterhouseCoopers, 2017). On the contrary, ride hailing revolved around car sharing is manifested through the following three forms: online car sharing agencies to create driving communities, online platforms intermediating between drivers offering shared journeys in their personal vehicles, and taxi companies promoting their services via an app (ride hailing – Uber, shared journey – Blabla car, MyTaxi – app-based cab services) (PricewaterhouseCoopers, 2017). The consulting firm segmented future mobility into four principal branches: unshared and not autonomous; unshared but not yet autonomous; unshared but autonomous; shared and autonomous (from most rudimentary to most sophisticated type of mobility). Share based travelling is projected to reach 10% of total mileage in Europe by the second half of the 2020s. In the US it is estimated that 33.5% of personal vehicle mileage will be shared, with 10% shifting to self-driven shared vehicles and 24% to autonomous shared vehicles (PricewaterhouseCoopers, 2017). Even more striking, in 2030 China is expected to have 45% of its personal mileage done in shared vehicles (PricewaterhouseCoopers, 2017).

Given China's forefront position as a car sharing innovative nation as per the analysis above, China is also leading the field in terms in terms of electric mobility. Namely, China had a 45% share of the global market for electric cars in 2018 (yet, note that electric cars account for a far less significant stake of 4.50% of the Chinese car market; data was extracted from IEA – the International Energy Agency) and trounced other nations even more decisively with respect to electric buses for which it accounts for 99% of the global sales (Kalthaus & Jiatang, 2021). The authors highlighted that the regional differences within China are noticeable with respect to regulatory incentives for distinct kinds of electric vehicles – Beijing subsidises solely BEVs in contrast to Shanghai which prioritises BEVs and PHEVs jointly, perhaps as a result of local protectionist concerns – BAIC – a car manufacturer specialising exclusively in BEVs is based in Beijing. Exemption from license-plate lotteries and auctions which were initially conceived to curb the dissemination of new ICE cars, applies to electric vehicles (Kalthaus & Jiatang, 2021).

The quite formidable role of Europe on the auto-manufacturing scene and the fact three European countries (Germany, France, and Italy) were incorporated in the study can perhaps be rationalised by the introductory section of El Khoury's (2015) journal article, which delineated the pinnacle role of the automotive industry in the EU – constituting 22.3% of manufactured vehicles globally in 2013 and 6.60% of EU GDP in 2013. However, China seemingly overtook rival markets in terms of production volume. Tang (2019) cited an OICA report centred on the phenomenal prowess of China as an automotive powerhouse, with production in China exceeding the combined output in the US and Japan combined since 2009.

3. Literature review

3.1 Empirical research on the effects of macroeconomic factors on stocks as a whole

Since the connection between macro and micro variables has been documented predominantly for all industries, this sub-section carries greater prominence in the literature review relative to the more narrowly focused papers on the automotive industry in Section 3.2. General macroeconomic factor research pinpointed inflation, industrial production, leading indicators, money supply measures, interest rates, unemployment, and commodities as significant drivers of stock returns.

One of the foundation papers in macroeconomic research written by Fama (1981) postulated that inflation and real activity were negatively correlated, bearing in mind the positive relationship between real activity and stock prices. Another intriguing study by Cheung and Ng (1998) implemented Johanson's cointegration technique and concluded a long-term relationship exists between share prices and macroeconomic factors such as real oil price, real consumption, real money supply and real GNP output. Celebi and Hönig (2019) found a positive significant relationship between the growth of the quarterly Composite Leading Indicator (CLI) and the DAX index stock returns. Also, unemployment was a significant factor with a positive direction of the impact in addition to significant exports, which conversely impacted the dependent variable negatively. All German government bond yields were significant regressors, negatively correlated with stock returns, whilst the Composite Leading Indicator lagged by two periods, the Export Expectations Index, and the Export Climate Index delivered positive and significant coefficients (Celebi & Honig, 2019). With respect to the money supply measures (M1, M2, and M3), the M1 lagged by two periods had a positive impact on stock returns, whilst M2 and M3 exhibited a negative impact (Celebi & Honig, 2019). The rationale behind the beneficial influence of M1 was the excess liquidity induced by expansionary monetary policies which decrease interest rates and escalate bond prices. In the pre-crisis period, none of the money aggregates were significant (Celebi & Honig, 2019). A study by Abbas et al (2018) focused on the G-7 economies pinpointed that money supply (M2) volatility was the most prominent factor shaping stock market volatility, ensued by inflation (CPI), oil prices, and exchange rates for the majority of G-7 countries. On a country level, Abbas et al (2018) stated that the most significant contribution of the spillover returns in a rolling window to the forecast error variance of the stock returns was evinced by oil price in the UK (2.3%), exchange rate in Canada (6%), industrial production index in Japan (2%), inflation in Germany (2%), industrial production index in France (4%), interest rate in Italy (4%), and industrial production index in the US (4%). Erdem et al (2005) delivered the insight that inflation had a negative spillover on the volatility of the Istanbul Stock Exchange staple index, whilst interest rate, exchange rates, and industrial production induced positive volatility spillover to the benchmark Turkish index. Benaković and Posedel (2010) investigated the Croatian capital market in the period January 2004 – October 2009 and revealed that the market index was the most significant factor to explain stock returns. Interest rates, oil prices and industrial production exhibited a positive correlation with stock performance in contrast to inflation which exhibited negative influence. Abbas and Wang (2020) employed a Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model for the conditional variance of Chinese and US stocks and proceeded by employing a multivariate VAR model to assess the interaction between respectively volatility and macroeconomic risk factors. Their dataset encompassed data from 1995 to 2018, and the variables such as industrial production, retail sales, terms of trade, hot money, money supply

(M3), 6-month treasury bill rate, 20-year treasury bond yield, consumer price index (CPI), gold price, and crude oil price. For China a one-way causal relationship was identified moving from the stock market to economic variables, particularly to trade and interest rates (if stock returns were reviewed), and industrial production, inflation, and S&P 500 (if stock volatilities were scrutinised) (Abbas & Wang, 2020). For Chinese stock data, the causality was weak, bidirectional, and inconsistent. Results were ameliorated when periods of crisis were incorporated, and a strong relationship was identified between stocks and macroeconomic variables. On the other hand, the US market displayed strong contemporaneous bidirectional causality between stock market and macroeconomic factors both at first and second moments (Abbas & Wang, 2020). Bagliano & Morana's (2009) journal article studied the following macroeconomic variables: CPI, real GDP, nominal long-term and short-term interest rates, nominal money balances, REER, real equity prices, and real oil price. From the perspective of their dynamic factor model, they estimated that the percentage of forecast error variance was predominantly attributed to output growth and inflation, whereas stock price and oil price shocks accounted for less than 5% of the forecast error variance for all variables (Bagliano & Morana, 2009). Mukherjee and Naka (1995) implemented a Johansen's Vector Error Correction Model (VECM) in order to prove the cointegration between macro factors and the Tokyo Stock Exchange (TSE) index. The authors ran an impulse response function analysis on demand-originating oil shocks such as precautionary demand for oil due to beliefs of insufficient future supply. According to Mukherjee and Naka (1995), positive shocks pertaining to the global demand for industrial commodities boost both real oil prices and stock prices. The authors postulated global production shocks did not exert such significance on the US market as global aggregate demand and precautionary demand. Mukherjee and Naka's (1995) findings bolstered previous research by Hamilton (2005), who posited that oil price hikes were chiefly driven by demand rather than supply reductions, hence global business expansion has been generally favourable to rising oil prices. The most useful implication by Mukherjee and Naka's work (1995) was dispelling the public misconception that oil price must always be negatively correlated with share prices.

Two studies by Gonzalo and Taamouti (2007) and Boyd et al. (2005) centred exclusively on the impact of unemployment on stock prices (of all industries) and they both refuted our null hypothesis that automotive stock returns are negatively related to unemployment. Our unemployment null hypothesis was based on El Khoury's (2015) findings specifically related to the automotive industry and the general economic intuition that cars are some high-ticket items in a consumer basket, so naturally customers tend to postpone purchases until the economy gains some upward momentum. On the contrary, Boyd et al. (2005) posited that on average escalating unemployment is a positive boost for stocks during times economic expansions and an impediment to stock growth in periods characterised by economic contraction. Unemployment encompasses two underlying indicators which are crucial for stock valuation – data regarding future interest rates and future earnings and dividends (Boyd et al., 2001). The author also claimed that a spike in unemployment brings about a decrease in interest rates, which is favourable for stock returns, but it can also lead to dampened future earnings and dividends. The magnitude of these two effects varies depending on the state of the economy. Boyd et al. (2005) continued by stating that rising unemployment suppresses stock prices, but this is a trend that is far more evident during bleak economic conditions than during economic expansions. The observation that a hike in unemployment unleashes heightened stock returns in economic rebound periods may be rationalised by the fact that lowered growth expectations are far outweighed by the downward revision in interest rates to stimulate the economy (Boyd et al., 2005). In less favourable economic conditions, lower interest rates do not suffice to counteract decreased growth expectations (Boyd et al., 2005). Gonzalo and Taamouti (2017) largely echoed Boyd et al.'s (2005) findings and their quantile regression analysis showed that unemployment exhibited a heterogeneous effect across quantiles. For the quantile range 0.35-0.80 anticipated changes in unemployment affected stock returns favourably (Gonzalo and Taamouti, 2017). The rationale behind the potentially positive influence of unemployment on stock returns shared the argumentation by Boyd et al. (2005) – that the Federal Reserve in the US responds to unemployment shocks by decreasing interest rates, which exerts an amicable effect on stock prices.

3.2 Empirical research on the effects of macroeconomic factors on automotive stocks

In accordance with the general stock findings by Mukherjee and Naka (1995), Pal and Mitra's (2019) study served well to refute the widespread notion that movements in crude oil were always counter-cyclical to automotive stock returns as the general consensus among media and analysts is that elevating crude oil prices dampen passenger vehicle sales, and correspondingly automotive stocks suffer. Two timeframes in the overall period 1 August 1996 – 20 June 2017, respectively: November 2000 – December 2002, and March 2006 – December 2009 were identified as signalling co-movement in the long-term (Pal & Mitra, 2019). Stock return was sensitive to higher oil prices originating from a demand shock.

Pereira (2017) analysed Ford's stock returns against the NASDAQ Index and found a negative correlation after Q1 2016 which only exacerbated upon global growth and oil price instability. Pereira (2017) cited statistics presented by Kallstrom (2015) that in the second quarter of 2014 the fraction of vehicles acquired with financing totaled 85%, hence a reduction in borrowing costs is conducive to the total amount in car loans outstanding. Kalthaus and Jiatang (2021) assessed the role of regulatory incentives for the proliferation of electric vehicles and buses in China. Four types of electric vehicles and their diffusion were dissected – battery electric (BEV) car and BEV buses in addition to plug-in hybrid (PHEV) electric cars and buses. Total monetary subsidies incentivise solely the purchase of BEV cars (Kalthaus & Jiatang, 2021). Non-monetary ownership policies such as license-plate lotteries and auctions were only effective for BEV cars. With regards to public infrastructure, charging points were decisive in the proliferation of electric cars whereas electric buses prevalence was positively correlated with the prevalence of charging stations. When it came to electric vehicles, air quality and pollution affect the diffusion of buses but not of cars. Lis et al. (2012) concluded that car company stocks in general were not more adversely affected by oil shocks than the broader market, whereas Japanese companies showcased no excess sensitivity whatsoever. German stocks tend to be sensitive to oil shocks, whereas the German and US stocks considered jointly were estimated to be more sensitive in the more recent periods. Lis et al.'s (2012) analysis covered three markets – Germany, USA, and Japan and segmented its sample period in three sub-periods. In the timeframe 8 January 1982 - 14 April 1986, only US automotive stocks plunged due to escalating oil prices – yet it was a period of oil price stability, and no expectations were set for the long-term increase of crude oil prices. The period 15 April 1986 – 2 October 1990 showed that US and German auto companies were negatively affected by increasing petroleum prices, and the timeframe 3 October 1990 – 23 April 1999 even strengthened this negative relationship, but Lis et al. (2012) could not deduce that auto-manufacturing was more affected to oil shocks than the broader market. El Khoury (2015) found that the returns of the selected benchmark (S&P 350) (at a 1% significance level), exports (at a 5% significance level), exchange rates (at a 5% significance level), unemployment (at a 10% significance level), platinum (at a 10% significance level) and aluminium (at a 10% significance level) were the significant factors underlying automotive stock returns. Additionally, El Khoury (2015) stated that expectedly unemployment exuded a negative effect on automotive stock returns, whereas a positive relationship was identified between exchange rates and stock returns. Depreciation of the euro is indicative of strengthened sales and profits, which may rationalise the decline of several European automakers in Q1 2011 (El Khoury, 2015). Unexpectedly, platinum correlated positively with automotive stock returns, at odds with El Khoury's (2015) preliminary hypothesis. The rationale is that platinum is a rare raw material predominantly used in luxury cars, whose demand is relatively inelastic (El Khoury, 2015). Vychytilová et al. (2019) conducted a study analysing 39 listed automaker shares from 11 countries and replicated the El Khory's (2015) article in its wide exposure to markets and variables, but it diverged from it owing to its focus on stock volatility rather than on stock returns. Vychytilová et al. (2019) conceived a five-factor mixed effect model, and concluded that stock market development, GDP, unemployment, money aggregate, and inflation impact stock volatility. Stock market development, GDP, and unemployment affected volatility positively, whereas inflation and money supply were inversely related to volatility (Vychytilová et al, 2019).

In contrast to the broad-spanning papers focused on multiple countries such as El Khoury's (2015) and Vychytilová et al.'s (2019), some papers adopted a narrower regional approach. Tang (2019) reached the conclusion that Chinese automobile firms were less influenced by currency movements at short-term horizons due to restrictions on the currency daily trading band, but asymmetric currency movements tend to be significant at longer term horizons due to the internationalisation of the RMB (Chinese yuan), as the trading volume of the RMB has grown exponentially. Finally, the nexus between inflation and automotive industry development in Turkey was monitored by Dinç and Gökmen (2019). Their study was quite relevant because even though Turkey does not have domestic automaker brands, it is a hub for automotive manufacturing outsourcing (in 2016 1.49 mln. Vehicles were produced in Turkey, which was a steady 10% rise Y-o-Y). Through a Vector Error Correction Model (VECM), Dinç and Gökmen (2019) determined that the error correction coefficient for inflation was negative and statistically significant at the 5% level as per the Granger causality test, thus a negative correlation between inflation and automotive production existed in the long run. The authors' study implications revolved around the need for governmental support for the automotive industry in Turkey during inflationary periods in order to increase output, suppress unemployment, incentivise exports, leading to an inflow of currency to the Turkish currency market, and spilling over to the reinforcement of related industries. A milestone paper by Friedman (1977) argued that when an economy transitions from a low-inflation one to a one characterised by high-inflation, economic balance deteriorates. This transition period, according to Friedman (1977), lasts for at least a couple of years and is etched by profound economic inflation volatility, which causes uncertainty, and eventually negative real effects on the economy. The situation may unfold in three distinct scenarios as the period of volatility is ensued by either an uptake in industrial rates signalling stability, or stagflation, or hyperinflation (Friedman, 1977). Inflation may cause a hike in precautionary savings, which are adverse to investment and GDP volume as the consumer confidence has been derogated.

3.3 Null hypotheses

H1: Automotive stock returns are positively related to their respective market index.

H2: Automotive stock returns are positively related to their respective automotive index.

H3: Automotive stock returns are positively related to essential chassis construction materials such as steel and aluminium.

H4: Automotive stock returns are negatively related to oil prices upon supply shocks, but we may expect a less negative or even positive correlation upon economic expansion.

H5: Automotive stocks returns are positively related to semiconductor stock returns.

H6: Automotive stock returns are negatively related to inflation.

H7: Automotive stock returns are positively related to the Industrial Production index.

H8: Automotive stock returns are positively related to the Broad Effective Exchange Rate.

H9: Automotive stock returns are negatively related to unemployment.

H10: Automotive stock returns are positively related to the Business Confidence Index.

H3 was chiefly driven by previous insights by Bagliano and Morana (2009), Mukherjee and Naka (1995) and Hamilton (2005). H4 was built on El Khoury's (2015) research, H6 was contingent upon findings by Dinç and Gökmen (2019), Fama (1981), and Benaković and Posedel (2010). *H7* pertaining to the Industrial Production Index was underpinned by Benaković and Posedel's (2010) study, whereas *H8* as a preliminary hypothesis was set up to test El Khoury's (2015) study. The latter study was also preferred as a foundation of *H9.* Celebi and Honig, 2019 studied the effects of variables amongst which leading indicators in the German market, and their finding that leading indicators exhibit a positive relationship with stock returns served as an inspiration for *H10.* Even though no articles were documented on *H1* and *H2*, this study place substantial emphasis on them due to renowned theories such as the Sharpe-Lintner Capital Asset Model, where excess asset returns are driven first and foremost by excess market return and some white noise. It can be also generalised that besides typical market indices such as the S&P 500 in the US or the CAC 40 in France, broader automotive indices can also serve as return drivers of automotive stocks. *H5* was based on anecdotal evidence on the impact of semiconductor shortages during the Covid-19 pandemic in 2020-2021, which disrupted some key supply chains in the automotive industry. Therefore, *H5* represents the novel feature of this study relative to historical papers.

4. Data

4.1 Selected variables and data sources

The sample includes 28 US-domiciled manufacturers, 10 German, 10 Chinese, 8 Japanese, 3 South Korean, 2 French, and 2 Italian manufacturers (Table 20). On the basis of previous empirical research and some data considerations during the process of data aggregation the following explanatory variables for the VAR model were selected: **market benchmark indices** (Table 21), **automotive industry indices** (Table 21), **the NYSE Arca Steel Index** (applied to all countries), **Brent crude oil** (applied to all countries), **aluminium 3-month rolling forwards** (applied to all countries), **semiconductor indices** (Table 21), **CPI** (standing for inflation), **Industrial Production index**, **Broad Effective Exchange Rate (BEER)**, **unemployment**, and **Business Confidence Index**. All the data was extracted for the study period – January 2007 – December 2021, with data being downloaded in a monthly format. Explanatory variable data was collected in a monthly frequency from various sources such as the Bloomberg terminal, Investing.com, FactSet, the Federal Bank of St. Louis (FRED), Euromonitor (Passport), and the Organization for Economic Cooperation and Development (OECD). Automotive stock prices were downloaded either from Bloomberg or Investing.com.

4.2 Descriptive statistics

	S&P 500	DAX	Shanghai Composite	Nikkei 225	KOSPI	CAC40	FTSE MIB Italy
Mean	0.03%	0.02%	0.01%	0.01%	0.02%	0.01%	-0.01%
Min	-4.58%	-13.94%	-9.26%	-12.11%	-11.17%	-13.10%	-16.90%
Max	4.27%	12.57%	9.03%	13.23%	11.28%	10.59%	10.22%
Standard deviation	1.15%	1.58%	1.59%	1.50%	1.25%	1.42%	1.59%
Skewness	-0.37	-0.23	-0.65	-0.45	-0.52	-0.28	-0.68
Kurtosis	5.53	10.80	7.90	10.88	12.76	11.18	11.17

Table 1: Descriptive statistics of country benchmark indices

	Dow Jones Automobiles Index	Stoxx 600 Asia Pacific Auto & Parts Index	Stoxx 600 Europe Auto & Parts Index
Mean	1.06%	0.01%	0.02%
Min	-60.76%	-7.73%	-32.06%
Max	67.65%	9.40%	40.03%
Standard deviation	12.58%	1.37%	2.26%
Skewness	0.59	0.09	1.82
Kurtosis	10.54	6.70	65.37

Table 2: Descriptive statistics of automotive benchmark indices

	Brent Crude Oil	Steel Index	Aluminium Forwards
Mean	0.01%	0.01%	0.00%
Min	-8.76%	-8.26%	-4.24%
Max	8.05%	7.70%	4.00%
Standard deviation	2.18%	2.34%	1.28%
Skewness	-0.31	-0.17	0.04
Kurtosis	6.06	4.22	3.75

Table 3: Descriptive statistics of commodity factors

	Dow Jones Semicon. Index	China Semicon. Index	France Semicon. Index	Germany Semicon. Index	Japan Semicon. Index	S&P Italy BMI Semicon. Index
Mean	0.05%	0.06%	0.03%	0.04%	0.06%	0.03%
Min	-6.42%	-13.16%	-17.60%	-50.58%	-11.31%	-17.38%
Max	5.74%	9.49%	13.28%	19.31%	16.47%	13.49%
Standard deviation	1.73%	2.38%	2.60%	3.03%	1.59%	2.51%
Skewness	-0.29	-0.63	-0.31	-1.46	-0.15	-0.37
Kurtosis	4.72	5.68	6.32	30.64	9.43	6.56

Table 4: Descriptive statistics of semiconductors indices

Kurtosis of a return distribution looks at the probability of significant shifts away from existing security prices. For instance, positive excess kurtosis is indicative of heightened risk compared to a Gaussian distribution (leptokurtic distribution).

