Julius-Maximilians-Universität Würzburg

Chair of China Business and Economics

Market forecasting in China:

An Artificial Neural Network approach to optimize the accuracy of sales forecasts in the Chinese automotive market

Inaugural-Dissertation

zur Erlangung der Doktorwürde der Philosophischen Fakultät
der Julius-Maximilians-Universität Würzburg

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Berlin, März 2020

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Tag des Kolloquiums: 12. Februar 2020

Abstract/Abstrakt

Sales forecasts are an essential determinant of operational planning in entrepreneurial organizations. However, in China, as in other emerging markets, *monthly* sales forecasts are particularly challenging for multinational automotive enterprises and suppliers. A chief reason for this is that conventional approaches to sales forecasting often fail to capture the underlying market dynamics.

To that end, this dissertation investigates the application of Artificial Neural Networks with an implemented backpropagation algorithm as a more "unconventional" sales forecasting method. A key element of statistical modelling is the selection of superior leading indicators. These indicators were collected as part of the researcher's expert interviews with multinational enterprises and state associations in China. The economic plausibility of all specified indicators is critically explored in qualitative-quantitative pre-selection procedures. The overall objective of the present study was to improve the accuracy of monthly sales forecasts in the Chinese automotive market. This objective was achieved by showing that the forecasting error could be lowered to a new benchmark of less than 10% in an out-of-sample forecasting application.

Absatzprognosen sind ein zentraler Bestandteil der operativen Unternehmensplanung. In China, wie auch in anderen Schwellenländern, stellen vor allem monatliche Prognosen jedoch eine besondere Herausforderung für multinationale Automobilhersteller und deren Zulieferer dar. Ein Grund hierfür ist, dass konventionelle Prognoseverfahren der außergewöhnlich hohen Marktdynamik nicht ausreichend gerecht werden.

In der vorliegenden Dissertationsschrift werden Künstliche Neuronale Netze mit integriertem Backpropagation-Algorithmus als alternatives Marktprognoseverfahren eingehend beleuchtet. Erprobt vor allem in hochvolatilen Finanzmarktanwendungen ist diese Form künstlicher Intelligenz imstande, hochkomplexe Zusammenhänge zu entschlüsseln und selbständig aus Prognosefehlern zu lernen. Ein Kernelement der statistischen Modellierung ist die Auswahl von geeigneten Frühwarnindikatoren, die unter anderem durch Experteninterviews in chinesischer Sprache bei Regierungsablegern erhoben wurden. Die ökonomische Plausibilität der genannten Indikatoren wird in qualitativ-quantitativen Vorauswahlverfahren kritisch reflektiert. Grundlegendes Ziel des Forschungsprojektes war es, die Güte der monatlichen Absatzprognosen im chinesischen Automobilmarkt zu verbessern. Dieses Ziel konnte mit Unterschreitung der entscheidenden 10%-Prognosefehlerschwelle im Validierungsdatensatz erreicht werden.

Danksagung

Die vorliegende Dissertationsschrift ist am Lehrstuhl für China Business and Economics an der Julius-Maximilians-Universität Würzburg entstanden. Daher möchte ich mich zunächst in aller Herzlichkeit bei meiner Doktormutter, Prof. Doris Fischer, und meinem Zweitgutachter, Prof. Björn Alpermann, für die umfassende Betreuung meines Forschungsprojektes bedanken. Ein besonderer Dank gebührt meinem Mentor, Gerhard Mennecke, der mir die Möglichkeit zur Anfertigung dieser Arbeit im Rahmen des VW-Doktorandenprogrammes ermöglicht hat. Hervorheben möchte ich zudem meinen Freund Jin Jianming, dem ich die meisten meiner Interviewkontakte und einzigartige Einblicke in die chinesische Automobilindustrie zu verdanken habe.

Die Widmung dieser Dissertationsschrift spreche ich meinen Eltern aus. Sie haben mich auch in schwierigen Zeiten jederzeit unterstützt und waren daher zusammen mit meinen beiden Schwestern der wichtigste Rückhalt in meinem persönlichen und akademischen Werdegang.

Miriam möchte ich für ihre Geduld in der Zeit der Anfertigung meiner Arbeit danken. Ebenso danke ich Elisa für Ihren moralischen Beistand in den letzten Monaten meiner Promotionszeit. Ohne das Verständnis der beiden an den vielen Wochenenden und im Urlaub wäre die Fertigstellung dieser Dissertationsschrift zum heutigen Zeitpunkt nicht möglich gewesen.

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List of abbreviations

ACF	Auto-correlation function
ADF	Augmented Dickey-Fuller test
AI	Artificial Intelligence
ANN	Artificial Neural Network
AQI	Air Quality Index
ARMA	Autoregressive moving average
ARIMA	Autoregressive integrated moving average
BEV	Battery electric vehicle
CAGR	Compound annual growth rate
CCF	Cross-correlation function
CDMA2000	Code Division Multiple Access 2000
CHIBOR	China Interbank Offered Rate
ConConf	Consumer confidence
CPI	Consumer Price Index
CSI 300	Capitalization-weighted stock market index 300
EUR	Euro
FDI	Foreign Direct Investment
FYP	Five-Year Plan
GDP	Gross domestic product
GNP	Gross national product
HDI	Human Development Index
HDR	Human Development Report
HEV	Hybrid electric vehicle
i.e.	id est
ICE	Internal combustion engine
M2	Money supply (second measurement)
MAPE	Mean absolute percentage error
MLP	Multi-layer perceptron
MNE	Multinational enterprise
MoM	Month-over-month
MPV	Multi-purpose vehicle
MSRP	Manufacturer’s suggested retail price
NBS	National Bureau of Statistics
NDRC	National Development and Reform Commission
NEV	New Energy Vehicles

NIE	New Institutional Economics
NPC	National People's Congress
OECD	Organization for Economic Cooperation and Development
PACF	Partial auto-correlation function
PBOC	People's Bank of China
PHEV	Plug-in hybrid electric vehicle
PPI	Producer Price Index
PV sales	Passenger vehicle sales
r	Coefficient of correlation
r^2	Coefficient of determination
RBV	Resource-based view
RMB	Renminbi
SDR	Special drawing rights
SHCOMP	Shanghai Stock Exchange Composite Index
SHIBOR	Shanghai Interbank Offered Rate
SIC	State Information Center
SLP	Single-layer perceptron
SPSS	Statistical Package for the Social Sciences (IBM software)
SUV	Sport utility vehicle
TD-SCDMA	Time Division-Synchronous Code Division Multiple Access
TMT	Telecommunication, (social) media and IT
Triple-A	Acquisition, assimilation, application (dynamic capability)
UN	United Nations
UNDP	United Nations development program
USD	U.S. dollar
VAR	Vector autoregressions
VRIN	Valuable, rare, imperfectly imitable, non-substitutable (resources)
VW	Volkswagen
W-CDMA	Wideband-Code Division Multiplexing Access
WTO	World Trade Organization
YoY	Year-over-year

I Research introduction

For many years, the Chinese automotive market has been a cash cow for multinational enterprises (MNEs). After China's accession to the World Trade Organization in 2001, the passenger car market registered an impressive compound annual growth rate of roughly 18%. In 2017 alone, passenger vehicle sales (PV sales) were at a record high, nearing 25 million units.[1] For this reason, all major automotive MNEs added China to their global sales strategy; they acknowledged that a presence in China is a "must-do", a question of medium-term survival.

What has however been widely disregarded is that the patterns seen in Chinese automotive market growth have been significantly shaped by massive state interference in the form of short-term and quick-impact policies.[2] These ad hoc policies can irrefutably be thought of as protective or remedial government action in response to adverse developments with nationwide implications, much like rising air pollution levels or subsiding economic growth rates. Viewed from the standpoint of a PV sales forecaster, this type of persistent **regulatory insecurity** leaves deep and permanent scars in the set of economic indicators to be analyzed, which, in turn, constitutes one decisive reason for inaccurate predictions. This circumstance is especially true for monthly PV sales forecasters who are, per se, faced with shorter reporting intervals and fewer opportunities to relativize and offset unexpected developments in their predictive modelling efforts.

Closely linked to regulatory insecurity is the aspect of state interference in China's national and local statistical work. Critics of Chinese official growth reports repeatedly charge that certain GDP data components have not been proven to be as reliable as their equivalents in more advanced economies, because they tend to overstate nominal GDP growth and understate inflation.[3] That said, it certainly comes as a surprise that well-established automotive market experts are still inclined to disregard this sort of **unreliable market information** in their quantitative models, thereby further inhibiting sound and conclusive assessments of the market's actual state of health.

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1 Data sources: Chinese Association of Automobile Manufacturers.
2 Fischer, Doris (2015), p. 18.
3 Koch-Weser, Iacob N. (2013), p. 4.

In literature, neither of the challenges mentioned above are considered a phenomenon specific to China. They are among the most cogent reasons for unsuccessful internationalization strategies on behalf of MNEs in emerging markets and commonly referred to as "**institutional voids**".[4] In business practice, the deficiency of dealing with institutional voids presents an intricate and as yet unresolved challenge for many MNEs. As a case in point, the levy on cars with an engine capacity up to 1.6 liters was cut in half to 5% in a short notice announcement issued by the Chinese Ministry of Finance in October of 2015. This came amid mounting concerns about overall Chinese economic development after the stock market crash in June of 2015. In the months that followed, PV sales forecasters, which were interviewed as part of this thesis, had no choice but to abandon their self-appointed objective of a 10% monthly forecasting error. Further, they felt forced to reveal that their conventional regression-based models, including a standard set of traditional economic leading indicators, were incapable of anticipating market development tendencies in times of drastic supply and demand changes.

To avoid future situations in which entrepreneurial decision-making is predominantly based on erratic sales planning premises and associated market dissonance, this thesis has been motivated by the conviction that a more "unconventional" approach to model building is key to capture the inherent characteristic of structural change in emerging markets. In that sense, this study leverages the unique merits of **Artificial Neural Networks** (ANNs), which have a long history of research on finance and economic modeling[5] in advanced economies and emerging markets[6]. ANNs belong to the category of structure-detecting non-parametric methods[7] and, as such, excel at exploring highly complex and dynamic data relationships.[8] It is exactly this distinguishing feature that makes them interesting to examine in the wider context of forecasting in emerging markets and in the more specific context of improving the accuracy of PV sales forecasts in the Chinese automotive market.