By default, a normal distribution delivers a kurtosis of three, whereas any number above this benchmark implies a greater acceptance of risk or indicates that asset prices may easily deviate from their mean price for a given timeframe. Leptokurtic distributions have heavier tails which represent a wider variety of extreme outcomes and showcase considerably higher Value at Risk (VaR) scores. The opposite of a leptokurtic distribution, or a distribution characterised by noticeably thinner tails, is a platykurtic distribution

On a basic level, positive skewness of financial asset returns is characterised by frequent small losses and few large gains, whereas negatively skewed returns confer frequent minor gains but few massive losses. Risk-averse investors mostly shun scenarios when negative skewness complemented by excess kurtosis trigger outlier returns, which will most probably take the shape of highly penalising losses.

S&P 500, DAX, and KOSPI were leading in terms of mean returns (Table 1). Lowest average performance by FTSE MIB Italy (the latter was the sole underlying index with negative mean return). Least risky in terms of standard deviation was S&P 500, the SSE Index (the Shanghai Composite Index) and FTSE MIB were the most volatile market indices (Table 1). All indices were negatively skewed – most negatively FTSE MIB Italy, least negatively – DAX. Highest excess kurtosis was recorded by KOSPI, lowest kurtosis by S&P 500. In other words, the S&P 500 represented the best compromise between risk and return.

In terms of auto benchmarks, Dow Jones Automobiles had the highest mean returns, it had the highest standard deviation – dramatic minimum and maximum returns were observed in the period from 2007 to 2021 – minimum of -61%, maximum of 68% (Table 2). All three indices had positive skewness but Stoxx Europe 600 had the highest positive kurtosis on top of the highest positive skew.

In terms of commodities, steel had the highest average return, the lowest was by the aluminium forwards. Steel was also the most volatile, and the least volatile were the aluminium forwards (Table 3). Brent crude oil had the most negative skew, aluminium was the only commodity with positive skew. Brent crude oil had the highest kurtosis, closely followed by steel and aluminium in this order. Aluminium forwards generate lowest profits for investors out of the selected commodity variables, but it is least risky and thinnest tailed (showcases a platykurtic distribution).

Japanese, Chinese, and US semiconductor proxies had the highest average return of semiconductor proxies, the lowest was by the registered by the French proxy. The German and French semiconductor indices were riskiest in terms of the standard deviation of their monthly returns, whilst the Japanese semiconductor index was the least risky (Table 4). All semiconductor proxies had a negative skewness – most negative was Germany, least negative was Japan. The German semiconductor index had a kurtosis of 30.64, which is exceptionally high (Japan ranked second with kurtosis of 9.43), the lowest kurtosis was observed in the case of the Dow Jones Semiconductor Index. The Japanese semiconductor proxy had the highest mean, lowest standard deviation, closest to positive skewness of the reviewed semiconductor indices, and a reasonably high kurtosis.

5. Methodology

5.1 Panel vector autoregression model

The Panel VAR consists of p lags of endogenous variables, predetermined variables, and strictly exogenous variables. Specification tests were also conducted such as the Hansen overidentification test, lag selection criterion, and stability test. The forward orthogonal transformations are utilised to remove the fixed effects. VARs are particularly beneficial in analysing models with more than one endogenous variable.

The main endogenous variables are returns of shares of automotive companies, market benchmark index and automotive industry index. The predetermined variables are steel, Brent crude oil, aluminium forwards, semiconductor index, CPI, Industrial Production Index, BEER, and Business Confidence Index.

$$y_{it} = \mu + \sum_{i}^{p} Ay_{it-p} + Bx_{it} + \alpha_i + \varepsilon_{it}$$

$y_{it} - vector\ of\ endogenous\ variables\ with\ i - id\ (id = country)\ and\ t - time\ period$

$\mu - constant$

$y_{i,i-p} - vector\ of\ mx1\ \ lagged\ dependent\ variables, m = 3\ in\ our\ case$

$x_{i,t} - vector\ of\ kx1\ vector\ of\ predetermined\ variables, k = 8$ in our case

$A - coefficient\ matrix\ of\ mxm\ dimension\ of\ lagged - dependent\ variables$

$B - coefficient\ matrix\ of\ mxk\ dimension\ of\ predetermined\ variebles$

$\alpha_i - fixed\ effect\ term$

$\epsilon_{it} - stohastic\ term$

$p - number\ of\ lags\ of\ the\ endogenous\ variables$

Exogenous variables are never correlated with the error term, whereas with predetermined variables future correlation with the error term are permissible (a less strict criterion). Returns (dependent variable) cannot affect the explanatory variables such as CPI and BEER in the current period but can potentially do so in a future period, thus we categorised the explanatory variables as predetermined. The endogenous variables are included with the lag generating lowest AIC and BIC criteria (in our case lag of one) and the endogenous variables can interact between one another. We remove the fixed effect in cases when we have omitted data with the forward orthogonal deviation.

We assumed all macroeconomic variables, market benchmark indices, and automotive indices are predetermined since the criteria for exogenous variables (to be uncorrelated with the error term) is too strict to hold true across such an extensive dataset. Through an Augmented Dickey Fuller test all X_{it} variables turned out to be stationary except for unemployment, which made sense given the monthly frequency of observations and the extended sample period – thus, it is likely mean-reversion was observed. Since our Panel VAR in levels should contain solely I(0) orders, we excluded the unemployment variable. If the variables are of a mixed order of integration, an ARDL model is usually executed (as in Sections 5.2, 6.2 and 6.3).
A fixed effect was incorporated to reflect the error terms as correlated within entities (or as having divergent means across each cross-sectional unit (CSU)) (Brooks, 2019). In plain English, a fixed effect can be construed as introducing a new intercept term for each CSU. The benefit of the panel data VAR approach is there are no independent variables in the purest sense, as impulse response functions can be drawn between all endogenous variables irrespective of whether they act as regressors or regressands. The attained coefficients via Panel VAR exemplify what the coefficients would like for an ID=country on average – in other words, how the coefficients would look like in an average country. In contrast to the forthcoming ARDL models, there is no "country" differentiating factor in the model.
To complete the VAR model, the libraries "panelvar" (Sigmund & Ferstl, 2021), "tseries" (Trapletti & Hornik, 2022), and "mice" (Buuren & Groothuis-Oudshoorn, 2011) in the RStudio software were utilised. The "mice" library was used to impute any outlier "NaN" values among stock prices and/or macroeconomic variables. Moreover, we derived the appropriate lag of the VAR model as per multivariate information criteria such as Bayesian Information Criterion (BIC), the Akaike Information Criterion (AIC), and the Hannan Quinn Information Criterion (HQ) (Andrews & Lu, 2001). The actual model was built through the "pvargmm" functionality. Impulse response functions were constructed through the "oirf" and "girf" functions, whereas a bootstrap function will plot the confidence intervals against the Generalised impulse response function (girf). A diagnostic stability test was run to assure that all eigenvalues/inverse unit roots lie within the inverse unit root – if they do, this will signal stability of the system ("stability" function in RStudio).

To determine the multi-variate relationship between the multiple panel-time series, we have employed panel VAR model analysis. It succeeds in tracing the dynamic relationship between all series in the panel framework and generates the impulse response functions which account for the shocks in the system and the fixed effect. First, we construct a panel VAR model to capture the dynamic relationship on a country level of automotive companies' returns and macroeconomic factors. The aim is to extract the heterogeneity stemming from distinct countries and attain macroeconomic coefficients applicable to automotive returns on a global scale.

The system GMM ("Generalized Methods of Moments") approach underpinning panel VAR is suitable for panels characterised by "small T, large N" (few time periods and a large number of individuals) and independent variables that are not necessarily exogeneous – the latter are correlated with the past and potentially current realisations of the error term (Roodman, 2009). Roodman (2009) also assumed that first differences of instrument variables are uncorrelated with the fixed effect, thereby enabling the introduction of additional instruments, which enhance efficiency substantially. According to some of the principal papers related to GMM, Arellano & Bover (1995) and Blundell and Bond (1998) system GMM variables serve to eliminate the endogeneity problem (the explanatory variable being correlated with the error term). The model instruments are transformed to be uncorrelated (exogenous) with the fixed effect. System GMM is based on two equations – the original equation and a transformed equation. Instead of normal demeaning, system GMM utilises orthogonal deviations. Forward orthogonal deviations mean that instead of subtracting the previous observation from the current one, the average of all available future observations for a given variable are subtracted from the contemporaneous observation (Arellano & Bover, 1995).

$$\Delta^* y_{it} = \sum_{i}^{p} A_p \, \Delta^* y_{i,i-p} + B\Delta^* x_{i,t} + \Delta\varepsilon_{i,t}$$

Δ^* refers to the forward orthogonal transformation, which exists for t={p+1,…..,T-1}

$y_{i,t+1}^{\perp}=c_{i,t}(y_{i,t} - \frac{1}{T_{i,t}} \sum_{s>t} y_{i,s})$, where $c_{i.t} = \sqrt{\frac{T_{i,t}}{T_{i,t}+1}}$

The two equations in the system GMM include the "levels" model – the model to be estimated, and the second model is the difference model:

$$y_{it} = \mu + \beta_1 x_{it-1} + \beta_2 x_{it-1} + a_i + \varepsilon_{it}$$

$$y_{it} - y_{it-1} = \beta_o + \beta_1(x_{it-1} - x_{it-2}) + \beta_2(y_{it-1} - y_{it-2}) + (\varepsilon_{it} - \varepsilon_{it-1})$$

It should be noted that the fixed effect "a" is correlated with every "y" – in other words, the "levels" equation suffers from an endogeneity pitfall (Arellano & Bover, 1995). $y_{it-1} - y_{it-2}$ and any earlier differences of "y" successfully eradicate this issue. We obtain our PVAR coefficients after executing the Windmeijer correction to eradicate the bias in small samples of the asymptotic variance estimator (Ferstl & Sigmund, 2021).

5.2 Autoregressive Distributed Lag Model (ARDL)

A prerequisite condition for VAR and OLS to guarantee unbiased estimates is that all variables must be stationary. In contrast, an ARDL model encompasses both I(0) and I(1) variables, whereas if a cointegration is identified in the system, an Error Correction Model (ECM) test or a causality test should be launched (Figure 12). The usage of non-stationary variables in an Ordinary Least Squares regression (OLS) may lead to spurious regressions – regressions where a significant relationship is fabricated between two variables when no actual relationship exists. Engle and Granger (1987) set up a cointegration test to analyse the equilibrium relationship in the long run between non-stationary variables.

The cointegration between Y_t and X_t materialises in the following manner:

$$\varepsilon_t = Y_t - \mu - \beta_1 X_t$$

The two-step Error Correction Models (ECT) coined by Engle and Granger (1987) for variables Y_t and X_t are depicted in the following way:

$$\Delta Y_t = \mu_y + \alpha_y \varepsilon_{t-1} + \sum_{h=1}^{l} \alpha_{1h} \Delta Y_{t-h} + + \sum_{h=1}^{l} \beta_{1h} \Delta Y_{t-h} + u_{yt}$$

$$\Delta X_t = \mu_x + \alpha_x \varepsilon_{t-1} + \sum_{h=1}^{l} \alpha_{2h} \Delta Y_{t-h} + + \sum_{h=1}^{l} \beta_{2h} \Delta Y_{t-h} + u_{xt}$$

Unlike the Johansen cointegration test, the autoregressive distributed lag model (ARDL) is an OLS-based model that can accommodate both non-stationary series, as well as series with a mixed order of integration. An Error Correction model (ECM) is an ARDL undergoing a simple linear transformation. The ECM model serves to combine the short-term dynamics with the long-term equilibrium – hence, long-term information is not lost (Shrestha & Bhatta, 2018). Furthermore, the issue of spurious regressions containing non-stationary data is also circumvented.

The ARDL model is illustrated in the following manner (Shrestha & Bhatta, 2018) They utilised x_t and z_t as explanatory variables:

$$y_t = \alpha + \beta x_t + \delta z_t + \varepsilon_t$$

The error correction model specifically applicable to an ARDL model can be referred to as a single error correction model (unlike the two-stage ECM devised by Engle and Granger) and it is the model that RStudio implements through its "uecm" and "recm" functionalities (Shrestha & Bhatta, 2018):

$$\Delta y_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \sum_{i=1}^{p} \varepsilon_i \Delta z_{t-i} + \lambda_1 y_{t-1} + \lambda_2 x_{t-1} + \lambda_3 z_{t-1} + u_t$$

The first part of the regression comprising the coefficients β, δ. and ε is illustrative of the short-term dynamics of the model. The second part with λs encapsulate the long-term relationships. The null hypothesis of $\lambda_1+\lambda_2+\lambda_3=0$ indicates the non-existence of a long-run relationship.

The bound testing by Pesaran et al. (2001) is a relatively more recent alternative to Johansen's approach – this technique can be applied regardless of whether the variables are I(0) or I(1). It is constructed based on Wald/F-statistics and follows a non-standard distribution (Thaker, 2016). The author further claimed that if the asymptotic F-statistics stands above the I(1) critical values put forward by Pesaran et al (2001) it is an evidence a long-run relationship exists between the variables. If the F-statistics falls below the lower bound I(0), no cointegration is identified. If the F-statistics falls between the I(1) and I(0) critical values, the test results are inconclusive.

If the ARDL Bound test successfully identifies a cointegrating relationship, it can be concluded that the correct model for an explained variable "Y" should encompass both the lagged changes of X and the lagged disequilibrium (Z_{t-1}). A time series is integrated if either the influence of its history is never dampened or if itself is a function of other integrated processes. As pinpointed by Engle and Granger (1987), a linear combination of two integrated variables will produce a third (also integrated) series. However, another linear combination Z_t may exist that is stationary. Z_t can be found by regressing Y_t on X_t. Z_t can be interpreted as equilibrium errors and its stationarity indicates Y_t and X_t sustain an equilibrium relationship induced by a "common stochastic trend" (Durr, 1992). In this article, the short-term ARDL equations contain the "error correction term" (ect) which signals how far away the short-term coefficients are for the equilibrium/long-run coefficients generated by the single Error Correction Model. A positive “Z” (the measure for disequilibrium, “ect”) is indicative of a too high “Y” (dependent variable” (or alternatively a too low independent variable “X”) which means “Y” should adjust downwards. A negative value means that “Y” has to adjust upwards.

An autoregressive distributed-lags model (ARDL) shows the short and long-term relationship (if such exists) between the independent and dependent time series. As it incorporates variables with different order of integration – I(0) and I(1), it suggests that a cointegration might be in place between the variables of interest. Before building the model, an Akaike-information criteria (AIC) has been used to determine the optimal lag length. The short- and long-term models implemented for each country were the models with lowest Akaike Information Criterion (AIC). The sub-parameter “top_orders” of the auto_ardl function from the ARDL package of RStudio generated for each country the 20 model variations with the lowest AIC criterion. We have picked the model with lowest AIC unless it fails to reject the null hypothesis of the ARDL Bound test that no cointegration exists between the variables in the system. If that was the case, the five subsequent in terms of lowest AIC information criterion model were tested, and if all of them were unable to reject the null of the ARDL Bound Test, we concluded that no long-run coefficients exist for our scrutinised macroeconomic variables (as it was the case for Germany and Japan). The ARDL Bound test was conducted for the purposes of identifying cointegration between returns and the explanatory variables via the “bounds_f_test” function in RStudio (this functionality was preferred to “ardlBound” function due to more rapid processing times of the former). The existence of cointegration proves the causation of independent factors on the dependent variable (automotive returns), Lastly, the error correction term (ECT) or the speed of adjustment is introduced, extracted from the restricted error correction model of the ARDL model, and is added to the short-run ARDL model. The long-run ARDL coefficients were extracted through the restricted error correction model at case 3 (model with unrestricted intercept and no trend).

6. Empirical results

6.1 Panel VAR results

The estimated regression for the panel VAR is the following:

$$\begin{aligned} Automotive\ returns_{it} &= \mu + Automotive\ returns_{it-1} + Market\ index_{it-1} \\ &+ Automotive\ Index_{it-1} + Steelx_{it} + Brent\ crude\ oil_{it} + Aluminium_{it} \\ &+ Semiconductors_{it} + CPI_{it} + Industrial\ production_{it} + BEER_{it} \\ &+ Business\ Confidence_{it} + \alpha_i + \varepsilon_{it} \end{aligned}$$

The endogenous variables in the Panel VAR were lagged by one period as any greater lags resulted in higher BIC, AIC, and HQIC information criteria. The standard stability test of the performed Panel VAR confirmed stability and absence of unit root in the unit cycle (Table 7 and Figure 2).

The coefficients of greatest magnitude for the review period January 2007 – December 2021 were BEER (0.1021), CPI (-0.0499), and the Business Confidence Index (0.0310) (Table 5). Hence, these three most prominent coefficients (significant at the 5% confidence interval) accepted respectively *H8*, *H6*, and *H10* of the null hypotheses. For instance, a 1% increase in BEER should induce a 0.10% hike in automotive returns in the current period on average for all countries. The remaining significant coefficients pertaining to returns lagged at one period, the market benchmark index proxy lagged at one period, the automotive index proxy lagged at one period, steel, and semiconductors exhibited a positive albeit weak effect on automotive company returns at time "t" on average for all countries in the sample (63 listed companies in 7 countries). The only coefficient apart from CPI that recorded a negative correlation with automotive returns was Brent crude oil (-0.0189). No robust coefficients could be estimated for aluminium forwards and the Industrial production index for our selected sample even though aluminium had a positive relationship with the returns of the other two endogenous variables – the market and automotive benchmark indices. To sum up, all coefficients, except the Industry Production index and aluminium, were statistically significant and affected slightly the returns of automotive stocks. We could accept all null hypothesis except for *H3* (the part about the influence of aluminium), *H7* (the coefficient of Industrial production in Panel VAR was insignificant), and *H9*. The latter could not be confirmed because the unemployment on average on a global scale in the Panel VAR was found to be non-stationary by the Augmented Dickey-Fuller test, and therefore could not be incorporated in this part of the analysis. The idiosyncrasy of the automotive sector compared to a market benchmark could be observed in the reversed coefficients for steel and semiconductors. Whereas steel and semiconductors were negatively related to the broader benchmark index, the returns of steel and semiconductors and moved in accordance with car stocks, hence exhibiting a positive coefficient, as expected by our null hypothesis.

The final part of the empirical model framework includes the Generalised Impulse Response Functions of the endogenous variables. Due to the computationally intensive nature of the simulations, solely 10 random samples were drawn from the population.

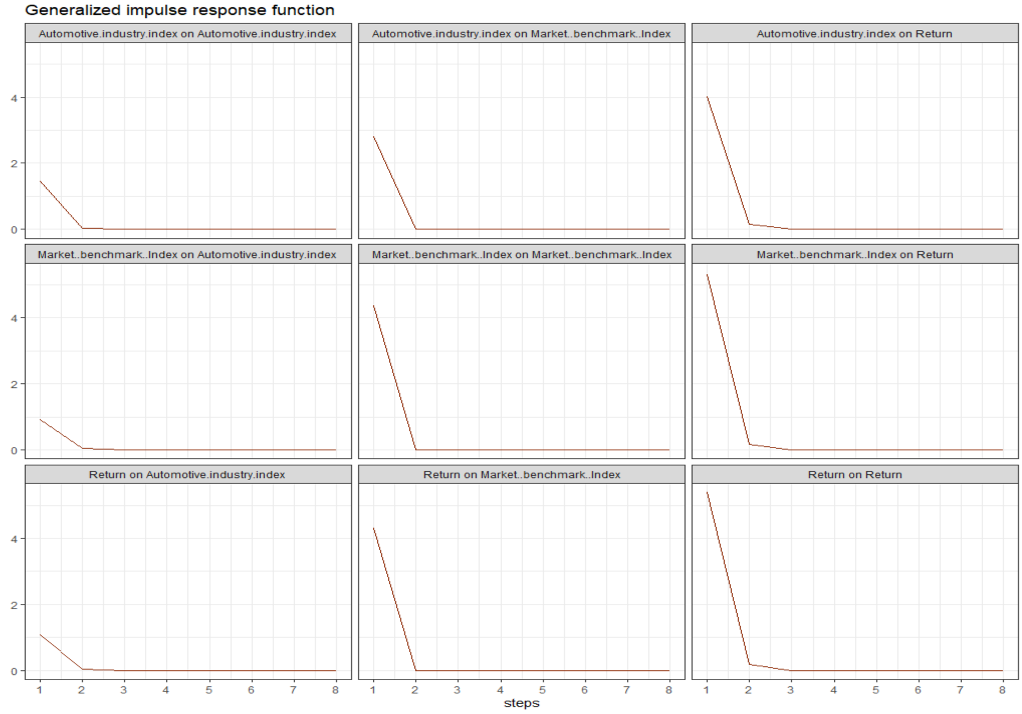

Figure 1: impulse response functions among the endogenous variables in the system GMM

We are chiefly interested in the third column of Figure 1– the impact of the two other endogenous variables (market index and automotive index) on the automotive stock returns. The shock occurs at time “t=0”. A one unit increase in the standard deviation of an automotive industry index increased the risk of returns of our selected car companies by four standard deviations (uppermost right rectangle in Figure 1). The effect of the shock fades away after two periods (two months in our sample as the data frequency was monthly). Any shock originating from the market benchmark index also had a transitory effect of two months, but it was larger in magnitude – a one unit increase in the standard deviation of the market benchmark index triggered a nearly 6% rise in the standard deviation of automotive companies’ returns (second row and third column of Figure 1). The last picture follows the path between return's causal relationship with itself. The shock-response endures for two periods and is again positive around six standard deviations. Short-lived effects upon shocks disrupting the system are not untypical – Nishi's (2011) VAR analysis for the growth regime and demand formations of the Japanese economy also showcased transient effects of the shocks.

6.2 Short-term coefficient dynamics – ARDL model

The generalised ARDL (p, q) model, with p equal to the number of lags of the dependent variable, and q set as the number of lags of the independent variables is illustrated as:

$$Y_t = \mu + \sum_{i=1}^{p} \delta_i Y_{t-i} + \sum_{i=0}^{q} \beta X_{t-i} + \varepsilon_t$$

The lag orders in RStudio were respectively ordered as {Return, Market Index, Automotive Index, Brent Crude Oil, Steel, Aluminium, Semiconductor Index, CPI, Industrial Production, Unemployment, BEER, Business Confidence}. An additional individual term is extracted from each country's restricted error correction model if the ARDL Bound test has identified a cointegrating/long-run relationship between the explained variable and its regressors. Respectively, the regressions for the different markets materialise as:

$$Auto\ returns_t = \mu + \sum_{i=1}^{10} \delta_1 Auto\ returns_{t-i} + \sum_{i=0}^{10} \beta_1 Market\ Index_{t-i} + \sum_{i=0}^{6} \beta_2 Automotive\ Index_{t-i} + \sum_{i=0}^{10} \beta_3\ Brent\ crude\ oil_{t-i} + \sum_{i=0}^{11} \beta_4 Steel_{t-i} + \sum_{i=0}^{12} \beta_5 Aluminium_{t-i} + \sum_{i=0}^{12} \beta_6 Semiconductors_{t-i} + \sum_{i=0}^{10} \beta_7 CPI_{t-i} + \sum_{i=0}^{12} \beta_8 Industrial\ Production_{t-i} + \sum_{i=0}^{10} \beta_9 Unemployment_{t-i} + \sum_{i=0}^{12} \beta_{10} BEER_{t-i} + \sum_{i=0}^{9} \beta_{11} Business\ Confidence_{t-i} + \varepsilon_t + ECT_{italy}$$

Italy – short-term ARDL model with maximum number of lags – {10,10,6,10,11,12,12,10,12,10,12,9} – prior to estimation

$$Auto\ returns_t = \mu + \sum_{i=1}^{12} \delta_1 Auto\ returns_{t-i} + \sum_{i=0}^{12} \beta_1 Market\ Index_{t-i} + \sum_{i=0}^{12} \beta_2 Automotive\ Index_{t-i} + \sum_{i=0}^{12} \beta_3\ Brent\ crude\ oil_{t-i} + \sum_{i=0}^{12} \beta_4 Steel_{t-i} + \sum_{i=0}^{12} \beta_5 Aluminium_{t-i} + \sum_{i=0}^{12} \beta_6 Semiconductors_{t-i} + \sum_{i=0}^{12} \beta_7 CPI_{t-i} + \sum_{i=0}^{12} \beta_8 Industrial\ Production_{t-i} + \sum_{i=0}^{12} \beta_9 Unemployment_{t-i} + \sum_{i=0}^{12} \beta_{10} BEER_{t-i} + \sum_{i=0}^{12} \beta_{11} Business\ Confidence_{t-i} + \varepsilon_t + ECT_{usa}$$

USA – short-term ARDL model with maximum number of lags – {12,12,12,12,12,12,12,12,12,12,12,12} – prior to estimation

$Auto\ returns_t = \mu + \sum_{i=1}^{12} \delta_1 Auto\ returns_{t-i} + \sum_{i=0}^{12} \beta_1 Market\ Index_{t-i} + \sum_{i=0}^{12} \beta_2 Automotive\ Index_{t-i} + \sum_{i=0}^{12} \beta_3\ Brent\ crude\ oil_{t-i} + \sum_{i=0}^{12} \beta_4 Steel_{t-i} + \sum_{i=0}^{12} \beta_5 Aluminium_{t-i} + \sum_{i=0}^{12} \beta_6 Semiconductors_{t-i} + \sum_{i=0}^{12} \beta_7 CPI_{t-i} + \sum_{i=0}^{12} \beta_8 Industrial\ Production_{t-i} + \sum_{i=0}^{12} \beta_9 Unemployment_{t-i} + \sum_{i=0}^{12} \beta_{10} BEER_{t-i} + \sum_{i=0}^{12} \beta_{11} Business\ Confidence_{t-i} + \varepsilon_t + ECT_{germany}$

Germany – short-term ARDL model with maximum number of lags – {12,12,12,12,12,12,12,12,12,12,12,12} – prior to estimation

$Auto\ returns_t = \mu + \sum_{i=1}^{10} \delta_1 Auto\ returns_{t-i} + \sum_{i=0}^{12} \beta_1 Market\ Index_{t-i} + \sum_{i=0}^{10} \beta_2 Automotive\ Index_{t-i} + \sum_{i=0}^{12} \beta_3\ Brent\ crude\ oil_{t-i} + \sum_{i=0}^{12} \beta_4 Steel_{t-i} + \sum_{i=0}^{12} \beta_5 Aluminium_{t-i} + \sum_{i=0}^{7} \beta_6 Semiconductors_{t-i} + \sum_{i=0}^{12} \beta_7 CPI_{t-i} + \sum_{i=0}^{12} \beta_8 Industrial\ Production_{t-i} + \sum_{i=0}^{12} \beta_9 Unemployment_{t-i} + \sum_{i=0}^{8} \beta_{10} BEER_{t-i} + \sum_{i=0}^{10} \beta_{11} Business\ Confidence_{t-i} + \varepsilon_t + ECT_{china}$

China – short-term ARDL model with maximum number of lags – {10,12,10,12,12,12,7,12,12,12,8,10} – prior to estimation

$Auto\ returns_t = \mu + \sum_{i=1}^{12} \delta_1 Auto\ returns_{t-i} + \sum_{i=0}^{12} \beta_1 Market\ Index_{t-i} + \sum_{i=0}^{12} \beta_2 Automotive\ Index_{t-i} + \sum_{i=0}^{12} \beta_3\ Brent\ crude\ oil_{t-i} + \sum_{i=0}^{12} \beta_4 Steel_{t-i} + \sum_{i=0}^{12} \beta_5 Aluminium_{t-i} + \sum_{i=0}^{12} \beta_6 Semiconductors_{t-i} + \sum_{i=0}^{12} \beta_7 CPI_{t-i} + \sum_{i=0}^{12} \beta_8 Industrial\ Production_{t-i} + \sum_{i=0}^{12} \beta_9 Unemployment_{t-i} + \sum_{i=0}^{12} \beta_{10} BEER_{t-i} + \sum_{i=0}^{12} \beta_{11} Business\ Confidence_{t-i} + \varepsilon_t + ECT_{japan}$

Japan – short-term ARDL model with maximum number of lags – {12,12,12,12,12,12,12,12,12,12,12,12} – prior to estimation

$Auto\ returns_t = \mu + \sum_{i=1}^{11} \delta_1 Auto\ returns_{t-i} + \sum_{i=0}^{12} \beta_1 Market\ Index_{t-i} + \sum_{i=0}^{12} \beta_2 Automotive\ Index_{t-i} + \sum_{i=0}^{12} \beta_3\ Brent\ crude\ oil_{t-i} + \sum_{i=0}^{12} \beta_4 Steel_{t-i} + \sum_{i=0}^{12} \beta_5 Aluminium_{t-i} + \sum_{i=0}^{12} \beta_6 Semiconductors_{t-i} + \sum_{i=0}^{12} \beta_7 CPI_{t-i} + \sum_{i=0}^{12} \beta_8 Industrial\ Production_{t-i} + \sum_{i=0}^{12} \beta_9 Unemployment_{t-i} + \sum_{i=0}^{12} \beta_{10} BEER_{t-i} + \sum_{i=0}^{12} \beta_{11} Business\ Confidence_{t-i} + \varepsilon_t + ECT_{korea}$

South Korea – short-term ARDL model with maximum number of lags – {11,12,12,12,12,12,12,12,12,12,12,12} – prior to estimation

$Auto\ returns_t = \mu + \sum_{i=1}^{10} \delta_1 Auto\ returns_{t-i} + \sum_{i=0}^{12} \beta_1 Market\ Index_{t-i} + \sum_{i=0}^{11} \beta_2 Automotive\ Index_{t-i} + \sum_{i=0}^{12} \beta_3\ Brent\ crude\ oil_{t-i} + \sum_{i=0}^{12} \beta_4 Steel_{t-i} + \sum_{i=0}^{11} \beta_5 Aluminium_{t-i} + \sum_{i=0}^{12} \beta_6 Semiconductors_{t-i} + \sum_{i=0}^{11} \beta_7 CPI_{t-i} + \sum_{i=0}^{12} \beta_8 Industrial\ Production_{t-i} + \sum_{i=0}^{12} \beta_9 Unemployment_{t-i} + \sum_{i=0}^{12} \beta_{10} BEER_{t-i} + \sum_{i=0}^{11} \beta_{11} Business\ Confidence_{t-i} + \varepsilon_t + ECT_{france}$

France – short-term ARDL model with maximum number of lags – {10,12,11,12,12,11,12,11,12,12,12,11} – prior to estimation

The necessary pre-requisite before launching any ARDL model is to verify that all variables are of mixed order of integration – either I(0) or I(1). With the null hypothesis of presence of a unit root for the ADF test we found that for the Italian sub-sample CPI, unemployment, and BEER were non-stationary (rejected the null hypothesis), in the German sub-sample – CPI, Industrial Production, unemployment, and BEER were non-stationary, in China – CPI, unemployment, and BEER, in Japan – CPI, Industrial Production, unemployment, Business confidence (stationary at a 90% significance level, non-stationary at 95% significance level), and BEER, in South Korea – CPI, Industrial Production, and unemployment, in France – CPI, unemployment, and BEER, and in the US – CPI, Industrial Production, Unemployment, and BEER. Thus, for all countries we observed a mixed order of integration for each country after running the diagnostic stationarity test, hence we could proceed to running the ARDL model.

The short-term coefficient dynamics empirical results sub-section applies to the ARDL coefficients embedded in Appendix B. The market benchmark index as an underlying factor of automotive stock returns was observed in all dissected markets estimated at a minimum of a 90% confidence interval. The magnitude of its effect was most striking in the US automotive industry, whereas China and France showcased more subdued market index coefficients of well below 0.8. Mixed evidence was aggregated with respect to the sign of the market benchmark coefficient – solely in Germany and France the coefficients were unanimously positive. For instance, in Germany, a 1% increase in DAX instantaneously affects German auto manufacturers' returns in the same period at a rate of 1.6% - thus, market index gains affect automotive stocks disproportionately positively. The beneficial implications of DAX upsurges remain positive albeit they abate somewhat – the other significant coefficient for the market benchmark index factor in Germany equalled 1.16 at a lag of 8 – thus, whenever DAX rose by 1%, 8 months later German automotive producers saw their shares leaping by 1.16%. In Italy the influence of the FTSE MIB Index on the shares of Ferrari and Pininfarina was mostly positive (with no lag, at 1st, 3rd, 5th, and 10th lag) with the notable aberration of the 7th lag when the market proxy coefficient was negative. Japan had a single market index coefficient being significant (precisely speaking, at the 5% level) and it was of a moderate magnitude (-0.68). The curious case of the US emerges due to the sizeable coefficients observed with regards to the S&P 500 (i.e. the market proxy). To put it in a nutshell, four months after a 1% gain in the S&P 500, US-domiciled automotive returns fall off a cliff at a rate of 3.89% downwards. At more distant short-term horizons though, the US market index strengthens automotive returns – a 1% increase in the S&P 500 translates into 1.81% and 2.95% hikes in car shares, correspondingly 8 and 11 months after the aforementioned market gain. In other words, automotive producers are more likely to benefit from S&P 500 shedding value in more recent periods, whilst on the other hand, more distant bullish trends in the S&P 500 are prone to boost automotive stock returns.

China and Japan regional samples confirm the null hypothesis that a broad automotive index returns are positively correlated with automotive stock returns, amongst which Japan showcased a stronger positive correlation – a 1% hike in the Stoxx 600 Asia Pacific Automobiles and Parts Index in period “t” materialise into a 0.93% rise in the individual car stock returns. In contrast, a fall of 1% 12 months ago in the Stoxx 600 Automobiles & Parts index pushes German car shares by 0.65% upwards. In the US and France, more recent lags of the performance of the respective automotive benchmark affected auto stock returns positively, whereas more distant temporally lags exhibited a negative correlation with individual stock returns. In Italy the trends were entirely reversed – more recent lags were characterised by a negative correlation, ensued by a positive correlation for more distant lags. No discernible pattern could be concluded from the South Korean sample but the greatest in magnitude automotive proxy coefficient was tracked in this market – namely, a negative coefficient of -1.65 registered in the 7th lag prior to the incumbent period.

The significant short-term coefficients pertaining to Brent crude oil were quite illuminating since only the South Korean sample provided mixed evidence about the sign of the coefficient at distinct lags. Chinese, Japanese, and French auto manufacturers do not reject the null hypothesis that automotive stock returns are inversely related to oil prices. On the contrary, Italy, US, and Germany reject the null hypothesis and unravel a positive correlation between oil returns and car share returns. The heftiest coefficients in absolute terms were monitored in the US sample, where a 1% increase in Brent crude oil prices at four lags engendered a 1.86% upward movement in US automotive shares. Brent Crude Oil is a robust factor for the prediction of automotive stock returns in the US for all lags from 4th to 8th inclusive – in other words, encompassing the timeframe from “t-4” to “t-8” from the perspective of the current period “t”. The influence of oil was reasonably delayed in both Italy and Germany – the 8th and 11th lag correspondingly were significant for these two markets, and the Italian automotive industry was nearly twice more influenced by Brent crude oil than the counterpart German industry. Japanese auto manufacturers were only marginally negatively affected by upsurges in Brent crude oil, yet Chinese and French carmakers exhibited a negative correlation with respect to Brent crude oil on multiple lags (the coefficients pertaining to China ranged from -0.18 to -0.86, whilst the ones for the French market were in the scope from -0.40 to -0.80).

In a similar vein to the coefficient sign patterns related to crude oil, China and Japan once again shared an identical in direction effect – this time with respect to steel, whereas Italy experienced a reversed effect, as it was the case with oil as well. In concrete terms, Chinese and Japanese automakers' share returns were positively correlated with steel returns at all 12 lags in the short run. In Italy, the negative correlation of steel with the shares of Italian producers – Ferrari and Pininfarina, strengthened in size the further away in time an incremental 1% change in the price of steel occurred. Precisely speaking, the size of the negative coefficient of steel in Italy dwindled in negative territory from -0.56 at lag 8 to -0.91 at lag 10. Hence, what is clearly evident is that the implications of steel price fluctuations lose momentum the closer they are to the present day, at least as the case study of Italy demonstrated. The other raw material utilised as a construction component in the automotive chassis – aluminium, similarly, provided a differentiated picture by affecting markets differently. No significant coefficient was identified for German automakers when it comes to aluminium. Conversely, aluminium had a crucial role to play in shaping US stock returns despite the lack of clear directionality of its coefficient. Shocks to the aluminium forwards market affected car returns negatively the further away they are in the past, whereas aluminium forward returns at one lag are positively correlated with the performance of automotive shares in the US. Therefore, we may expect that as aluminium gets pricier by 1%, in a period of one month US auto manufacturers will avail of a 1.31% hike in their share prices. However, as time progresses, the aluminium price gain of 1% 8 months ago will result in a 1.1% drop in automotive stock returns due to the negative coefficient sign of aluminium forwards at the 8th lag for the US market. Counter-intuitively to our null hypothesis of an inverse relationship between auto share returns and aluminium prices, manufactures in China (coefficients ranging from 0.33 to 0.65) and Japan (coefficient determined to be 0.45) had their stock momentum positively entwined with the movements of aluminium forwards to a moderate extent. Solely Japan fits into the argumentation behind our null hypothesis for aluminium – the negative coefficient of Japan with respect to aluminium stood at -0.4.

China was the market which confirmed our preliminary hypothesis that the welfare of semiconductor manufacturers is positively related to the robustness of car brands albeit some of the significant coefficients tied to the Chinese market were of minuscule magnitude. Initially, semiconductors stock rising by 1% exert a noticeably infinitesimal influence on car stock returns at a rate of 0.07% but the more distant a semiconductor shock to the market is, the more evident its impact is - thus, up to a lag of 5, the coefficient for a semiconductor proxy rose to 0.45 before subsequently falling to 0.22 at a lag of 7. Our sample of Japanese companies seems surprisingly immune to semiconductor turbulences since no significant coefficient was generated. In spite of the mixed nature of semiconductor effects, the US sample delivered greatest coefficients in absolute terms. The strongest US semiconductors coefficient was 2.36 accepted at the 99.9% confidence interval at a lag of 4. The US semiconductors coefficient declined in size at the 6th lag (1.21), whilst developments in the semiconductor sectors 10 months ago/10 lags ago impacted US producers least convincingly in size but negatively in sign (the coefficient at the 10th lag stood at -1.02). Hence, we can conclude that generally the US automotive industry affirms the common sense to be positively related to the stability of semiconductor suppliers up to the 10th lag.