I.1 Theory

The example of inaccurate PV sales forecasts in the Chinese automotive market illustrates that Western MNEs have to deal with certain operational challenges in emerging markets that they

4 Khanna, Tarun; Palepu, Krishna G. (2010), pp. 13 f.
5 Huang, Wei; Lai, Kin Keung; Nakamori, Yoshiteru (2007), p. 114.
6 See for e.g. Maciel, Leandro S.; Ballini, Rosangela (2010); Zhang, Dabin; Yu, Lean; Wang, Shouyang et al. (2010); Chen, An-Sing; Leung, Mark T.; Daouk, Hazem (2003).
7 Backhaus, Klaus; Erichson, Bernd; Plinke, Wulff et al. (2018), p. 15.
8 Zhang, Peter G. (2004b), pp. 2 f.; Haykin, Simon (2009), p. 3.

are not accustomed to in their home countries[9]. These challenges can be mainly attributed to the presence of institutional voids, a term used by Khanna and Palepu to explain the imponderables that MNEs typically face in emerging markets due, in large part, to a lack of assertive formal institutions and intermediaries.[10]

Based on the fundamentals of the New Institutional Economics theory, and especially in line with Williamson's view on the importance of institutions at the micro-analytic level of organization[11], Khanna and Palepu acknowledge the essential role of institutions to mediate transactions between economic agents and, as a result, avoid unnecessarily high transaction costs.[12] They point out that a clear understanding of institutional voids is an indispensable necessity for MNEs that are seeking to mitigate entrepreneurial uncertainty and thereby hope to gain a foothold in emerging markets.[13] In this vein, they call for a more viable entrepreneurial approach to managing institutional voids, one that helps them outmaneuver any sort of operational challenges emanating from these voids or even capitalizing on palpable opportunities to build businesses based on filling them.[14] Among a set of four principal strategic choices, one such approach is to adapt the most crucial enterprise-internal business processes in a way that matches the emerging market's institutional environment.[15]
With that in mind, the underlying research question of this thesis is as follows:
How, from a MNE's point of view, does one adapt in-house forecasting processes in a way that adequately responds to institutional void-related risks in emerging markets?

One critical assumption of this thesis is that the resource-based view (RBV) on an enterprise represents a pragmatic entrepreneurial framework to address the prevalence of institutional void-related risks in emerging markets. Generally speaking, the RBV suggests that an enterprise's potential to build and sustain competitive advantage is contingent upon its idiosyncratic bundle of resources and capabilities.[16] This bundle may either already reside within or is to

9 In the following, it is assumed that MNEs are based in advanced economies.
10 Khanna, Tarun et al. (2010), pp. 15 f.
11 Williamson, Oliver E. (1996), 326 ff.; Williamson, Oliver E. (2000), p. 597.
12 Khanna, Tarun et al. (2010), p. 16, 21.
13 Khanna, Tarun et al. (2010), p. 86.
14 Khanna, Tarun et al. (2010), p. 16, 44.
15 Khanna, Tarun et al. (2010), pp. 40 ff.
16 Glowik, Mario (2016), p. 72; Henry, Anthony E. (2018), p. 115.

be acquired by an enterprise.[17] Learning how to mobilize this bundle is an essential outcome that decision-makers seek when examining their organization.[18]

In other words, the RBV considers strategy analysis from the standpoint of an enterprise's (internal) business environment, whereas the concept of institutional voids tends to focus more on the (external) market environment.[19] This thesis investigates how both environments can be aligned and converted into a **dynamic process of forecasting with ANNs**, a process that will serve to close the research gap presented by existing literature on business forecasts in emerging markets.

I.2 Research strategy

This thesis reverts to the use of the two predominant dimensions of research strategy[20], i.e. qualitative and quantitative research. As such, qualitative research highlights peoples' words in the collection and analysis of data. It reflects a process of induction to the relationship between theory and research, and involves drawing generalizable inferences out of observations. Therefore, the main emphasis of qualitative research is to be placed on the generation of theories.[21] By contrast, quantitative research, as the name implicates, focuses on quantification in the collection and analysis of data. It represents a process of deduction to the relationship between theory and research, in which theory guides research rather than being its outcome.[22] Thus, the chief emphasis of quantitative research is to be placed on the testing of theories.[23]

Investigations on the dissemination of various research strategies across different fields have shown that there has indeed been an increase in empirical articles based on a combination of qualitative and quantitative attributes within a single project.[24] Exponents of this so-called "mixed methods" research approach advocate a pragmatic over a principled method of data collection and data analysis, arguing that the selection of an appropriate research strategy should be driven first and foremost by the research objective(s).[25] On the other hand, positions

17 Henry, Anthony E. (2018), p. 116.
18 Hitt, Michael A.; Ireland, R. Duane; Hoskisson, Robert E. (2016), p. 80.
19 Henry, Anthony E. (2018), p. 115.
20 Bryman, Alan; Bell, Emma (2015), p. 37.
21 Bryman, Alan et al. (2015), p. 25.
22 Bryman, Alan et al. (2015), p. 19.
23 Bryman, Alan et al. (2015), p. 25.
24 Bryman, Alan et al. (2015), p. 643.
25 Biesta, Gert (2012), p. 147; Bryman, Alan et al. (2015), p. 643.

against the use of mixed methods research strategies usually center on the idea that qualitative and quantitative research attributes are distinctively entrenched in epistemological and ontological commitments and thus methodologically incompatible[26].