In the sample review period covering the timeframe 2007 – 2021, inflation did not seem to be one of the primary triggers for automotive companies' performance. To begin with, Germany and Japan have no significant coefficients pertaining to CPI at any lag. The remaining countries had several significant coefficients, yet the greatest of them, which was recorded in Italy, did not exceed 0.45 in absolute terms. The Italian CPI coefficient shifted its sign from positive to negative as more time elapsed. Hikes in the CPI 5 and 9 months prior to the current period in Italy affected Italian producers' stocks favourably, whilst CPI accelerating by 1% 10 months ago resulted in a decline of 0.44% in the returns of Italian automotive producers in the current period. The US sub-sample bolstered previous empirical findings and displayed negative coefficients in the range 0.26-0.30. In an inflationary environment, rises in the CPI are most likely to afflict US producers in the period of the shock and 5 months post-shock. However, if there was a factor with less influential coefficients than inflation, industrial production could qualify as such. In the short term, US and German automakers are unperturbed by industrial production fluctuations. The remainder of the markets had significant, yet very slight coefficients – in the case of China, Korea, and France of mixed signs as opposed to Japan and Italy where the coefficients were negative. Hence, in the short run at least, we cannot support our previously stipulated null hypothesis of positive correlation between automotive stock returns and the industrial production index. All markets had significant short-term coefficients related to BEER, however, they were of negligible size despite being greater than the weights attached to the industrial production index. All countries apart from Germany provided mixed evidence about the sign of the BEER coefficient, whilst the German short-run ARDL displayed a negative albeit very slight relationship between industrial production and German carmakers.

The German sub-sample registered a finding that is further deliberated on in the discussions section – a 1% increase in unemployment four periods preceding the current period bolstered car stock returns by 0.72%. The Chinese unemployment coefficient is monumental in magnitude indicating unemployment is quintessential to the performance of Chinese manufacturers. In the shortest-term horizons in the current period "t" and the previous period "t-1" a 1% rise in unemployment favoured auto returns positively at rates of respectively 1.80% and 12.17%. Conversely, automotive producers in China struggle when accelerating unemployment is observed at lags of 2 and 11 months – their coefficients were respectively found to be -9.24 and -10.2. If we consider the Business Confidence Index, the US is congruent with the null hypothesis of the positive correlation between car shares performance and the Business Confidence Index indicating that perhaps previous research covering this factor has been US-centric. In the case of the US, the effect of the Business Confidence Index on US shares emerges reasonably protractedly 12 months after an alteration in the index. A 1% increase in the Business Confidence Index in the US spurred a 0.41% upside movement in shares originating from the automotive industry. Highest business confidence coefficients were outlined in Italy and South Korea. In Italy, coefficients continuously shifted in sign from the 5th to the 9th lag, whereby the most substantial coefficients were registered in the case of the 6th (positive: 2.87) and 7th lag (negative: -2.44). In South Korea, the strongest Business Confidence parameters were evinced at the 1st (negative: -2.46) and 2nd lag (positive: 2.96).

A commonality across all macroeconomic factors was that Japan was far more scarcely affected than other markets by macroeconomic factors and the factors that actually affect Japanese carmakers' stock returns exude their impact at far less lags than other countries. Also, the FactSet customised index of Japanese semiconductor manufacturers, CPI, Unemployment, and Business Confidence did not project a single significant coefficient, and thus cannot be regarded as robust predictors of automotive stock performance in the short run.

6.3 Lond-term coefficient dynamics – ARDL model

The long-term coefficient dynamics empirical results sub-section applies to the ARDL coefficients embedded in Appendix C. The long-term equation was a lot more simplistic than the short-term equation as it solely constituted the long-term coefficients (LTCs) of the explanatory variables and unlike the short-term regression the lags of the explained variable – automotive returns – do not impact its long-term trend. The long-run coefficients of a country "i" were estimated through the equation:

$$Auto\ return_i = \mu + \lambda_1 Market\ Index_{LTC} + \lambda_2 Automotive\ Index_{LTC} + \lambda_3 Brent\ crude\ oil_{LTC} + \lambda_4 Steel_{LTC} + \lambda_5 Aluminium_{LTC} + \lambda_6 Semiconductors_{LTC} + \lambda_7 CPI_{LTC} + \lambda_8 Industrial\ Production_{LTC} + \lambda_9 Unemployment_{LTC} + \lambda_{10} BEER_{LTC} + \lambda_{11} Business\ Confidence_{LTC}$$

For this part of the analysis, Germany and Japan were excluded as the null hypothesis of no cointegration in the ARDL bound test could not be rejected, hence no long-run coefficients could be formulated. South Korea will also be largely omitted due to the scarcity of significant result besides its significant BEER coefficient. Overall, the market index had a positive influence for those markets where it was found to be significant. Particularly, in Italy the FTSE MIB Index had a spectacular for a long-run coefficient magnitude 1.97. China registered a positive coefficient for its market proxy of 0.2, the remaining markets failed to record a statistically significant market parameter. Chinese car shares move in accordance with the broader automotive index and, thus, have a positive coefficient of 0.63. A similar scenario was monitored in France where the automotive coefficient is set at 0.50. On the other hand, US manufacturers moved at odds with the Dow Jones Automobiles Index. Brent crude oil is indicative of a negative correlation with Chinese and French manufacturers, but rising oil prices induced increases in US carmaker shares. China and France mimicked a similar pattern with respect to steel as well as companies domiciled in these countries ostensibly flourished amid increasing steel prices based on their positive coefficients related to steel (respectively, 0.48 and 0.61). Aluminium was determined to be a significant long-run predictor solely in China where perhaps counter-intuitively investors in China-domiciled auto companies could expect to see their shares gaining upward momentum amid soaring aluminium prices – a 1% rise in the price of aluminium was determined to engender a 0.55% rise within the price of automotive shares in China. Semiconductors is a factor to be reckoned with in US and China, where it exhibited positive influence on carmakers. Therefore, if semiconductor manufacturers experience substantial operational and/or financial woes, their clients in the automotive industry are likely to struggle themselves – a scenario which has been perfectly illustrated ever since the inception of the pandemic in 2020. In contrast, the French semiconductor index has a negative long-run coefficient assigned to it, indicating that French semiconductor manufacturer shares may serve as a hedge in a portfolio of French automotive producers. The questionable sign of the coefficient corresponding to French semiconductor may be to the bespoke nature of the FactSet French semiconductor index encompassing solely French-domiciled semiconductor manufacturer whereas one of the two constituents of the French carmakers incorporated in this study – Stellantis – is a conglomerate of French, Italian, German, and US carmakers, thus they may source semiconductor components from a variety of countries. The parameters pertaining to CPI were minor in size, with China and Italy fitting the narrative that inflation is adverse to car companies in the long-run. On the contrary, US and France had positive CPI coefficients, but none of the markets could showcase a particularly high and meaningful CPI coefficient although all of the countries, which had a cointegrating relationship with CPI, delivered significant CPI coefficients. As it was the case with short-term coefficients as well, industrial production coefficients were even lower than the ones generated by CPI, with China and France exhibiting positive correlation between industrial production and automotive stock returns in the long run as opposed to Italy where the identical coefficient was with a negative sign. Industrial production was a factor of secondary importance given its low coefficients. It was positively related to Chinese and French companies, and negatively related to their Italian counterparts. BEER showcased negative coefficients in the China and Korea samples, whilst the fortunes of the euro against the basket of other currencies in the broad effective exchange rate in France was positively correlated with the returns of French allocated producers Renault Group and Stellantis. In Italy, a long-run tendency is that a 1% increase in unemployment should dampen Italian-based car manufacturer stock returns by 0.01% in the long-run. US and France presented completely contrary findings with their 0.02 positive unemployment coefficients indicating that car manufacturers returns are boosted reasonably weakly upon rises in unemployment. An improving Business Confidence indicator signals a better stock performance by Italian automotive manufacturers due to the 0.04 long-run coefficient at a 99.9% significance level assigned to Business Confidence in Italy. Conversely, Chinese manufacturers had their returns performing somewhat negatively against the backdrop of an elevating Business Confidence Index (a 0.02% should be the outcome of a 1% hike in the Business Confidence Index in China in the long run).

In a nutshell, for the five markets for which the ARDL bound test revealed cointegration of returns, Brent crude oil was the factor explaining most effectively the long-run fluctuations in automotive returns in three markets – US, China, and France. In China and France oil price upsurges turned out to be detrimental for stock performance but the coefficient for crude oil in US was positive, hence we can conclude the effect of oil is heterogeneous on a regional basis. Italian car manufacturers' returns were extremely positively correlated with the FTSE MIB Index – a 1% gain in the Italian benchmark index leads to an explosive 1.97% growth in any of the two constituent stocks in the Italian sample, which is in conformity with our PVAR results. The only significant factor that contributes to our understanding of the triggers behind the stock fluctuations of Hyundai, Kia, and Ssang Yong in South Korea is BEER, which as argued, sustains a negative relationship with stock returns due to its negative coefficient of -0.003.

One of the key limitations of this study is the quite low negative coefficient of the error correction terms in the short-term ARDL models. ECT (found in the restricted error correction model) is the main factor in the short-run dynamic which stabilises the short-run equation and pushes automotive returns (the dependent variable). The ideal case would be an "ect" term between 0 and -2 (or -1 depending on different authors' opinions), any number below -2 may signal that the short-run coefficients are substantially away from their long-run equilibrium, in other words the models may suffer from model misspecification, most notably the China ARDL model. The South Korean "ect" of -1.84 indicates that the incorporated variables fit automotive stock returns reasonably well, at least compared to the other sampled markets. On the bright side, all "ect" coefficients for all countries were found to be negative, in congruence with best practices. The negative sign of the error correction term indicates convergence in the long run, whereas a positive sign signals the model is merely explosive.

7. Discussion

The aim of the discussion section is to shed light on the most the most significant in terms of magnitude regional long-run coefficients such as Brent crude oil in the US, semiconductor index in the US, market benchmark index in the Italy and unemployment. Specific attention shall be paid to deviations from the null hypothesis such as the positive long-run Brent crude oil coefficient and the positive long-run unemployment coefficient in Italy

Initially, a search with regards to oil-related keywords in the EDGAR section of the U.S. Securities and Exchange Commission's (SEC) website was conducted. At the end of FY 2020, Ford claimed that "Oil prices are expected to remain volatile, and on a lower long-term trend than in prior commodity cycles" (SEC, 2021). At the end of 2019, Ford reported that a key risk factor for Ford are spiking oil prices due to a potential shift away from larger vehicles, a trend that Ford believe may "result in an immediate and substantial adverse effect" on the firm financial conditions (SEC, 2020). Despite this claim, in 2021 (high oil price year) Ford's revenues increased to 126.15 billion USD (an 8.85% hike Y-o-Y), whilst net income (loss) turned from a loss of 1.276 billion USD in 2020 (low oil-price year) to a solid profit of 17.937 billion USD in 2021 (SEC, 2021). Admittedly, recovery from the pandemic supported strong financial results, quantitative easing programmes by central banks inflated the stock market, and Ford's objective to electrify its gamut with trending new vehicles such as the Ford Mach-E and its first fully electrified pick-up truck – the electric version of the trademark F-150 – are the likely reason oil prices failed to scathe both company fundamentals and its booming stock prices towards the end of FY 2021. The 2014 Ford annual report (SEC, 2015) explained declines in Brent crude oil prices in the second half of 2014 as driven by weak demand against the backdrop of strong global supply. In other words, the latter statements certified previous empirical research that oil shock nowadays are influenced by demand shocks rather than supply shocks, which confirms previous empirical findings by Mukherjee and Naka (1995) that positive demand-side shocks boost real oil prices and stock prices – in that sense, the positive long-run coefficient of Brent crude oil for the US is perfectly rational. In terms of the short-run dynamics in the interplay between Brent crude oil returns and Ford returns was also supported. A simple review of the return charts of Ford and Brent Crude oil somewhat confirmed our short-term ARDL coefficients – that US automotive stock returns are positively correlated with oil returns at the 4th, 5th, 6th, 7th, and 8th lag (Figure 3). In May 2008 oil prices surged, a move attributed to the insufficient supply to cater for demand, particularly originating from China, as well as a weakened US dollar.

The May 2008 Brent crude oil gains coincided with solid but less pronounced positive returns by Ford in the same period but were also followed 6 periods/months later in November 2008 by a significant hike in Ford stock returns.

In order to describe the findings about the relationship between a semiconductor proxy (Dow Jones US Semiconductor Index, in short - DJUSSC) in the US and US automotive stock returns we shall pick Tesla as an example, since aforementioned it is the largest in terms of market cap US-domiciled company in the sample. Overall, for all US companies the long-run coefficient with respect to semiconductors is significant and positive (0.85). The short-term coefficients are also largely positive – particularly at lag "t-4" the coefficient is quite large in magnitude (2.36), positive at lag 6 (1.21), and negative at lag 10 (-1.02). The Q2 2021 financial results of Tesla (SEC, 2021) depicted some of the most pressing issues for the company in recent times – namely, logistics and supply chain woes such as "increased port congestion, intermittent supplier delays and a shortfall of semiconductor supply". Even the most crucial for the company planned production premises such as Gigafactory Shanghai, Gigafactory Berlin, and Gigafactory Texas seemed to be at stake due to the semiconductor shortage, and the inability to procure additional components for its Model 3 and Model Y flagships (SEC, 2021), thus outlining its tight relationship with the fortunes of a high-tech automotive manufacturer such as Tesla. The Q2 2021 report for General Motors echoed Tesla findings, stating that GM prioritised its most highly sought vehicles such as SUVs, EVs, and trucks in the face of chip shortages. A comparison of the return dynamics chart of the Dow Jones Semiconductor Index against the EV pioneer Tesla and a US legacy automotive conglomerate – General Motors – revealed that Tesla was significantly more volatile (quite logical given its growth/meme stock status) than GM, and especially the US semiconductor proxy – in fact over the period all of these three shares (November 2010) have been traded, the σ (standard deviation) of Tesla was 16%, for GM it was 8.92%, and for DJUSSC it was the reasonably modest 5.79%, indicating a far more subdued risk for semiconductor investors. We can glean some evidence for the positive short-term ARDL coefficients pertaining to semiconductors in the US by reviewing the price charts since January 2020 – the March 2020 moderate increase in DJUSSC monthly returns to 8.79% was matched in August 2020 by a significant hike in GM monthly returns, up to 19.65% (Figure 4). The January 2021 rise in DJUSSC monthly return to 7.10% was ensued 5 months later by the gigantic spike in Tesla's monthly returns to 36.22%. Furthermore, the negative short-run coefficient relating to semiconductors at the 10th lag was buttressed by price charts as well.

The March 2020 increase in semiconductor returns predated negative returns of -16.10% of Tesla in January 2021 % (Figure 4). In contrast, the long-run coefficient for semiconductors in Italy was insignificant. Until the end of 2021 Ferrari only launched a single model based on hybrid technology – the Ferrari LaFerrari). In other words. Ferrari had limited experience building more advanced hybrid and electric powertrains, thus the demand for semiconductors was likely more subdued than it was, for example, in the case of high-tech producers such as Tesla or Rivian in the US. The second Italian stock in this study – Pininfarina – is an illustrious car design firm, historically associated with predominantly Alfa Romeo, Ferrari, and Peugeot models, and only in 2021 Pininfarina commenced production of its first in-house automobile – the electric hypercar named Battista (Auto Express, 2021), and thus its demand for semiconductors until 2021 was non-existent. Therefore, these considerations make justify the insignificant long-run semiconductor parameter in Italy, although as previously argued, Italian producers are dependent on Italian semiconductor performance in the short run.

We can find the rationale why the market index is the strongest positive influence on our reviewed Italian manufacturers (Ferrari and Pininfarina), as well as behind the lagged by one period positive significant coefficient for the market benchmark index of the global macroeconomic review executed through the Panel VAR analysis. A glance at the top 30 constituents of FTSE MIB Italy is quite enlightening about the significant long-run market index coefficient in Italy of 1.90. Out of the 30 companies, 6 of them can be classified as quite intricately intertwined with the automotive industry – Atlantia SpA (management of motorways and airports under concession), Pirelli & C. S.p.A (tyre manufacturer), Eni S.p.A (operating in the oil and gas industry), Ferrari N.V. (one of our reviewed companies), STMicroelectronics (production of vehicle control units), and Saipem SpA (an oilfield service company).

Emphasis should be placed on the sole significant long-run coefficient of the ARDL part of the analysis with regards to South Korea – the Broad Effective Exchange Rate. The coefficient was minuscule in magnitude - 0.003 but negative in direction. BEER is exceptionally useful when trying to analyse whether a currency has appreciated against a basket of currencies. Overall, for the reviewed period Jan 2007 – Dec 2021 the South Korean wan depreciated against a basket of selected foreign currencies as the BEER indicator showed (Figure 5). According to economic intuition, currency devaluation makes exports cheaper, imports get more expensive, as well as some short-term effects such as rise in inflation and enhanced demand for exports. However, if the state of the global economy is recessionary, currency devaluation may not be as affective in boosting exports. In other words, the winners in currency devaluation are exporters, the losers are importers, economic growth is likely to rise if the demand for exports and imports is elastic, whereas domestic countries may suffer if they import a large chunk of their raw materials and components from overseas. According to Taub et al. (2019), the primary materials for vehicle construction nowadays are high-strength steel, aluminium, magnesium, and polymer composites. Since 37.7% of Hyundai's revenues in 2020 were represented by small SUVs (Statista, 2021), and the best-selling model of Hyundai in the US in 2021 was the Hyundai Tucson (Best-selling cars, 2022), we can deduce the raw materials used in Hyundai vehicles using the Tucson as a proxy. Findings by the World Steel Association (2015) asserted that in the 2015 generation of the Tucson high-strength steel accounted for more than 50% of its structure. Ducker Worldwide (2016) also confirmed the Tucson was a model with below average aluminium content. According to the FactSet platform, Hyundai, being the leading South Korean automotive manufacturer in terms of average market capitalisation in the reviewed period, derives 35.1% of its 2021 revenues from its domestic market, which is comparatively high compared to other manufacturers. For instance, Tesla derived 44.5% of its revenue from the US, Volkswagen – 17.7% from Germany, Xpeng – 97.6% from mainland China, Toyota – 25.1% from Japan, Ferrari – 9.6% from Italy, and Stellantis – 10.3% from France. In other words, Hyundai is a carmaker which is relatively less dependent on exports than German, Japanese, Italian, and French manufacturers and outsources mostly steel and to a lesser extent aluminium to construct its vehicles. In terms of raw materials, despite its comparatively modest territory, South Korea is a significant crude steel producer – behind steel powerhouses such as China, India, Japan, the US, and Russia, but for instance producing more steel than the whole South America according to FactSet data. South Korea ranked 13th worldwide as an exporter of aluminium and aluminium products (Statista, 2020) (Figure 7). In other words, in the case of South Korea we have an automotive industry less focused on exports and comparatively self-sufficient in terms of raw materials. The BEER coefficient for South Korea is minor but significant and negative. Since South Korean BEER declined over the period, the Korean won depreciated. The negative coefficient indicates that when the currency depreciated against a set of other currencies, the returns of South Korean carmakers surged albeit slightly. Exports became cheaper (64.90% of total production) which spurs economic growth and respectively automotive stock prices. Thus, the slight but negative long-run BEER coefficient is a result of rising stock prices in an economy characterised by a depreciating domestic currency.

Italy may have recorded a negative coefficient concerning unemployment in contrast to US and France because its macroeconomy was in far worse shape than the French and US economies for our sampled period (2007 – 2021). Apart from the period April 2020 – June 2020, ever since November 2011 Italy registered a far higher unemployment rate than both Germany and US until the end of the reviewed period (December 2011) (Figure 6). According to a Financial Times article (2018), Italian GDP per capita has been subdued below German, Spanish, and French GDP since 1998 (Figure 8). 95% of Italian business were SMEs in 2018, with headcount less than 10 employees, a tendency that limits labour productivity (Figure 9), stifles R&P expenditure and respectively innovation on a global scale (Financial Times, 2018). A relatively less agreeable business environment could be evinced by Italy ranking 51st out of 190 countries in terms of ease of doing business in the "Doing Business 2019" report released by the World Bank Group (2018), which measures the ease of obtaining building permits, availability of credit, attainment of electricity connection, contract enforcement, resolution of insolvency, ease of international trade, tax payment, and protection of minority investors, with Italy being consistently below the other 6 reviewed countries. Furthermore, Italy suffered from low greenfield foreign investments (Figure 10) and extremely high rate of interest expenditure on public debt (Financial Times, 2018) (Figure 11). In other words, consistent with Boyd et al.'s (2005) research on the relationship between unemployment and stock prices, Italy's negative long-run unemployment coefficient (-0.01) can be rationalised by its inferior economic growth compared to France and the US. The French and US economy were in a far better shape for the whole period Jan 2007 – Dec 2021, hence in economic expansion periods the coefficient between unemployment and stock prices is positive (France – 0.02, US – 0.02), whereas Italian companies align far more with the economic contraction scenario of a negative correlation between unemployment and stock prices, which is also one of our null hypotheses.

According to Edmunds (2013), 2013 was a strong year for automotive sales in the US due to post-financial crunch unleashing of pent-up demand, attractive interest rates, and wealth effects from a well-performing stock market. The author posited that the sole macroeconomic factor seemingly at odds with the picture of a rebounding economy was the unemployment rate – in April/May 2013 unemployment was still quite high at 7.5%-7.6%. The French economy also gained momentum. France registered a sound trend in minimising its unemployment rate. In Q4 2019 unemployment fell to 8.1%, down from 8.5% Q-o-Q, which represented a nadir in unemployment rate (Financial Times, 2020).

Edmunds (2013) made the shrewd argument that contrary to common sense (that a higher unemployment rate may impede the purchase of big-ticket items such as cars), a higher unemployment rate may preclude the Federal Reserve from curbing its quantitative easing programme to buy Treasury bonds and mortgage bonds in order to revitalise the economy and lower interest rates, which ultimately open up greater avenues to purchase a vehicle (Edmunds, 2013).

Therefore, as stated previously, the long-term coefficient with respect to unemployment for France and the US were positive due to the strong momentum their economies gained throughout the reviewed sample period in contrast to the Italian economy, which stagnated, and thereby recorded a negative long-term unemployment coefficient.

8. Conclusions

This study encompassed an exceptionally broad geographic and country view of the automotive sector in seven countries. On the basis of the perused previous empirical research only two other papers by El Khoury (2015) and Vychytilová et al (2019) analysed automotive stocks in more than a single country. Our panel VAR findings for the automotive industry in general (globally) were largely consistent with preliminary hypotheses outlined in the empirical research section of this paper. Null hypotheses *H1*, *H2*, *H4*, *H5*, *H6* and *H8* were confirmed by the Panel VAR approach.

As expected, the short-term ARDL coefficients were very volatile, frequently reversing their sign up to lag 12 measured from the current date. The short-term relationship coefficients in ARDL delineated the relationship between variables attributable to different shocks, in a similar fashion to the impulse response functions from the Panel VAR analysis. The long-term coefficients derived from the Error Correction Model after the confirmation of a cointegrating relationship between the automotive returns and the independent variables are a lot more stable and amenable for conclusions. From a regional perspective, we could confirm *H1* (positive correlation between automotive returns and their respective market index) for Italian and Chinese manufacturers, *H2* (positive correlation between automotive returns and an automotive benchmark index) was accepted for Chinese and French carmakers, *H3* (negative correlation between automotive returns and Brent crude oil) was confirmed for Chinese and French carmakers, whereas *H4* (indicative of the positive relationship between a semiconductor index returns and individual car stock returns) was evident in the US and

China. Long-run ARDL/ECM coefficients were particularly strong in magnitude in the aforementioned variables – market index, automotive index, Brent crude oil, and semiconductor index, hence we can conclude these are the key return drivers on a regional basis.

A potential remedy for the deliberated in Section 6 limitation of the study of a very low error correction term below -1 can be the Zivot Andrews test for structural break, which incorporates a dummy variable for structural break in the short-run ARDL equation. Experimentally, we launched the Zivot Andrews' test (1992) in the ARDL equation for Italy but for this specific sample the benefits of the Zivot and Andrews' (1992) test were none – the coefficients for both short- and long-run equations were preserved in sign with some very minor fluctuations but the error correction term decreased from -3.857 in our normal ARDL short-run model to -3.9435, hence the very low negative number implies that returns are above their long-term equilibrium point and they should be corrected by almost 394%. The correction is very high, taking into consideration that usually is between 0 and -1. Therefore, the structural break test cannot serve as a panacea for the limitation of this study. A more theoretical "trial-and-error" approach yet time-consuming and by no means guaranteed may be to select a distinct combination of explanatory variables. This approach may prove especially fruitful if prospective authors are able to capitalise on an expanding set of academic papers about the effects of macroeconomic variable on stock returns.

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Appendices

Appendix A: Panel VAR regressions and diagnostic tests

	Return	Market Index	Automotive index
lag1_Return	0.0227 * (0.0096)	-0.0008 * (0.0004)	0.0043 * (0.0018)
lag1_Market Ind	0.0110 * (0.0046)	0.0015 * (0.0006)	0.0027 * (0.0011)
lag1_Auto Ind	0.0141 * (0.0060)	0.0009 * (0.0004)	0.0090 * (0.0038)
Steel	0.0199 * (0.0084)	-0.0011 * (0.0005)	-0.0048 * (0.0024)
Brent CO	-0.0189 * (0.0083)	0.0186 * (0.0077)	-0.0274 * (0.0119)
Aluminium	0.0010 (0.0006)	0.0092 * (0.0038)	-0.0071 * (0.0031)
Semicon Ind	0.0193 * (0.0082)	-0.0035 * (0.0015)	0.0010 * (0.0005)
CPI	-0.0499 * (0.0251)	0.0039 (0.0047)	-0.0615 * (0.0282)
Ind Prod	-0.0111 (0.0113)	-0.0018 (0.0028)	0.0160 (0.0135)
BEER	0.1021 * (0.0420)	-0.0052 (0.0029)	0.1054 * (0.0441)
Business Conf	0.0310 * (0.0132)	0.0652 * (0.0271)	-0.0518 * (0.0235)
const	-0.0000 * (0.0000)	-0.0000 * (0.0000)	0.0001 * (0.0000)

Standard errors in parentheses
**** p<0.0001, ** p<0.01, *p<0.05, .p<0.1*
Table 5: Panel VAR coefficients of the selected endogenous variables

MMSC_BIC	MMSC_AIC	MMSC_HQIC
-41941.8	-11778	-24278.7

Table 6: Information criteria for lagged by 1 period endogenous variables in the system GMM as per the Andrews_Lu_MMSC functionality of RStudio (Andrews & Lu, 2001)

	Eigenvalue	Modulus
1	0.025928686	0.025928686
2	0.005449031	0.005449031
3	0.001724177	0.001724177

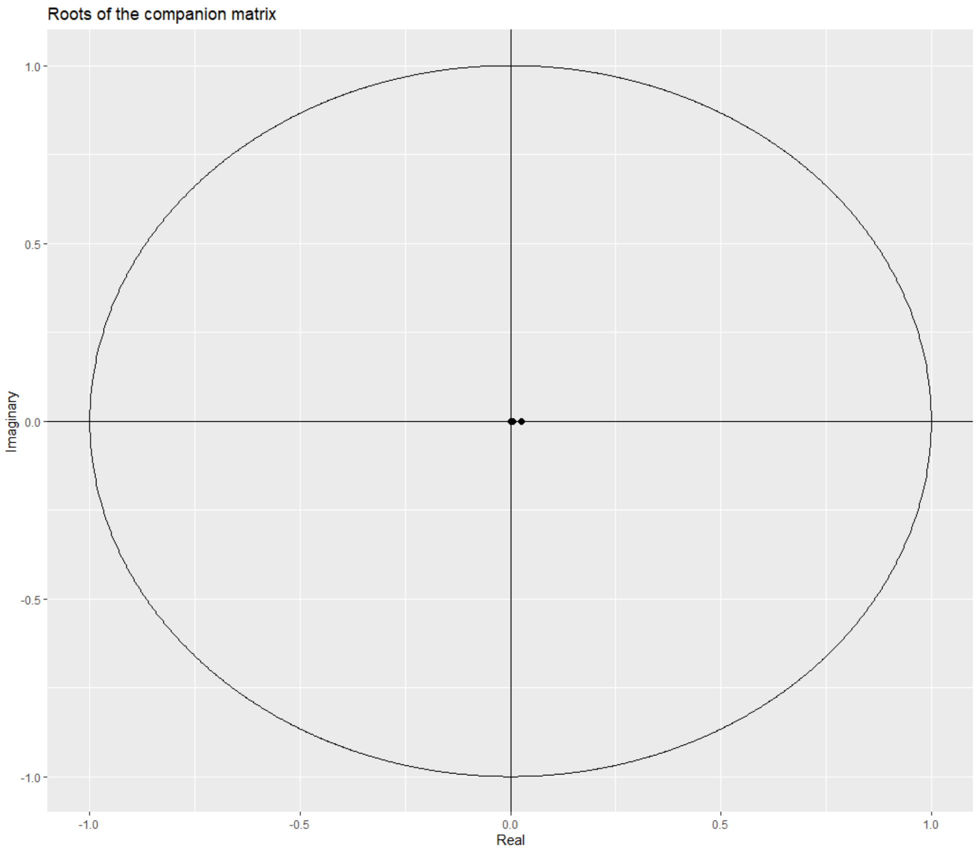

Table 7 and Figure 2: PVAR stability conditions. All the eigenvalues lie inside the unit circle. PVAR satisfies stability condition.

Appendix B: Short-run ARDL equations

	Estimate	Std. Error	t value	p-value	Significance
(Intercept)	-10.2000	4.0880	-2.4940	0.0182	*
L(Return, 2)	-0.2741	0.1328	-2.0640	0.0475	*
L(Return, 3)	-0.2797	0.1255	-2.2280	0.0333	*
L(Return, 5)	-0.2286	0.1243	-1.8390	0.0756	.
L(Return, 6)	-0.3031	0.1594	-1.9010	0.0666	.
L(Return, 8)	-0.3971	0.1429	-2.7790	0.0092	**
L(Return, 9)	-0.5303	0.1364	-3.8880	0.0005	***
L(Return, 10)	-0.2610	0.1337	-1.9530	0.0599	.
Market Ind	1.9530	0.4842	4.0330	0.0003	***
L(Market Ind, 1)	1.7230	0.5155	3.3420	0.0022	**
L(Market Ind, 3)	0.9639	0.4872	1.9790	0.0568	.
L(Market Ind, 5)	0.8233	0.4719	1.7450	0.0910	.

L(Market Ind, 7)	-0.7921	0.4663	-1.6990	0.0994	.
L(Market Ind, 10)	0.7228	0.3727	1.9390	0.0616	.
L(Auto Ind, 1)	-0.5854	0.2897	-2.0210	0.0520	.
L(Auto Ind, 4)	0.4767	0.2257	2.1120	0.0428	*
L(Auto Ind, 6)	0.7338	0.2230	3.2910	0.0025	**
L(Brent CO, 8)	0.7424	0.2384	3.1140	0.0040	**
L(Steel, 4)	0.4617	0.2688	1.7180	0.0958	.
L(Steel, 5)	0.4807	0.2468	1.9480	0.0605	.
L(Steel, 6)	-0.5391	0.2764	-1.9510	0.0602	.
L(Steel, 8)	-0.5558	0.2529	-2.1980	0.0356	*
L(Steel, 9)	-0.7005	0.3041	-2.3030	0.0281	*
L(Steel, 10)	-0.9144	0.3084	-2.9650	0.0058	**
Aluminium	-0.8724	0.3456	-2.5250	0.0169	*
L(Aluminium, 1)	-1.1240	0.3845	-2.9240	0.0064	**
L(Aluminium, 9)	1.1140	0.4220	2.6410	0.0128	*
L(Aluminium, 10)	1.6020	0.4742	3.3780	0.0020	**
L(Aluminium, 12)	-0.5921	0.3190	-1.8560	0.0730	.
L(Semicon Ind, 1)	-0.3982	0.2033	-1.9590	0.0592	.
L(Semicon Ind, 7)	0.3554	0.2041	1.7410	0.0916	.
L(CPI, 5)	0.2157	0.1265	1.7060	0.0981	.
L(CPI, 9)	0.3648	0.1279	2.8510	0.0077	**
L(CPI, 10)	-0.4465	0.1243	-3.5910	0.0011	**
L(Ind Prod, 4)	-0.0040	0.0021	-1.8680	0.0712	.
L(Ind Prod, 5)	-0.0038	0.0021	-1.7970	0.0821	.
L(Ind Prod, 6)	-0.0072	0.0025	-2.9510	0.0060	**
L(Ind Prod, 7)	-0.0068	0.0021	-3.2890	0.0025	**
L(Ind Prod, 8)	-0.0049	0.0019	-2.6030	0.0140	*
L(Ind Prod, 10)	-0.0033	0.0017	-1.9380	0.0618	.
L(Unemployment, 3)	-0.1900	0.0749	-2.5370	0.0164	*
L(Unemployment, 4)	0.1584	0.0720	2.2000	0.0354	*
L(Unemployment, 5)	0.1407	0.0794	1.7720	0.0863	.
L(Unemployment, 8)	-0.1565	0.0800	-1.9570	0.0594	.
L(Unemployment, 9)	0.1536	0.0825	1.8610	0.0723	.
L(Unemployment, 10)	-0.1397	0.0725	-1.9280	0.0631	.
BEER	0.0673	0.0303	2.2230	0.0336	*
L(BEER, 3)	-0.0837	0.0399	-2.0990	0.0440	*
L(BEER, 4)	0.0883	0.0464	1.9050	0.0661	.
L(BEER, 10)	0.0673	0.0367	1.8340	0.0763	.
L(Business Conf, 5)	-1.9090	0.8019	-2.3810	0.0236	*
L(Business Conf, 6)	2.8720	0.7902	3.6350	0.0010	***

L(Business Conf, 7)	-2.4400	0.8006	-3.0470	0.0047	**
L(Business Conf, 8)	1.5660	0.6550	2.3910	0.0230	*
L(Business Conf, 9)	-0.4740	0.2563	-1.8490	0.0740	.
ect (from restricted ECM)	-3.8570	0.5338	-7.2270	0.0000	***

**** p<0.0001, ** p<0.01, *p<0.05, .p<0.1*

Adjusted R^2=0.6255; F-statistic= 3.054; Model p-value=0.0002912

Table 8: Italy – short-run equation with ARDL (solely significant coefficients) with maximum number of lags of the regressand (returns) and regressors set to (10,10,6,10,11,12,12,10,12,10,12,9). The model was preferred to its counterpart model with maximum number of lags of 12 on all variables, which also produced the lowest AIC value. This models with maximum number of lags of (10,10,6,10,11,12,12,10,12,10,12,9) is preferred because the best model with all variables set to up to 12 lags failed to reject the F-significance test of the ARDL bound test, and respectively we re-ran the test with the second and third best models in terms of lowest AIC information criterion.

	Estimate	Std. Error	t value	p-value	Significance
L(Return, 1)	-1.1232	0.2205	-5.0950	0.0003	***
L(Return, 2)	-1.1722	0.2567	-4.5660	0.0008	***
L(Return, 3)	-0.7741	0.1934	-4.0030	0.0021	**
L(Return, 6)	-0.7861	0.2230	-3.5250	0.0048	**
L(Market Ind, 4)	-3.8876	1.0035	-3.8740	0.0026	**
L(Market Ind, 8)	1.8220	0.8929	2.0410	0.0660	.
L(Market Ind, 10)	2.1993	1.0480	2.0990	0.0598	.
L(Market Ind, 11)	2.9527	0.9109	3.2410	0.0079	**
L(Auto Ind, 1)	0.6013	0.3171	1.8960	0.0845	.
L(Auto Ind, 8)	-1.0961	0.3275	-3.3470	0.0065	**
L(Brent CO, 4)	1.8469	0.6128	3.0140	0.0118	*
L(Brent CO, 5)	1.1674	0.5038	2.3170	0.0408	*
L(Brent CO, 6)	1.1891	0.4455	2.6690	0.0218	*
L(Brent CO, 7)	1.7077	0.4924	3.4680	0.0053	**
L(Brent CO, 8)	1.1645	0.6274	1.8560	0.0904	.
Steel	0.9606	0.4661	2.0610	0.0638	.
L(Steel, 2)	-1.1375	0.4343	-2.6190	0.0239	*
L(Steel, 10)	1.3804	0.6745	2.0460	0.0654	.
L(Steel, 11)	1.1167	0.4420	2.5270	0.0281	*
L(Aluminium, 1)	1.3133	0.6628	1.9810	0.0731	.
L(Aluminium, 8)	-2.5128	0.8642	-2.9080	0.0142	*
L(Aluminium, 9)	-2.0124	0.9712	-2.0720	0.0625	.
L(Semicon Ind, 4)	2.3632	0.5557	4.2530	0.0014	**
L(Semicon Ind, 5)	1.0776	0.5281	2.0410	0.0660	.
L(Semicon Ind, 6)	1.2065	0.5132	2.3510	0.0384	*
L(Semicon Ind, 10)	-1.0201	0.5128	-1.9890	0.0721	.
CPI	-0.2598	0.1022	-2.5430	0.0273	*
L(CPI, 5)	-0.3013	0.1418	-2.1250	0.0571	.

L(Unemployment, 4)	0.1310	0.0565	2.3190	0.0406	*
L(Unemployment, 5)	-0.1159	0.0611	-1.8960	0.0845	.
L(BEER, 1)	-0.1298	0.0464	-2.7980	0.0173	*
L(BEER, 3)	0.0770	0.0324	2.3810	0.0365	*
L(BEER, 8)	0.0825	0.0369	2.2350	0.0471	*
L(Business Conf, 12)	0.4088	0.2113	1.9350	0.0792	.
ect (from restricted ECM)	-5.6323	0.5909	-9.5320	0.0000	***

**** p<0.0001, ** p<0.01, *p<0.05, .p<0.1*
Adjusted R^2= 0.7934; F-statistic= 5.114; Model p-value=0.002328
Table 9: US – short-run equation with ARDL (solely significant coefficients) with maximum number of lags of the regressand (returns) and regressors set to (12,12,12,12,12,12,12,12,12,12,12,12).