Notwithstanding the latter argument against a combination of both research dimensions, mixed methods research has gained importance in empirical research and is now employed regularly as a distinctive research strategy.[27] This statement holds particularly true in the field of business research, where a comprehensive survey of 142 articles in four different subfields[28] has determined that 12-17% of all investigated articles between 2003 and 2012 were based on both qualitative and quantitative research.[29] This survey further revealed that the vast majority of articles followed a sequential rather than a concurrent use of both research dimensions, meaning that qualitative research preceded quantitative research attributes or vice versa. Moreover, quantitative research constituted the "leading" research dimension in most of the 142 articles investigated in this survey.[30]

Based on these conclusions, this thesis follows an exploratory sequential mixed methods research design, in which the process of research can be divided into three distinct phases.

The first phase consists of a case study[31] at the Volkswagen Passenger Cars brand in Wolfsburg, Germany. In this case study, **participant observation** was used as a vehicle to collect qualitative data between October of 2015 and March of 2016. During this period of time, the author immersed into the daily work routine of the "China market intelligence" department in Wolfsburg, which has been, together with the market intelligence department at the

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[26] Following this notion, there are two fundamental differences between both approaches that are said to be incompatible: As for the epistemological orientation, whereas quantitative research incorporates the practices and norms of the natural scientific model and of positivism in particular, qualitative research rejects this stance in favor of an emphasis on the ways in which individuals interpret their social world. Concerning the ontological orientation, quantitative research takes a view of social reality as an external and objective reality, whereas qualitative research sees social reality as a constantly shifting emergent property of individuals' creation.
For further elaboration see: Bryman, Alan et al. (2015), pp. 26 ff.

[27] Bryman, Alan et al. (2015), pp. 643 f.

[28] 64 articles were published in the "Strategic Management Journal" (2003-2009), 43 articles in nine marketing journals (2003-2009), 20 articles in the "Journal of Organizational Behavior" (2003-2009), and another 15 articles in the "Leadership Quarterly" (2004-June 2012).
See: Bryman, Alan et al. (2015), p. 645.

[29] Bryman, Alan et al. (2015), pp. 643 ff.

[30] Bryman, Alan et al. (2015), pp. 644 ff.

[31] The comprehensive case study of this thesis deals with forecasting in emerging markets. It will subsequently be called "emerging market case study". Within the emerging market case study, the "case study of PV sales in China" intends to improve sales forecasts in the Chinese automotive market. As part of this case study, the "Volkswagen case study" mainly refers to the participant observation phase of this research.

Volkswagen Group of China, responsible for all of the enterprise's forecasting activities in China. The author was requested to join the regular interaction between all stakeholders in the process of PV sales forecasting, with the underlying expectation of improving the accuracy of sales forecasts as part of his three-year Ph.D. program at the Volkswagen AG. Overall, the seven-month participant observation has led to the recognition that

i) a great deal of uncertainty existed as to which indicators should be considered for PV sales forecasts in the Chinese automotive market;
ii) regression models used for PV sales forecasts excluded any outliers caused by government policies, although policies were considered an integral part of automotive development in China;
iii) significantly high forecasting errors are likely to occur in monthly forecasts, as exhibited during and after the Chinese stock market crash in June of 2015.

In addition, another major outcome was that several stakeholders from the Volkswagen Group of China, who had well-networked working relationships with forecasters from other organizations, indicated similar forecasting challenges across the entire Chinese automotive industry. On the assumption that the author faced a problem of industry-wide significance, he complemented the Volkswagen case study with another cross-sectional study – the second phase of the underlying research process. In general, the emphasis of cross-sectional studies is placed on a sample of cases aimed at generalizing research results, with little regard for the unique context of each case. Therefore, a cross-sectional study is to be distinguished from a multiple-case study, the latter of which can be considered an extension of the single-case study approach, which, in turn, illuminates the peculiarities of each individual case.[32] During the cross-sectional study phase of this research, qualitative data was collected by means of **ten semi-structured interviews**, which were conducted in November of 2016. When compared to participant observation, semi-structured interviews allow for a greater breadth of thematic coverage and grant access to a wider variety of experts and situations. Moreover, based on the findings of the Volkswagen case study, the author had a very clear focus on his specific research objectives. Both arguments were reason enough to employ a more structured interview approach rather than use an unstructured participant observation for the second phase of this research.

[32] Bryman, Alan et al. (2015), p. 72.

Essentially, one of the three main findings during the participant observation phase was that a revised set of leading indicators were needed to improve the accuracy of PV sales forecasts in the Chinese automotive market. Therefore, the primary research objective of the expert interviews was to identify a portfolio of leading indicators with superior predictive power. As for the final indicator selection, the author deemed it necessary to **triangulate** the key interview deliverables through comprehensive literature research on the reliability of Chinese economic data. By definition, triangulation encompasses a method of corroborating collected data by comparing it to other sources.[33] In this study, the author assumed that the interviewees were not fully aware of the political interference in China's statistical work, which is why triangulation served as a cross-validating method to eliminate the bias emanating from the "wind of [data] falsification and embellishment"[34]. This bias may have been inherent to some of the interviewees' statements on the usefulness of Chinese economic data for quantitative research.