	Estimate	Std. Error	t value	p-value	Significance
Market Ind	1.5999	0.5067	3.1570	0.0091	**
L(Market Ind, 8)	1.1625	0.5701	2.0390	0.0662	.
L(Auto Ind, 12)	-0.6543	0.3013	-2.1710	0.0527	.
L(Brent CO, 11)	0.3841	0.1974	1.9450	0.0777	.
L(Steel, 1)	0.9446	0.3762	2.5110	0.0290	*
L(Steel, 11)	-0.5809	0.2729	-2.1280	0.0568	.
L(Semicon Ind, 8)	-1.4009	0.7740	-1.8100	0.0977	.
L(Unemployment, 4)	0.7248	0.3319	2.1840	0.0515	.
L(BEER, 8)	-0.0845	0.0400	-2.1140	0.0581	.
L(Business Conf, 5)	-2.0744	1.0607	-1.9560	0.0764	.
L(Business Conf, 6)	2.3926	1.2296	1.9460	0.0777	.
L(Business Conf, 10)	-2.1716	1.0406	-2.0870	0.0610	.
L(Business Conf, 11)	1.9631	0.7485	2.6230	0.0237	*
L(Business Conf, 12)	-0.6466	0.2263	-2.8570	0.0156	*

**** p<0.0001, ** p<0.01, *p<0.05, .p<0.1*
Adjusted R^2= 0.7541; F-statistic= 4.285; Model p-value=0.005139
Table 10: Germany – short-run equation with ARDL (solely significant coefficients) with maximum number of lags of the regressand (returns) and regressors set to (12,12,12,12,12,12,12,12,12,12,12,12). ***Since the null of no cointegration in the ARDL Bound test failed to be rejected for any of the 6 best short-term ARDL models with lowest AIC information criterion, no long-run relationship was identified between automotive returns and the macroeconomic variables in Germany in Appendix C.***

	Estimate	Std. Error	t value	p-value	Significance
(Intercept)	19.6700	2.9660	6.6300	0.0000	***
L(Return, 1)	-0.7273	0.1347	-5.4000	0.0000	***
L(Return, 2)	-0.7812	0.1090	-7.1680	0.0000	***
L(Return, 3)	-0.5112	0.1246	-4.1030	0.0004	***
L(Return, 4)	-0.5834	0.1037	-5.6240	0.0000	***
L(Return, 5)	-0.5789	0.1187	-4.8760	0.0000	***
L(Return, 6)	-0.7419	0.1332	-5.5690	0.0000	***
L(Return, 7)	-0.4872	0.1276	-3.8190	0.0007	***
L(Return, 8)	-0.4519	0.1107	-4.0820	0.0004	***
L(Return, 9)	-0.5061	0.1028	-4.9210	0.0000	***
L(Return, 10)	-0.2002	0.1131	-1.7690	0.0886	.
L(Market Ind, 3)	-0.4279	0.1347	-3.1760	0.0038	**
L(Market Ind, 5)	-0.4531	0.1450	-3.1240	0.0043	**
L(Market Ind, 8)	0.4572	0.1509	3.0300	0.0055	**
L(Market Ind, 9)	0.7210	0.1478	4.8790	0.0000	***
L(Market Ind, 10)	0.5134	0.1620	3.1690	0.0039	**
L(Market Ind, 12)	0.3080	0.0851	3.6180	0.0013	**
L(Auto Ind, 1)	0.4282	0.1413	3.0310	0.0055	**
L(Auto Ind, 2)	0.7385	0.1442	5.1220	0.0000	***
L(Auto Ind, 3)	0.4063	0.1745	2.3280	0.0279	*
L(Auto Ind, 4)	0.7981	0.1552	5.1420	0.0000	***
L(Auto Ind, 5)	0.8083	0.1689	4.7860	0.0001	***
L(Auto Ind, 6)	0.3486	0.1489	2.3410	0.0272	*
L(Auto Ind, 9)	0.2825	0.1449	1.9500	0.0620	.
L(Brent CO, 2)	-0.3536	0.1060	-3.3360	0.0026	**
L(Brent CO, 3)	-0.3938	0.1085	-3.6310	0.0012	**
L(Brent CO, 4)	-0.6607	0.1317	-5.0170	0.0000	***
L(Brent CO, 5)	-0.8645	0.1248	-6.9290	0.0000	***
L(Brent CO, 6)	-0.5424	0.1521	-3.5660	0.0014	**
L(Brent CO, 7)	-0.7183	0.1522	-4.7180	0.0001	***
L(Brent CO, 8)	-0.5738	0.1579	-3.6350	0.0012	**
L(Brent CO, 10)	-0.5163	0.1101	-4.6910	0.0001	***
L(Brent CO, 11)	-0.1837	0.1024	-1.7940	0.0845	.
L(Brent CO, 12)	-0.2416	0.0988	-2.4440	0.0216	*
L(Steel, 2)	0.3204	0.1187	2.6990	0.0121	*
L(Steel, 3)	0.5084	0.1317	3.8590	0.0007	***
L(Steel, 4)	0.4835	0.1351	3.5780	0.0014	**
L(Steel, 5)	0.6615	0.1336	4.9510	0.0000	***
L(Steel, 6)	0.3111	0.1316	2.3640	0.0259	*
L(Steel, 7)	0.4892	0.1619	3.0220	0.0056	**
L(Steel, 11)	0.2263	0.0894	2.5310	0.0177	*
L(Aluminium, 5)	0.3321	0.1517	2.1890	0.0378	*
L(Aluminium, 6)	0.6458	0.1656	3.9010	0.0006	***
L(Aluminium, 7)	0.5768	0.1797	3.2090	0.0035	**
L(Aluminium, 9)	0.3319	0.1764	1.8820	0.0711	.

L(Aluminium, 10)	0.5732	0.1996	2.8720	0.0080	**
L(Aluminium, 12)	0.6456	0.1554	4.1550	0.0003	***
Semicon Ind	0.3539	0.0783	4.5180	0.0001	***
L(Semicon Ind, 1)	0.1895	0.0881	2.1510	0.0409	*
L(Semicon Ind, 2)	0.3992	0.0917	4.3530	0.0002	***
L(Semicon Ind, 5)	0.4507	0.0955	4.7210	0.0001	***
L(Semicon Ind, 7)	0.2198	0.0896	2.4530	0.0212	*
L(CPI, 5)	-0.1655	0.0217	-7.6300	0.0000	***
L(CPI, 6)	0.0617	0.0271	2.2800	0.0311	*
L(CPI, 9)	0.0599	0.0247	2.4270	0.0224	*
L(Ind Prod, 4)	0.0052	0.0017	2.9850	0.0061	**
L(Ind Prod, 7)	-0.0028	0.0016	-1.8210	0.0802	.
Unemployment	-5.4940	1.7930	-3.0640	0.0050	**
L(Unemployment, 1)	12.1700	4.4520	2.7330	0.0111	*
L(Unemployment, 2)	-9.2430	5.2420	-1.7630	0.0896	.
L(Unemployment, 11)	-10.2000	4.5470	-2.2430	0.0336	*
L(Unemployment, 12)	5.3300	1.7060	3.1250	0.0043	**
BEER	-0.0257	0.0074	-3.4500	0.0019	**
L(BEER, 1)	0.0283	0.0107	2.6500	0.0135	*
L(BEER, 2)	-0.0385	0.0115	-3.3470	0.0025	**
L(BEER, 3)	0.0472	0.0128	3.6950	0.0010	**
L(BEER, 4)	-0.0422	0.0144	-2.9310	0.0070	**
L(BEER, 5)	0.0272	0.0129	2.0980	0.0458	*
L(BEER, 6)	-0.0254	0.0108	-2.3520	0.0266	*
L(BEER, 8)	0.0150	0.0064	2.3580	0.0262	*
Business Conf	0.0367	0.0190	1.9300	0.0646	.
L(Business Conf, 1)	-0.0648	0.0377	-1.7170	0.0979	.
L(Business Conf, 5)	-0.1204	0.0503	-2.3940	0.0242	*
L(Business Conf, 6)	0.1163	0.0573	2.0300	0.0527	.
L(Business Conf, 7)	-0.1117	0.0627	-1.7820	0.0864	.
L(Business Conf, 10)	-0.0547	0.0263	-2.0770	0.0478	*
ect (from restricted ECM)	-6.5690	0.5832	-11.2650	0.0000	***

**** p<0.0001, ** p<0.01, *p<0.05, .p<0.1*

Adjusted R^2= 0.8981; F-statistic= 11.45; Model p-value=0.0000000006951

*Table 11: China – short-run equation with ARDL (solely significant coefficients) with maximum number of lags of the regressand (returns) and regressors set to (*10,12,10,12,12,12,7,12,12,12,8,10*). The model was preferred to its counterpart model with maximum number of lags of 12 on all variables, which also produced the lowest AIC value. This models with maximum number of lags of*

(10,10,6,10,11,12,12,10,12,10,12,9) is preferred because the best model with all variables set to up to 12 lags failed to reject the F-significance test of the ARDL bound test, and respectively we re-ran the test with the second and third best models in terms of lowest AIC information criterion.

	Estimate	Std. Error	t value	p-value	Significance
L(Market Ind, 5)	-0.6751	0.2803	-2.4080	0.0347	*
Auto Ind	0.9263	0.2313	4.0040	0.0021	**
L(Brent CO, 2)	-0.1761	0.0852	-2.0680	0.0630	.
L(Steel, 2)	0.2356	0.1138	2.0700	0.0628	.
L(Steel, 7)	0.2340	0.0967	2.4190	0.0341	*
L(Aluminium, 5)	-0.3989	0.1882	-2.1200	0.0576	.
Ind Prod	-0.0039	0.0016	-2.4350	0.0331	*
L(Ind Prod, 12)	0.0027	0.0015	1.8470	0.0917	.
BEER	-0.0095	0.0045	-2.0920	0.0604	.
L(BEER, 3)	-0.0172	0.0074	-2.3340	0.0396	*
L(BEER, 11)	0.0133	0.0073	1.8190	0.0963	.

**** p<0.0001, ** p<0.01, *p<0.05, .p<0.1*

Adjusted R^2= 0.9044; F-statistic= 11.13; Model p-value=0.00005391

Table 12: Japan – short-run equation with ARDL(solely significant coefficients) with maximum number of lags of the regressand (returns) and regressors set to (12,12,12,12,12,12,12,12,12,12,12,12). ***Since the null of no cointegration in the ARDL Bound test failed to be rejected for any of the 6 best short-term ARDL models with lowest AIC information criterion, no long-run relationship was identified between automotive returns and the macroeconomic variables in Japan in Appendix C.***

	Estimate	Std. Error	t value	p-value	Significance
(Intercept)	-12.7600	5.1790	-2.4640	0.0298	*
L(Return, 1)	-0.4826	0.2004	-2.4090	0.0330	*
L(Return, 2)	-0.4898	0.1759	-2.7850	0.0165	*
L(Return, 3)	0.5193	0.2204	2.3560	0.0363	*
L(Return, 6)	-0.7363	0.2290	-3.2150	0.0074	**
L(Return, 8)	-0.4314	0.1646	-2.6210	0.0223	*
L(Return, 11)	0.3992	0.2012	1.9840	0.0706	.
Market Ind	1.9810	0.5532	3.5810	0.0038	**
L(Market Ind, 1)	2.6020	0.5838	4.4560	0.0008	***
L(Market Ind, 2)	1.6430	0.6138	2.6760	0.0202	*
L(Market Ind, 5)	-1.1900	0.6426	-1.8520	0.0888	.
L(Market Ind, 9)	1.8320	0.5323	3.4410	0.0049	**
L(Market Ind, 10)	1.0480	0.4177	2.5100	0.0274	*
Auto Ind	-0.6641	0.2717	-2.4440	0.0309	*
L(Auto Ind, 1)	-0.6178	0.2570	-2.4040	0.0333	*
L(Auto Ind, 3)	0.6739	0.3285	2.0520	0.0627	.
L(Auto Ind, 4)	0.7143	0.2674	2.6720	0.0204	*

L(Auto Ind, 5)	1.2230	0.3003	4.0720	0.0015	**
L(Auto Ind, 7)	-1.6470	0.4025	-4.0920	0.0015	**
L(Auto Ind, 8)	-1.4020	0.3437	-4.0780	0.0015	**
L(Auto Ind, 11)	1.0270	0.3307	3.1050	0.0091	**
Brent CO	0.2358	0.1167	2.0200	0.0663	.
L(Brent CO, 2)	-0.3286	0.1371	-2.3970	0.0337	*
L(Brent CO, 5)	-0.2896	0.1426	-2.0300	0.0651	.
L(Brent CO, 6)	0.4227	0.1470	2.8770	0.0139	*
L(Brent CO, 7)	-0.2431	0.1355	-1.7950	0.0979	.
L(Brent CO, 9)	-0.7605	0.2320	-3.2780	0.0066	**
Steel	-0.6254	0.1956	-3.1970	0.0077	**
L(Steel, 4)	0.7497	0.2441	3.0710	0.0097	**
L(Steel, 5)	0.9992	0.1960	5.0980	0.0003	***
L(Steel, 7)	0.6588	0.2174	3.0310	0.0105	*
L(Steel, 8)	-0.3915	0.2165	-1.8090	0.0956	.
L(Steel, 9)	0.4515	0.2051	2.2010	0.0480	*
L(Steel, 11)	0.3525	0.1714	2.0570	0.0621	.
Aluminium	0.7670	0.3789	2.0240	0.0658	.
L(Aluminium, 1)	-0.5858	0.3155	-1.8560	0.0881	.
L(Aluminium, 4)	-0.8001	0.2319	-3.4510	0.0048	**
L(Aluminium, 5)	-1.0420	0.2440	-4.2700	0.0011	**
L(Aluminium, 9)	-0.5242	0.2623	-1.9990	0.0688	.
L(Aluminium, 10)	-0.8687	0.2453	-3.5410	0.0041	**
L(Semicon Ind, 1)	-0.9719	0.2717	-3.5780	0.0038	**
L(Semicon Ind, 3)	-0.8798	0.2337	-3.7650	0.0027	**
L(Semicon Ind, 4)	-0.6330	0.2438	-2.5960	0.0234	*
L(Semicon Ind, 8)	0.5944	0.3177	1.8710	0.0859	.
L(Semicon Ind, 9)	-0.5932	0.3191	-1.8590	0.0877	.
L(Semicon Ind, 10)	-0.6584	0.2984	-2.2060	0.0476	*
L(Semicon Ind, 12)	0.7196	0.3986	1.8050	0.0961	.
L(CPI, 2)	-0.1203	0.0661	-1.8190	0.0939	.
L(CPI, 6)	0.1497	0.0584	2.5650	0.0248	*
L(CPI, 7)	-0.1283	0.0664	-1.9340	0.0771	.
L(CPI, 11)	-0.2396	0.1145	-2.0930	0.0583	.
L(CPI, 12)	0.1903	0.0752	2.5320	0.0263	*
L(Ind Prod, 1)	-0.0066	0.0032	-2.0710	0.0606	.
L(Ind Prod, 3)	-0.0120	0.0037	-3.2030	0.0076	**
L(Ind Prod, 8)	0.0088	0.0031	2.8220	0.0154	*
L(Ind Prod, 11)	-0.0093	0.0035	-2.6210	0.0223	*
L(Unemployment, 1)	0.2218	0.0747	2.9700	0.0117	*
L(Unemployment, 7)	-0.1608	0.0533	-3.0160	0.0107	*
L(Unemployment, 12)	0.2592	0.0926	2.7990	0.0161	*
BEER	-0.0229	0.0088	-2.6100	0.0228	*
L(BEER, 7)	0.0217	0.0115	1.8910	0.0830	.

L(BEER, 11)	-0.0283	0.0125	-2.2670	0.0427	*
L(BEER, 12)	0.0346	0.0096	3.5930	0.0037	**
Business Conf	0.9313	0.2819	3.3040	0.0063	**
L(Business Conf, 1)	-2.4530	0.7782	-3.1520	0.0083	**
L(Business Conf, 2)	2.9630	1.0590	2.7970	0.0161	*
L(Business Conf, 3)	-2.0610	1.0710	-1.9240	0.0784	.
L(Business Conf, 11)	-1.1950	0.6290	-1.8990	0.0818	.
L(Business Conf, 12)	0.7370	0.2584	2.8520	0.0146	*
ect (from restricted ECM)	-1.8480	0.2053	-9.0020	0.0000	***

**** p<0.0001, ** p<0.01, *p<0.05, .p<0.1*

Adjusted R^2= 0.807; F-statistic= 5.506; Model p-value=0.001045

Table 13: South Korea – short-run equation with ARDL (solely significant coefficients) with maximum number of lags of the regressand (returns) and regressors set to (11,12,12,12,12,12,12,12,12,12,12,12). The model was preferred to its counterpart model with maximum number of lags of 12 on all variables, which also produced the lowest AIC value. This models with maximum number of lags of (11,12,12,12,12,12,12,12,12,12,12,12) is preferred because the best model with all variables set to up to 12 lags could reject the F-significance test of the ARDL bound test only at the 90% significance level and produced no significant long-term coefficients. By selecting the (11,12,12,12,12,12,12,12,12,12,12,12) model instead, the null hypothesis of no cointegration in the ARDL Bound test was rejected at the 95% significance level (even better) but still only one of the long-term coefficients was significant, as it will be shown in Appendix C (the coefficient pertaining to BEER)

	Estimate	Std. Error	t value	p-value	Significance
(Intercept)	-9.42415	2.461277	-3.829	0.001344	**
L(Return, 1)	-0.83433	0.226681	-3.681	0.001854	**
L(Return, 2)	-0.71452	0.260859	-2.739	0.013984	*
L(Return, 3)	-0.60138	0.200767	-2.995	0.008134	**
L(Return, 6)	-0.50069	0.256589	-1.951	0.067696	.
L(Return, 7)	-0.64012	0.22305	-2.87	0.01062	*
L(Return, 8)	-0.45073	0.210571	-2.141	0.047103	*
L(Market Ind, 8)	0.626208	0.31106	2.013	0.060213	.
L(Market Ind, 9)	0.685511	0.28018	2.447	0.025585	*
Auto Ind	0.883078	0.190462	4.637	0.000236	***
L(Auto Ind, 1)	0.631298	0.294068	2.147	0.046532	*
L(Auto Ind, 6)	0.645978	0.248052	2.604	0.018518	*
L(Auto Ind, 11)	-0.34502	0.154985	-2.226	0.039818	*
L(Brent CO, 2)	-0.71097	0.231608	-3.07	0.00694	**
L(Brent CO, 3)	-0.71342	0.246413	-2.895	0.010064	*
L(Brent CO, 4)	-0.57816	0.203313	-2.844	0.011223	*
L(Brent CO, 8)	-0.40539	0.165853	-2.444	0.025712	*
L(Brent CO, 9)	-0.80184	0.188409	-4.256	0.000533	***
L(Brent CO, 10)	-0.66102	0.190304	-3.473	0.002906	**
L(Brent CO, 11)	-0.54962	0.173399	-3.17	0.005601	**

L(Brent CO, 12)	-0.67041	0.182367	-3.676	0.001872	**
Steel	-0.38165	0.171607	-2.224	0.039988	*
L(Steel, 4)	0.417456	0.212771	1.962	0.066348	.
L(Steel, 9)	0.597465	0.179602	3.327	0.003994	**
L(Steel, 10)	0.702816	0.220899	3.182	0.005459	**
L(Steel, 11)	0.480721	0.177192	2.713	0.014769	*
L(Steel, 12)	0.559114	0.189553	2.95	0.008966	**
L(Aluminium, 11)	0.452401	0.219491	2.061	0.054927	.
L(Semicon Ind, 2)	-0.72662	0.404638	-1.796	0.090334	.
L(Semicon Ind, 3)	-0.95049	0.442124	-2.15	0.046256	*
L(Semicon Ind, 8)	-0.73102	0.352472	-2.074	0.053586	.
L(Semicon Ind, 9)	-0.87696	0.340964	-2.572	0.019792	*
L(Semicon Ind, 10)	-0.88337	0.366811	-2.408	0.027661	*
L(Semicon Ind, 11)	-1.01954	0.38694	-2.635	0.017377	*
CPI	0.089839	0.043903	2.046	0.056517	.
L(CPI, 1)	0.145966	0.055731	2.619	0.017956	*
L(CPI, 3)	-0.08319	0.043721	-1.903	0.074156	.
L(CPI, 4)	-0.15955	0.061809	-2.581	0.019416	*
L(CPI, 7)	0.144606	0.052422	2.759	0.013426	*
L(CPI, 9)	-0.13312	0.067601	-1.969	0.06544	.
Ind Prod	-0.00445	0.002421	-1.839	0.083482	.
L(Ind Prod, 3)	0.00621	0.001953	3.18	0.00548	**
L(Ind Prod, 4)	0.003548	0.001693	2.096	0.051369	.
L(Ind Prod, 6)	-0.00342	0.00158	-2.165	0.044928	*
L(Ind Prod, 9)	0.002883	0.001564	1.844	0.082717	.
L(Ind Prod, 10)	0.004678	0.001973	2.371	0.029809	*
Unemployment	0.24614	0.081623	3.016	0.007791	**
L(Unemployment, 7)	0.239519	0.13672	1.752	0.097809	.
L(Unemployment, 8)	-0.30588	0.099656	-3.069	0.006945	**
L(Unemployment, 9)	0.248865	0.107503	2.315	0.033375	*
L(Unemployment, 10)	-0.21133	0.115836	-1.824	0.085718	.
L(BEER, 7)	-0.04549	0.024891	-1.828	0.085203	.
L(BEER, 8)	0.043447	0.02054	2.115	0.049477	*
ect (from restricted ECM)	-5.4413	0.6669	-8.1590	0.0000	***