The purpose of the last phase of this research was to have qualitative findings followed up by quantitative investigation. To this end, the author referred to the most popular and successfully implemented model in **ANN forecasting**, namely a three-layered feedforward multi-layer perceptron with gradient-descent algorithm.[35] The configuration of hyper-parameters in such a structure-detecting non-parametric model can be categorized as a quasi-experimental design. Quasi-experiments contain some of the characteristics of experimental research designs, but do not necessarily fulfill all the internal validity requirements.[36] One of these internal validity requirements is that the experiment engenders considerable confidence in the robustness and trustworthiness of a causal relationship between one or more input variable(s) and the output variable(s).[37] Applied to the case study of PV sales in China, this would have presupposed a causal model in which all parameters that determine the future values of PV sales are known, quantifiable, and available from January of 2004 to June of 2017 – a highly unlikely assumption in market reality.[38] Even so, ANNs resemble the characteristics of an experimental research design in many respects. This is all the more true considering that successful modelling

33 Corrigan, Michael W.; Grove, Doug; Vincent, Philipp F. (2011), p. 94.
34 Holz, Carsten A. (2014), p. 311.
This slogan is frequently used to describe a systematic process of data falsification in China. It will be discussed in further detail in section V.1.
35 Kruse, Rudolf; Borgelt, Christian; Klawonn, Frank et al. (2016), p. 47.
36 Bryman, Alan et al. (2015), p. 53.
37 Bryman, Alan et al. (2015), p. 57.
38 Ord, Keith; Fildes, Robert (2013), p. 206, 234.

encompasses a great deal of trial and error due to a wide array of input data representation choices to be made in ANNs.[39]

In summary, the first phase of research provided the author with in-depth insight on the key challenges of PV sales forecasting in China. These findings were later contextualized in a broader theoretical framework, which was then used to derive the underlying research question. In the second phase, one of the objectives was to generalize the previous findings in the Volkswagen case study for the Chinese automotive industry. To that end, the author conducted ten semi-structured expert interviews, which also enabled the collection and analysis of qualitative data. This paved the way for an eclectic selection of leading indicators with superior predictive performance. In the third phase of research, quantitative investigation was introduced to follow up qualitative findings by assembling the fragmented mosaics into a gradient descent-based technique of ANN learning.

	I. Qualitative research 09/2015 - 03/2016	II. Qualitative research 04/2016 - 05/2017	III. Quantitative research 06/2017 - 01/2018
Design/ Method	– Case study: Forecasting in emerging markets – Within-case: Forecasting passenger vehicle sales in China – Unstructured participant observation at VW AG	– Cross-sectional study – Semi-structured expert interviews in Chinese automotive industry – Conduct of interviews in November of 2016 in China	– Quasi-experiment – Artificial Neural Network modelling with gradient-descent algorithm – Reference to monthly time series data from 01/2004 to 06/2017
Objec-tives	– Explore challenges of automotive sales forecasting in China – Contextualize findings in theory → derive research question of thesis	– Generalize findings in VW case study for the Chinese automotive industry – Collect data to be used as input for subsequent quantitative research	– Select leading indicators for automotive sales forecasting in China – Generate monthly sales forecasts based on trial-and-error learning
Data triangu-lation		– Credibility of China's economic data → "wind of falsification and embellishment"	

Figure I-1: Exploratory sequential mixed method research design

[39] Kaastra, Iebeling; Boyd, Milton et al. (1996), p. 217; Du, Ke-Lin; Swamy, M.N.S. (2014), p. 96.

I.3 Structure of this thesis

Following the introductory chapter of this thesis, chapter II begins with a series of definitions of the term "emerging market" as presented by well-established international organizations, namely the International Monetary Fund (IMF), World Bank, and United Nations (UN). It provides a detailed discussion on the prevalence of macro and micro risks in emerging markets, with particular attention paid to the micro dimension of risk. As part of this, the concept of institutional voids is presented, set in the frame of New Institutional Economics and transaction costs theory. Chapter II concludes with the recognition that MNEs have to adapt their most decisive business processes in a way designed to match the institutional environment in emerging markets.

Chapter III serves as an introduction to the emerging market case study, depicting the fundamental importance and core challenges of sales forecasting in emerging markets. A special emphasis is placed on how a RBV on an enterprise can contribute to a more dynamic forecasting process in order to address extraordinary market volatility. Based on these research results, chapter III elucidates a set of methodological implications for the subsequent case study of PV sales in China. As part of these implications, a key element of forecasting success is ascribed to the use of a structure-detecting non-parametric ANN method, the concept of which is explained at the end of this chapter.

Chapter IV delves into the case study of PV sales in China. It begins by sketching the key milestones of development in the Chinese automotive market, thereby illustrating the fundamental role that government policies have played in this development. A detailed elaboration of the expert interview results is presented at a later juncture in the chapter. The interview results are considered instrumental in comprehending the prevalence of regulatory insecurity, the first main dimension of institutional voids, in the Chinese automotive market. The chapter concludes with a brief summary of these deliverables.

Chapter V addresses the second dimension of institutional voids in the Chinese automotive market, namely the existence of unreliable market information. This entails a comprehensive literature review on the credibility of Chinese economic data. The author then concentrates on a multi-leveled indicator selection process, one that aims at reconciling the interviewees' statements with the key findings from the (triangulating) literature research on Chinese economic data credibility.

The penultimate chapter describes the univariate pre-processing of time series data to be used for ANN forecasting. The ultimate objective of pre-processing is to determine the lead-lag relationship between all input and output variables, the results of which are fed into the input layer of the multivariate ANN forecasting model. Furthermore, the experimental setup and final results of ANN forecasting in the case study of PV sales in China are described and discussed in detail.

The final chapter concludes with the major research results obtained by this work. It further provides an outlook of potential developments in the area of ANN forecasting in China and suggests specific areas for future research in this field.

II Multinationals and their exposure to idiosyncratic risks in emerging markets

As proven time and again, internationalization strategies of MNEs[40] in emerging markets necessarily assume a thorough understanding of the host country's underlying macroeconomic forces.[41] That said, to prevent an unexpected financial loss, MNEs need to closely monitor any symptom of **macro risks** that could possibly hint at the gestation of an economic crisis. This advice seems to be particularly appropriate for MNEs intending to internationalize to Latin America, given the frequent ups and downs that many Latin American economies have seen over the past four decades.[42]

In this macro risk regard, the Chinese state has, by and large, successfully managed to navigate around the most serious macroeconomic pitfalls between 1978 and 2016[43], and delivered on the high expectations that were set, or partly even claimed, by the international community. However, a look behind the scenes unveils that parts of the double-digit growth in China was achieved by massive government spending in key industrial sectors of strategic development[44] or in the form of fiscal stimulus packages – with the automotive industry harvesting the fruits of both.[45] Without a doubt, this sort of state investment can be seen as an attempt of active state interference and thus in line with the country's overarching economic development strategy.

On the flipside of the coin, any such kind of state interference in emerging markets also invariably entails a certain degree of **risk at a micro level** of economic activity.[46] This sort of risk can be mainly traced back to an emerging market's less pronounced institutional framework, the transparency and trustworthiness of which is considered a decisive element for an efficient functioning of markets in more advanced economies. The upshot is that MNEs, which are accustomed to relying on a well-founded institutional framework in their home countries, are typically faced with considerably higher transaction costs in emerging markets. It is this circumstance that places MNEs at a competitive disadvantage relative to local incumbents.

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40 For further elaboration on internationalization strategies of MNEs, the reader may refer to the "Internationalization Product Life-Cycle Theory" for e.g. by Vernon, Raymond (1966, 1972); the Network model for e.g. by Johanson, Jan; Mattson, Lars-Gunnar (1988); the Diamond model for e.g. by Porter, Michael E. (1990); the "Internationalization Theory" for e.g. by Buckley, Peter J; Casson Marc C. (1991); the Uppsala model for e.g. by Carlson, Sune (1996); the "Eclectic Paradigm" for e.g. by Dunning, John H. (2001).

41 Glowik, Mario (2016), p. 46.

42 Herr, Hansjörg; Priewe Jan (2005), p. 91 f.

43 Naughton, Barry (2018), p. 456.

44 Fischer, Doris (2015), p. 18.

45 To be discussed in section IV.1.

46 Mody, Ashoka (2004), p. 13.

With that in mind, this chapter elaborates on both macro and micro risks for MNEs in emerging markets. With respect to macro risks, a comparative perspective of economic development over the past forty years in Argentina and China is taken, with a special focus placed on the contrasting interpretations of state interference under the "Washington Consensus". Closely connected to these findings, the concept of institutional voids is introduced to explain the major sources of micro risk and associated operational challenges for MNEs emanating from the emerging market's institutional environment. This chapter concludes by proposing a principal set of generic strategies to mitigate institutional void-related micro risks, one of which is deployed in the underlying case study of PV sales forecasting in China.

II.1 Following the growth narrative

The commitment behind strategic decisions made by MNEs when entering markets in foreign countries can be traced back to different internationalization motives. In the wake of globalized manufacturing and distributions chains, MNEs are often integrated into the supply chain of a large international company or, when operating more independently, requested to follow a strategically important customer abroad. A further compelling argument paving the way to internationalization can be found in the enterprises' desire to get access to rare and/or expensive resources, which only reside in the region of interest or appear to be more promising in terms of cost and/or quality there. In an endeavor to realize viable economies of scale and/or strategic market positioning, MNEs might also contemplate internationalizing as an integral part of concentric industry clusters, as examples from the automotive industry in Chennai (India)[47] and Kaluga (Russia)[48] vividly demonstrate.[49]

These principle motives for internationalization aside, it is beyond dispute that a MNE's most cogent decision rationale whilst considering entering into a foreign market is to harness the untapped potential of customer demand.[50] This statement holds particularly true for MNEs originating from more advanced economies. To compensate for the saturated markets in their home country[51], MNEs are screening extensively for countries that are "emerging" by virtue

47 Barnes, Tom (2018), p. 82.
48 Bareev, Timur (2014), p. 46.
49 Glowik, Mario; Smyczek, Slawomir (2011), pp. 10 ff.
50 Magnani, Giovanna; Zucchella, Antonella; Floriani, Dinora (2018), p. 3.
51 Glowik, Mario et al. (2011), p. 8 f.

of their fast-evolving economy and associated rising customer demand.[52] Therefore, a key task for internationalizing MNEs is to assess "emerging" country attractiveness by finding a well-tuned balance between a MNE's growth imperative as well as the "liability of foreignness[53]" resulting from geographic, cultural, and institutional distances to the host country.[54]