**** $p<0.0001$, ** $p<0.01$, *$p<0.05$, .$p<0.1$*

Adjusted R^2= 0.8931; F-statistic= 10.31; Model p-value=0.000001088

Table 14: France – short-run equation with ARDL (solely significant coefficients) with maximum number of lags of the regressand (returns) and regressors set to (10,12,11,12,12,11,12,11,12,12,12,11) - the two combinations producing a lower AIC did not reject the null of no cointegration of the ARDL Bound test at the 5% confidence interval

Appendix C: Long-run ARDL equations

	term	estimate	std.error	t.statistic	p.value
1	(Intercept)	-2.6433*	1.1302	-2.3388	0.0260
2	Market Ind	**1.9698** **	0.5009	3.9322	0.0004
3	Auto Ind	0.2126	0.2700	0.7874	0.4370
4	Brent CO	0.0930	0.3404	0.2733	0.7864
5	Steel	-0.2748	0.3290	-0.8353	0.4099
6	Aluminium	0.1146	0.6396	0.1792	0.8589
7	Semicon Ind	-0.1185	0.2560	-0.4631	0.6466
8	CPI	**-0.0080** **	0.0025	-3.2022	0.0031
9	Ind Prod	**-0.0091** **	0.0017	-5.4564	0.0000
10	Unemployment	**-0.0148** .	0.0075	-1.9612	0.0589
11	BEER	0.0021	0.0043	0.4830	0.6325
12	Business Conf	**0.0423****	0.0108	3.9057	0.0005

**** p<0.0001, ** p<0.01, *p<0.05, .p<0.1*

Table 15: Italy – long-run equation with ARDL with maximum number of lags of the regressand (returns) and the regressors set to (10,10,6,10,11,12,12,10,12,10,12,9).

	term	estimate	std.error	t.statistic	p.value
1	(Intercept)	1.2731	1.3170	0.9667	0.3545
2	Market Ind	1.0889	0.7945	1.3705	0.1978
3	Auto Ind	**-0.3855** .	0.1929	-1.9989	0.0709
4	Brent CO	1.9009 *	0.6717	2.8300	0.0164
5	Steel	0.2700	0.6426	0.4201	0.6825
6	Aluminium	-0.5516	1.4305	-0.3856	0.7072
7	Semicon Ind	**0.8503** *	0.3756	2.2639	0.0448
8	CPI	**0.0095** **	0.0029	3.3028	0.0070
9	Ind Prod	-0.0016	0.0039	-0.4193	0.6830
10	Unemployment	**0.0247** .	0.0090	2.7546	0.0187
11	BEER	-0.0224	0.0136	-1.6418	0.1289
12	Business Conf	1.2731	1.3170	0.9667	0.3545

**** p<0.0001, ** p<0.01, *p<0.05, .p<0.1*

Table 16: US – long-run equation with ARDL with maximum number of lags of the regressand (returns) and the regressors set to (12,12,12,12,12,12,12,12,12,12,12,12).

	term	estimate	std.error	t.statistic	p.value
1	(Intercept)	**2.9938** ***	0.3719	8.0492	0.0000
2	Market Ind	**0.2040** *	0.0762	2.6774	0.0127
3	Auto Ind	**0.6289** ***	0.0959	6.5552	0.0000
4	Brent CO	**-0.8294** ***	0.1431	-5.7967	0.0000
5	Steel	**0.4777** **	0.1128	4.2334	0.0003
6	Aluminium	**0.5529** **	0.1597	3.4622	0.0019
7	Semicon Ind	**0.3000** ***	0.0403	7.4535	0.0000
8	CPI	**-0.0104** ***	0.0016	-6.7022	0.0000
9	Ind Prod	**0.0018** ***	0.0004	4.7609	0.0001
10	Unemployment	0.0128	0.0114	1.1228	0.2718
11	BEER	**-0.0030** ***	0.0003	-9.3341	0.0000
12	Business Conf	**-0.0192** ***	0.0027	-7.1108	0.0000

**** p<0.0001, ** p<0.01, *p<0.05, .p<0.1*

Table 17: China – long-run equation with ARDL with maximum number of lags of the regressand (returns) and the regressors set to (10,12,10,12,12,12,7,12,12,12,8,10).

	term	estimate	std.error	t.statistic	p.value
1	(Intercept)	-6.9059	5.3606	-1.2883	0.2219
2	Market Ind	3.8738	2.9706	1.3041	0.2167
3	Auto Ind	-0.0280	0.9188	-0.0305	0.9762
4	Brent CO	-0.5566	0.6017	-0.9251	0.3732
5	Steel	1.7295	1.2715	1.3602	0.1988
6	Aluminium	-1.5616	1.4618	-1.0683	0.3064
7	Semicon Ind	-1.4052	1.0356	-1.3569	0.1998
8	CPI	0.0173	0.0157	1.0954	0.2948
9	Ind Prod	-0.0096	0.0091	-1.0585	0.3107
10	Unemployment	-0.0180	0.0530	-0.3389	0.7406
11	BEER	**-0.0032** .	0.0016	-2.0482	0.0631
12	Business Conf	0.0677	0.0509	1.3285	0.2087

**** p<0.0001, ** p<0.01, *p<0.05, .p<0.1*

Table 18: South Korea – long-run equation with ARDL with maximum number of lags of the regressand (returns) and the regressors set to (11,12,12,12,12,12,12,12,12,12,12,12).

	term	estimate	std.error	t.statistic	p.value
1	(Intercept)	**-1.7320** ***	0.3347	-5.1746	0.0001
2	Market Ind	0.3477	0.5028	0.6915	0.4986
3	Auto Ind	**0.5002** *	0.1747	2.8637	0.0108
4	Brent CO	**-1.0055** **	0.2400	-4.1901	0.0006
5	Steel	**0.6084** **	0.1911	3.1833	0.0054
6	Aluminium	0.0600	0.3337	0.1799	0.8594
7	Semicon Ind	**-1.0013** **	0.2825	-3.5451	0.0025
8	CPI	**0.0045** *	0.0015	2.8948	0.0101
9	Ind Prod	**0.0028** *	0.0012	2.3702	0.0299
10	Unemployment	**0.0177** *	0.0075	2.3456	0.0314
11	BEER	**0.0043** *	0.0019	2.2875	0.0353
12	Business Conf	0.0039	0.0035	1.0992	0.2870

**** p<0.0001, ** p<0.01, *p<0.05, .p<0.1*

Table 19: France – long-run equation with ARDL with maximum number of lags of the regressand (returns) and the regressors set to (10,12,11,12,12,11,12,11,12,12,12,11).

Appendix D: Other graphs

Company	Average market cap (2007 - 2021) in million USD	Country of domicile
TESLA INC	169,714.27	USA
TOYOTA MOTOR CORP.	164,801.25	JAPAN
RIVIAN AUTOMOTIVE INC	93,353.91	USA
VOLKSWAGEN AG	73,020.58	GERMANY
XPENG INC	67,663.10	CHINA
MERCEDES-BENZ GROUP AG	58,702.06	GERMANY
GENERAL MOTORS CO	54,457.71	USA
FORD MOTOR CO	44,363.09	USA
BAYERISCHE MOTOREN WERKE AG	44,339.26	GERMANY
LI AUTO INC	41,445.45	CHINA
MITSUBISHI CORP	36,812.69	JAPAN
NISSAN MOTOR CO LTD	34,219.38	JAPAN
LUCID GROUP INC	32,617.17	USA

SAIC MOTOR CORP LTD	32,413.18	CHINA
HYUNDAI MOTOR CO	28,807.54	SOUTH KOREA
AUDI AG	27,101.01	GERMANY
FERRARI NV	26,564.10	ITALY
STELLANTIS NV	25,878.18	FRANCE
BYD CO LITD	23,780.09	CHINA
RENAULT SA	19,429.21	FRANCE
PORSCHE AUTOMOBIL HLDG-PRF	17,657.61	GERMANY
KIA CORP	15,866.37	SOUTH KOREA
SUZUKU MOTOR CORP	14,700.30	JAPAN
SUBARU CORP	14,146.26	JAPAN
GREAT WALL MOTOR CO	11,245.58	CHINA
GEELY AUTOMOBILE HOLDINGS LTD	10,659.78	CHINA
HARLEY-DAVIDSON INC	8,607.96	USA
MAZDA MOTOR CORP	7,012.56	JAPAN
CHONGQING CHANGAN AUTOMOBILE CO LTD	6,441.25	CHINA
YAMAHA MOTOR CO LTD	6,415.96	JAPAN
BRILLIANCE CHINA AUTOMOTIVE HOLDINGS LTD	5,372.38	CHINA
MOTORS LIQUIDATION CO	5,365.54	USA
HINO MOTORS LTD	4,910.81	JAPAN
FAW JIEFANG GROUP CO LTD	3,781.43	CHINA
FISKER INC	2,523.82	USA
CANOO INC	1,834.93	USA
DONGFENG AUTOMOBILE CO LTD	1,697.19	CHINA
GENERAL MOTORS FINANCIAL CO	1,668.09	USA

LORDSTOWN MOTORS CORP-CL A	1,416.89	USA
MOTORS LIQUIDATION CO GUC TR	726.89	USA
ELECTRIC LAST MILE SOLUTIONS	674.51	USA
SSANGYONG MOTOR CO	516.00	SOUTH KOREA
LIGHTNING EMOTORS INC	395.88	USA
VOLCON INC	186.93	USA
ARCIMOTO INC	177.15	USA
FOX E-MOBILITY AG	151.95	GERMANY
VRDT CORP	114.17	USA
PININFARINA SPA	105.43	ITALY
ELIO MOTORS INC	95.38	USA
ENVIROTECH VEHICLES INC	85.51	USA
MULLEN AUTOMOTIVE INC	55.28	USA
AYRO INC	25.64	USA
CLEAN LOGISTICS SE	14.00	GERMANY
SALEEN AUTOMOTIVE INC	11.92	USA
CURTISS MOTORCYCLES CO INC	5.66	USA
VIPER POWERSPORTS INC	5.43	USA
PROUT AG	2.94	GERMANY
T3 MOTION INC	2.14	USA
KOEGEL FAHRZEUGWERKE AG-VORZ	0.42	GERMANY
PALADIN HOLDINGS INC	0.05	USA
MICROHOLDINGS US INC		USA
RODEDAWG INTERNATIONAL INDUS		USA
GEMBALLA HOLDING SE		GERMANY

Table 20: The reviewed sample of 63 auto manufacturers from seven distinct countries ranked from highest to lowest in terms of average yearly market capitalisation in the period January 2007 – December 2021

Name	Type	Country
S&P 500	Market benchmark index	USA
DAX	Market benchmark index	GERMANY
SSE COMPOSITE INDEX	Market benchmark index	CHINA
NIKKEI 225	Market benchmark index	JAPAN
KOSPI	Market benchmark index	SOUTH KOREA
CAC 40	Market benchmark index	FRANCE
FTSE MBI ITALY INDEX	Market benchmark index	ITALY
DOW JONES AUTOMOBILES INDEX	Automotive benchmark index	USA
STOXX 600 EUROPE AUTOMOBILES AND PARTS INDEX	Automotive benchmark index	GERMANY, ITALY, FRANCE
STOXX 600 ASIA PACIFIC AUTOMOBILES AND PARTS INDEX	Automotive benchmark index	CHINA, JAPAN, AND SOUTH KOREA
DOW JONES US TOTAL MARKET SEMICONDUCTORS INDEX	Semiconductor index	USA
GERMANY SEMICONDUCTORS INDEX (FI1305DE) - BY FACTSET	Semiconductor index	GERMANY
CHINA SEMICONDUCTORS INDEX (FI1305CN) - BY FACTSET	Semiconductor index	CHINA
JAPAN SEMICONDUCTORS INDEX (FI1305A3) - BY FACTSET	Semiconductor index	JAPAN
KRX SEMICONDUCTOR INDEX	Semiconductor index	SOUTH KOREA
FRANCE SEMICONDUCTORS INDEX (FI1305FR) - BY FACTSET	Semiconductor index	FRANCE
S&P ITALY BMI SEMICONDUCTORS INDEX - BY FACTSET	Semiconductor index	ITALY

Table 21: Explanatory variables used in regressions including the market, automotive, and semiconductor indices across seven divergent countries

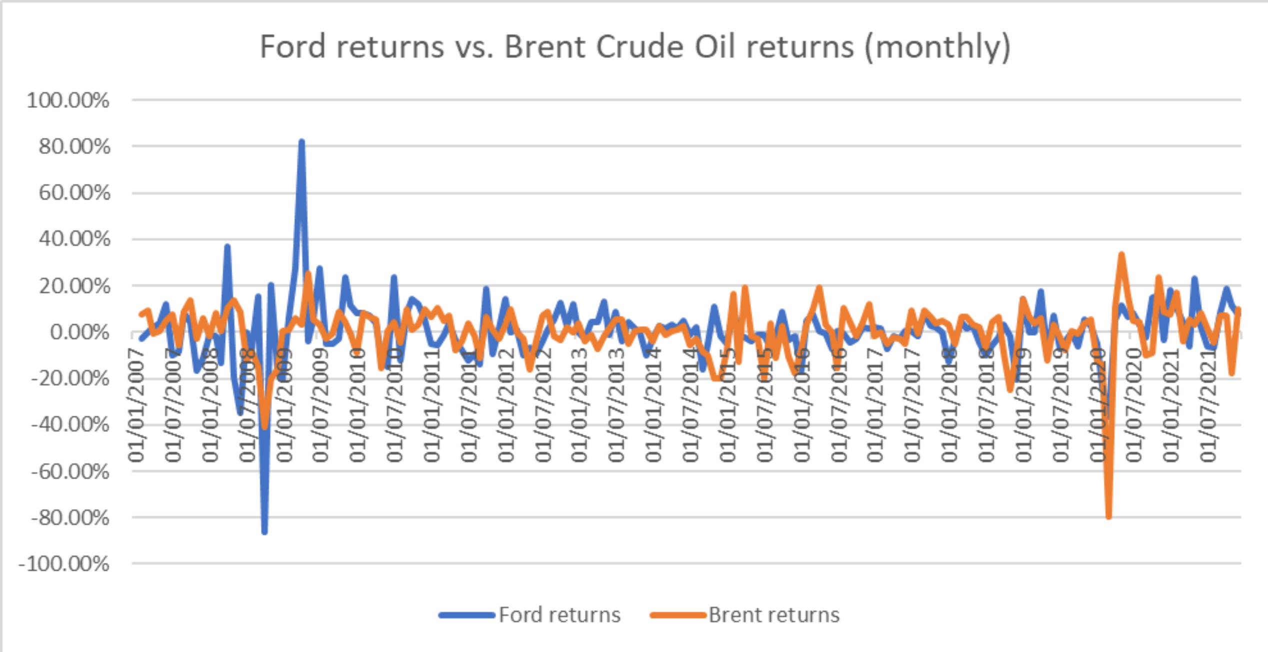

Figure 3: Interplay between Ford returns and Brent crude oil return (January 2007 – December 2021)

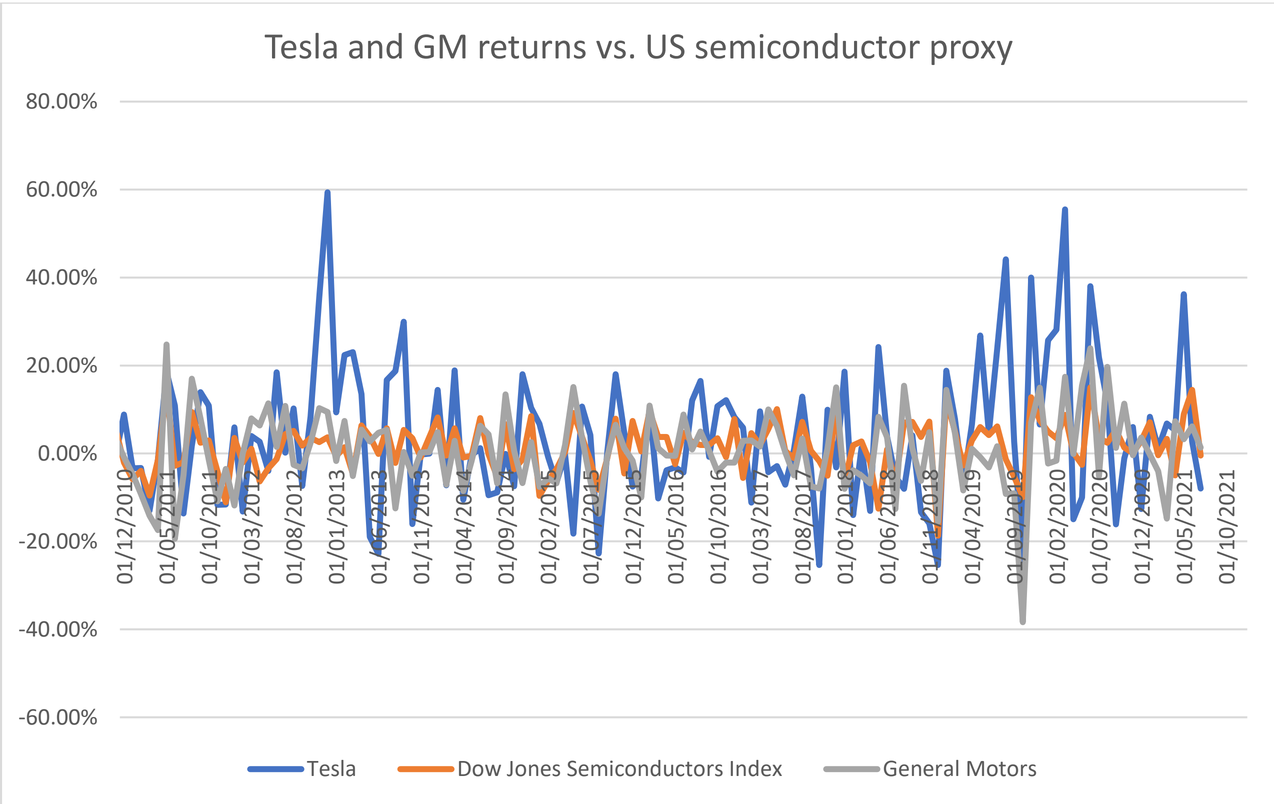

Figure 4: Interplay between Tesla and General Motors (respectively – an EV pioneer and a legacy US automaker) in the timeframe December 2010 – December 2021 (period was restrained because GM's IPO took place in November 2010)