II.1.1 Classification of an emerging market by IMF, World Bank, and UNDP

Although there is little consensus about which set of indicators to use in gauging the extent of country attractiveness, international market screening literature espouses the use of economic growth rates, particularly growth of gross domestic product (GDP) and/or gross national product (GNP).[55] These metrics are frequently used as initial indicators for quantifying the potential of a host country's product and services markets.[56] In this regard, the (estimated) compound annual growth rate (CAGR) of GDP prices in Figure II-1 reveals that "emerging markets and developing economies", a term coined by the IMF, and subsequently referred to as "**emerging markets**", provide mid to long-term growth opportunities for MNEs that no longer, or only to a diminishing degree, exist in more advanced economies.[57] The growth narrative attributed to these markets praises their lower level of competitiveness, increasing disposable incomes, large populations of young consumers, and economic liberalization, all of which have attracted much attention on the part of MNEs. It constitutes a key starting point for MNEs intending to internationalize into a country that they consider instrumental in the pursuit of their formulated strategic growth objectives.[58]

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52 Khanna, Tarun et al. (2010), p. 4.

53 "Liability of foreignness", a terminology conceptualized by Stephen H. Hymer (1976), refers to the idea that MNEs are – relative to a domestic enterprise – put at a competitive disadvantage, given their unfamiliarity with several aspects of the host country`s market environment.
See: Zaheer, Srilata; Mosakowski, Elaine (1997), pp. 439 f.

54 Magnani, Giovanna et al. (2018), p. 3.

55 GDP measures all income produced within the borders of a nation, whether the income generated from this domestic production is to be received by domestic residents or by foreigners. GNP is the gross aggregate income earned by domestic residents, whether from domestic production or foreign production. As for GNP, one must add to GDP the foreign generated income earned by domestic firms and residents and subtract the domestically generated income earned by foreign firms and residents to obtain aggregate income earned by domestic residents.
See: Davidson, Paul (2002), p. 139.

56 Sakarya, Sema; Eckman, Molly; Hyllegard, Karen H. (2007), pp. 212 ff.; Russow, Llyod C.; Okoroafo, Sam C. (1996), pp. 48 ff.

57 International Monetary Fund (n.d.; a).

58 Sakarya, Sema et al. (2007), p. 215.

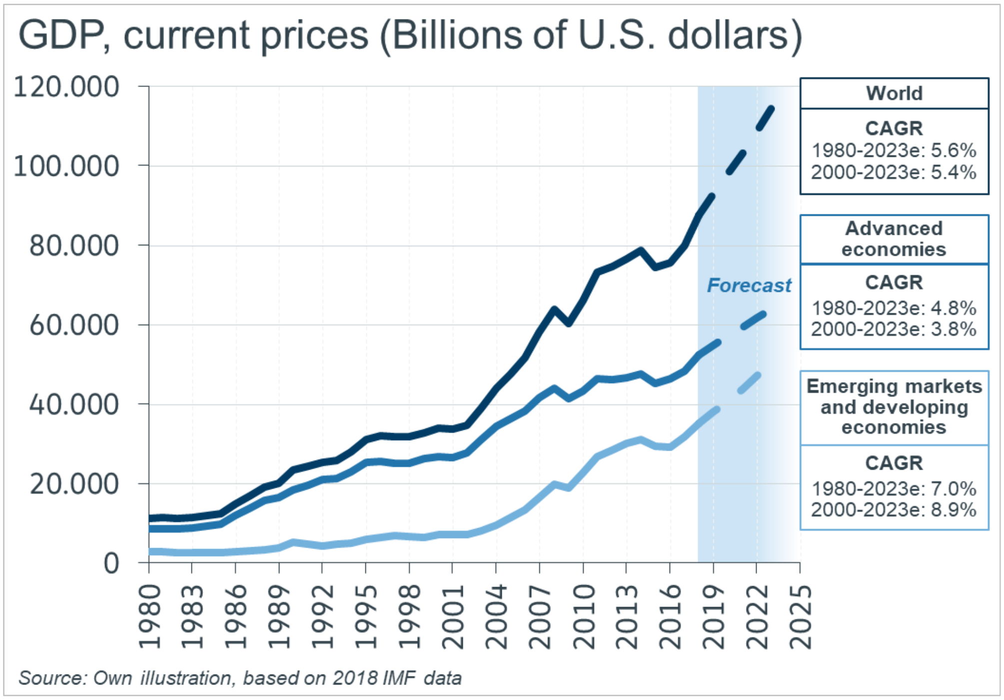

Figure II-1: Comparative growth rates of emerging markets & developing economies

Along these lines, well-established international organizations – namely the International Monetary Fund (IMF), World Bank, and UN – lay down divergent, and in part controversial, definitions of the term “emerging market”, depending on their underlying country classification systems in use.