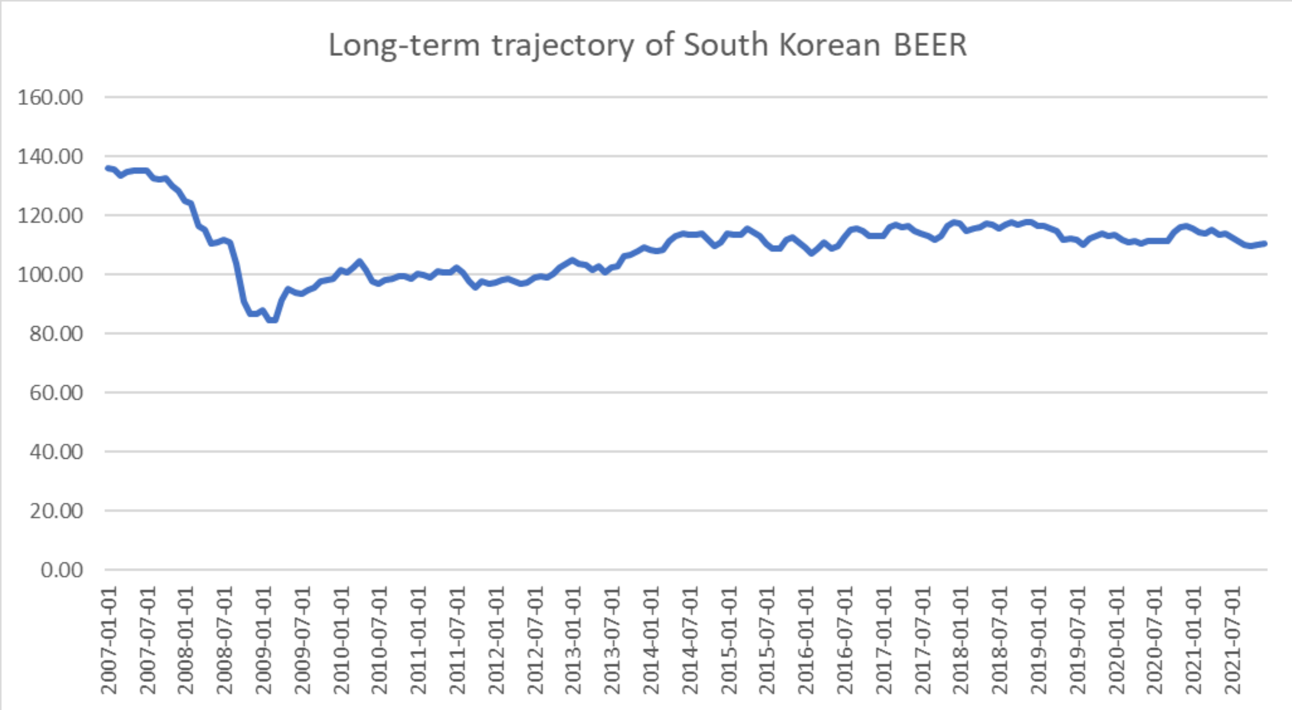

Figure 5: Long-term trajectory of the levels of the Broad Effective Exchange Rate (BEER) in South Korea (January 2007 – December 2021)

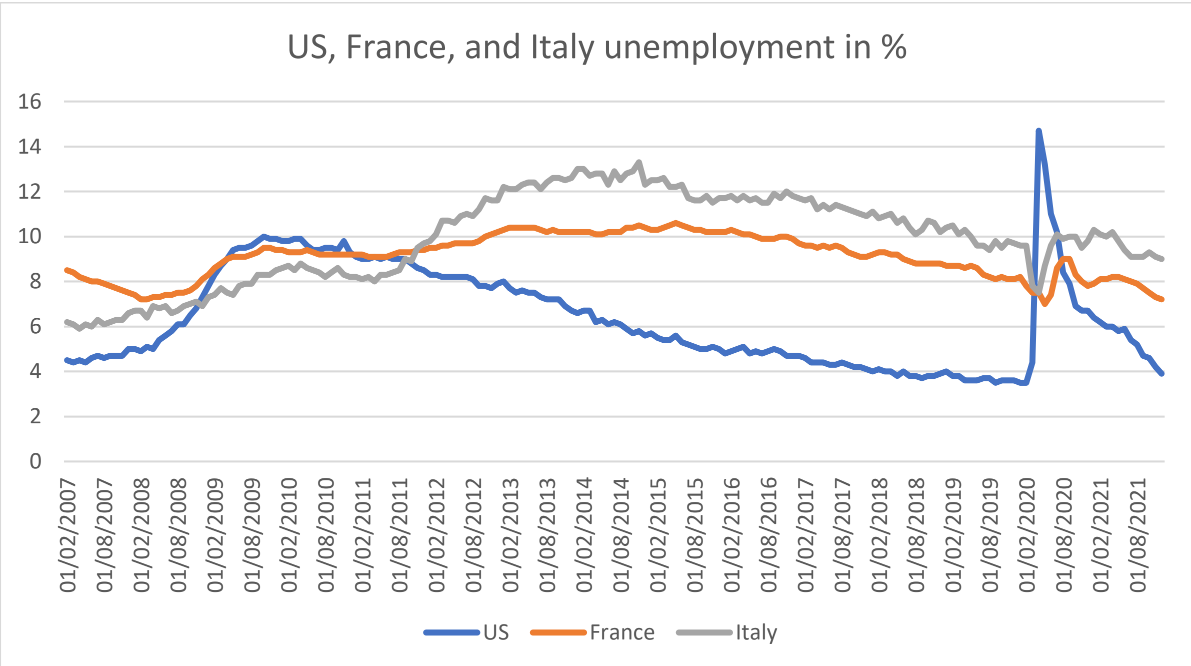

Figure 6: Comparison of unemployment in the US, France, and Italy (January 2007 – December 2021)

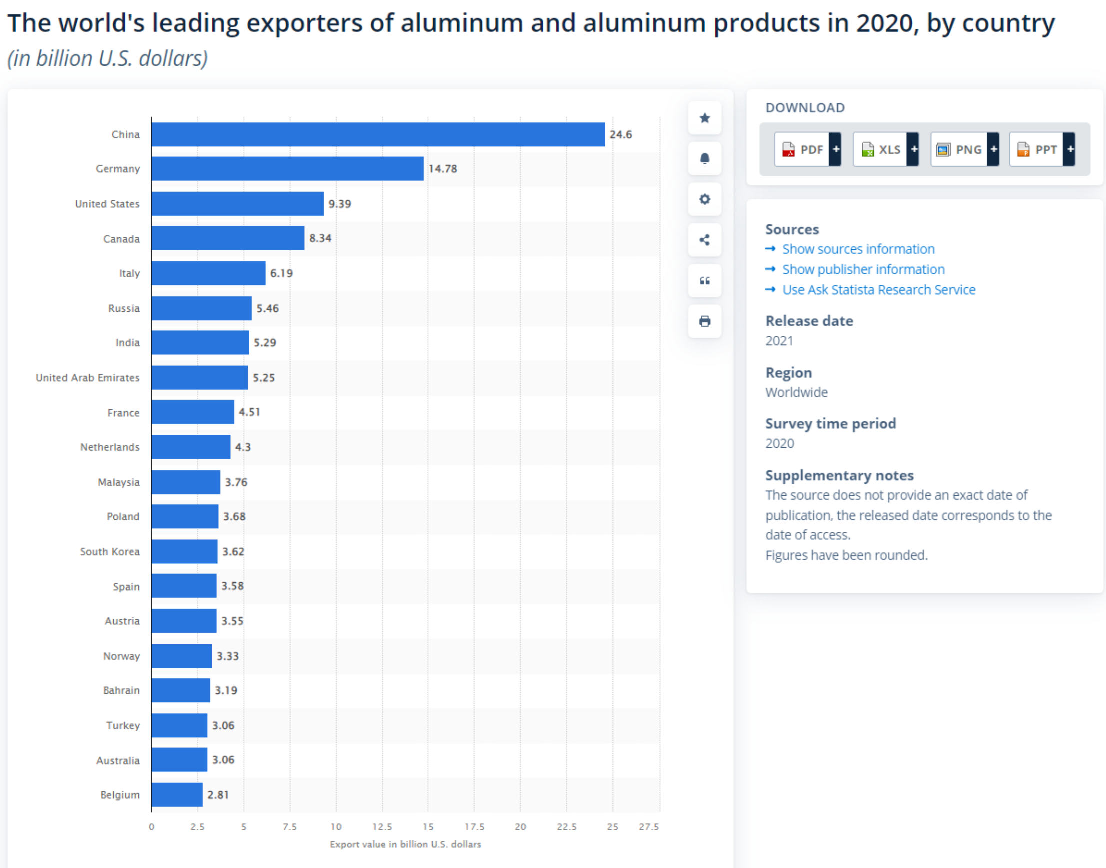

Figure 7: Leading aluminium exporters (Statista, 2020)

Figure 8: GDP per capita trends among EU member states (1998 – 2018) (Financial Times, 2018)

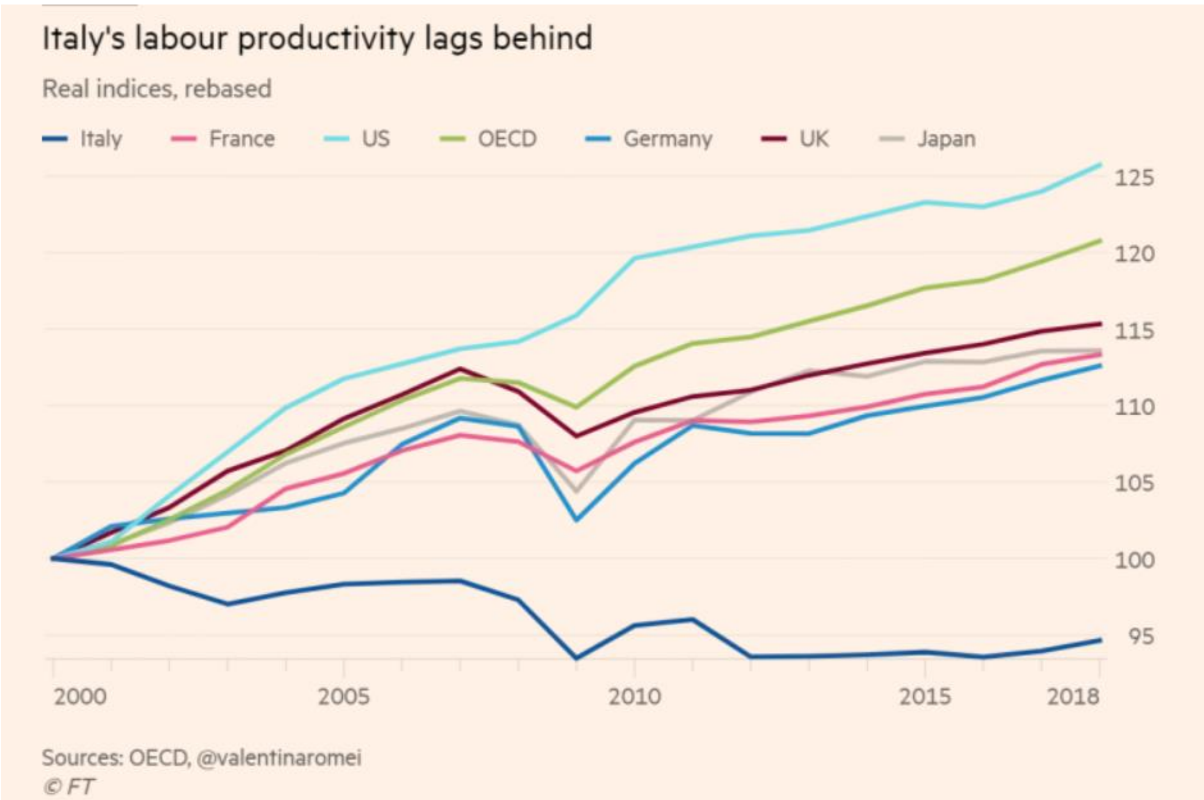

Figure 9: Labour productivity in OECD countries (Financial Times, 2018)

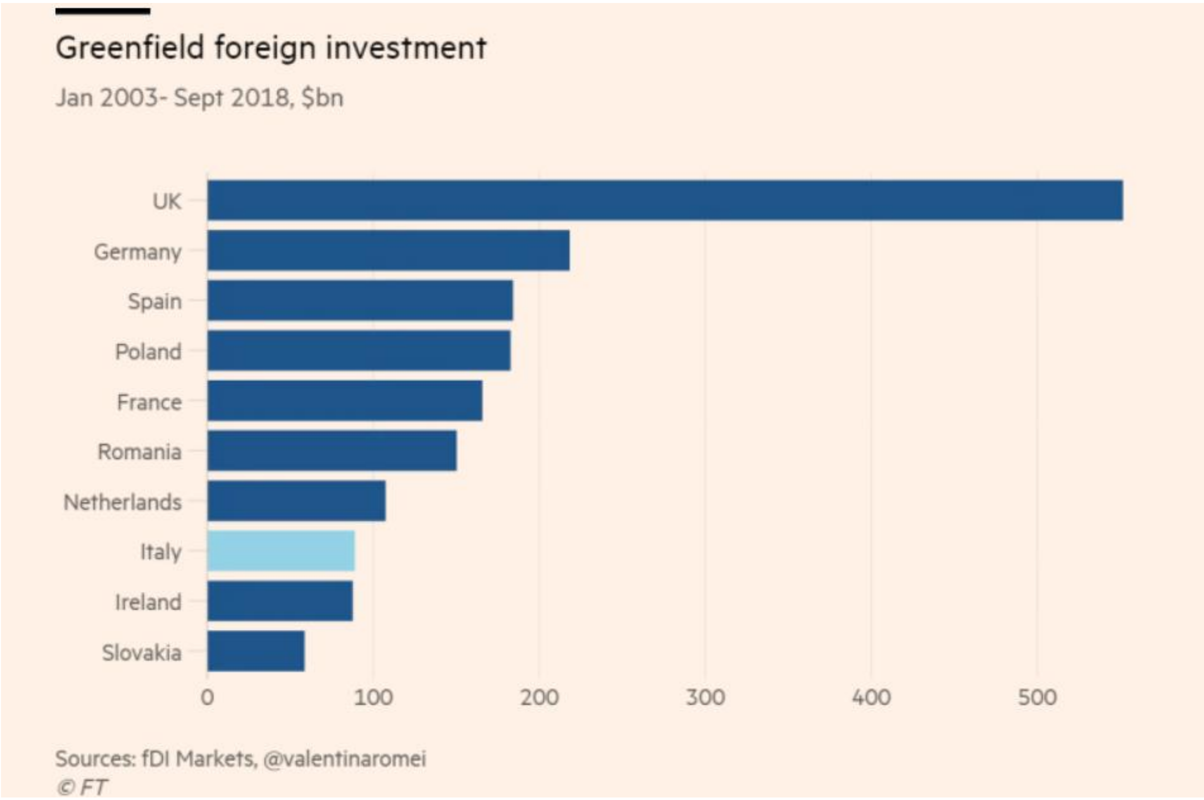

Figure 10: Greenfield foreign investments in EU member states (Financial Times, 2018)

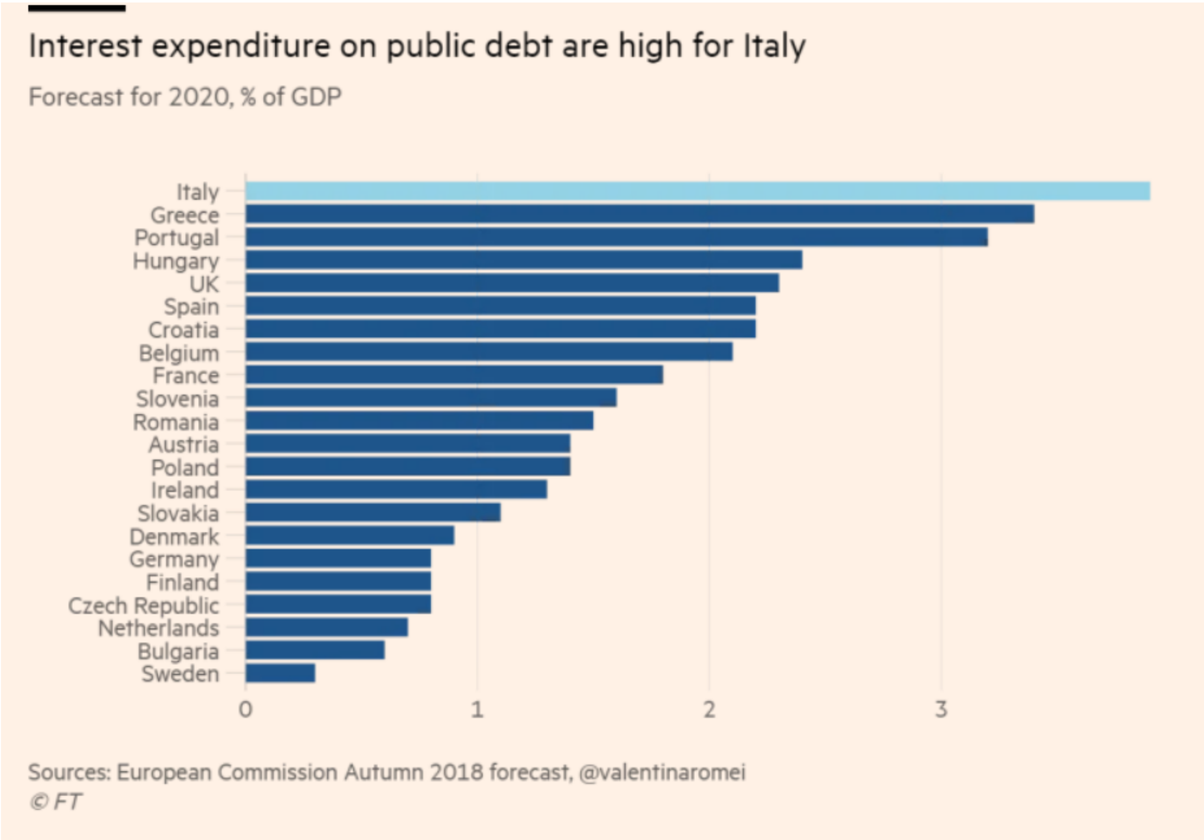

Figure 11: Interest expenditure on public debt in EU member states (Financial Times, 2018)

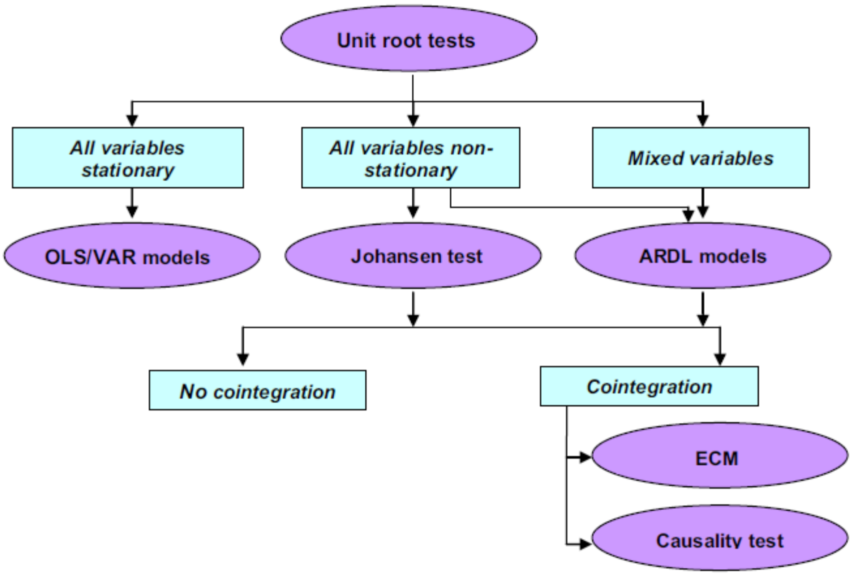

Figure 12: How does stationarity of time series shape the implementation of different statistical models? (Shrestha & Bhatta, 2018)