As indicated above and outlined in Annex 1 and 2, the analytical[59] country classification system of the IMF divides the globe into two main taxonomies, namely “advanced economies” and “emerging markets and developing economies”. The major criteria used by the IMF to classify countries in either taxonomy are threefold: first, per capita income levels; second, export diversification so as to exclude those whose high GDP per capita levels are mainly achieved through oil exports; third, degree of integration into the global financial system.[60] By definition, the IMF classification is rather vague, because it is not built upon explicitly specified absolute or relative development thresholds.[61] As a case in point, when Lithuania joined the eurozone on January 1st of 2015 the IMF immediately reclassified the country from being an “emerging market and developing economy” to the taxonomy of being one of the “advanced economies”.[62] Similar to the

59 The country classification systems of the IMF and World Bank are utilized for both operational and analytical purposes. Only the latter purpose of country classification is covered hereinafter.
60 Kouneva-Loewenthal, Neli; Vojvodic, Goran (2012), p. 350.
61 International Monetary Fund (2018), p. 218.
62 International Monetary Fund (2015), p. 2.

IMF, the analytical country classification of the World Bank draws upon a system that distinguishes between two different categories, i.e. high-income countries and low and middle-income countries. The distinction as to whether a country belongs to either category is contingent on an explicitly formulated *absolute* benchmark of USD 6,000 gross national income (GNI) per capita in 1987 prices[63], meaning that countries below this development threshold pertain to the low and middle-income taxonomy.[64] Lastly, the country classification system used by the UN development program (UNDP) differentiates between "developed" and "developing" countries and is chiefly based on the Human Development Index (HDI), which is usually published together with the Human Development Report (HDR). To grasp the multidimensional nature of economic development, the HDI represents a composite index of three indices: first, *income*, which is measured by gross national income per capita (GNI/n) with local currency estimates converted into equivalent U.S. dollars using purchasing power parity; second, *longevity*, which is determined by life expectancy at birth; third, *education*, a proxy variable that is constructed by combining measures of actual and expected years of schooling. According to the logic provided in this country classification, countries are assigned to either category based on a relative development threshold. "Developed" countries are those in the top quartile of HDI-distribution, whereas countries in the bottom three quartiles are labelled as "developing".[65]

That said, on the assumption that the definition of emerging markets is to be understood in classification *labels*, *criteria*, and *thresholds*, Figure II-2 depicts that the IMF, World Bank, and UNDP refer to a fundamentally different set of country classification premises.

63 Fantom, Neil; Serajuddin, Umar (2016), p. 9.
64 Nielsen, Lynge (2011), p. 13.
65 Nielsen, Lynge (2011), pp. 8 f.

	IMF	World Bank	UNDP
Label of "emerging" markets	Emerging markets & developing countries	Low- and middle-income countries	Developing countries
Label of "advanced" economies	Advanced economies	High-income countries	Developed countries
Main classification criteria	1. Per capita income 2. Export diversification 3. Integration in global financial system	1. Per capita income	1. Per capita income 2. Longevity 3. Education
Classification threshold	Not specified	Absolute: USD 6,000 GNI per capita in 1987-prices	Relative: 75 percentile in HDI distribution
Share of countries "emerging"	39 advanced 154 emerging = 79.8% (in 2018)	78 advanced 140 emerging = 64.2% (in 2018)	51 advanced 137 emerging = 72.9% (in 2016)

Source: Own illustration, based on Nielsen, Lynge (2011), p. 19

Figure II-2: Definition of "emerging markets" across different organizations

At the same time, despite the lack of a uniformly applied framework of country classification, a more profound inspection of all three approaches discloses two important commonalities. First, the criteria used for country classification revolve around "per capita income", measured in GNI/n, which the World Bank considers to be "the best single indicator of economic capacity and progress"[66]. Second, with emerging markets taking a share of 79.8% (IMF)[67] and 64.2% (World Bank) in 2018[68] and 72.9% (UNDP)[69] in 2016, broadly similar conclusions as to the proportion of countries "emerging" are obtained.

II.1.2 Two-dimensional source of macro risk in emerging markets

The growth narrative initially provides a strong argument in favor of business expansion in emerging markets.[70] With that in mind, one decisive task for MNEs is to legitimize addressable sales potentials vis-à-vis existing concomitants that might ultimately affect market attractiveness.[71] In this regard, the IMF takes a critical look at its own growth-centric perspective of

66 Nielsen, Lynge (2011), pp. 9 ff.
67 International Monetary Fund (2018), p. 218.
68 World Bank (n.d.; a).
69 United Nations Development Programme (2016), pp. 198 ff.
70 Glowik, Mario (2016), p. 130.
71 Sakarya, Sema et al. (2007), p. 209.

development, arguing that the structural evolvement of emerging markets may appear to be desirable in terms of long-term aggregate rates of growth, but is often accompanied by a certain degree of macro risk that usually manifests itself in two dimensions, i.e. high volatility and transitional characteristics.[72]

The core issue in assessing the aspect of **high volatility** in emerging markets is whether it stems from uncontrollable, but not frequently-occurring, factors such as natural disasters, or if it is the result of the policy environment within which the country is governed. In reference to the latter – and far more severe – source of volatility, emerging markets suffer from perceived arbitrariness in policymaking, which is considered as impeding growth significantly, because it reduces (foreign) investor confidence in the stability of the countries' long-term progress of economic development[73]. Thus, rather than serving as a stabilizing force, as is the case in more advanced economies, policies in emerging markets are inclined to follow a pro-cyclical "when-it-rains-it pours" syndrome[74], meaning that the macroeconomic cycle of economic booms and recessions on the one hand and the capital flow cycle on the other hand reinforce one other. Closely linked to this is the second dimension of macro risk, the **transitional characteristics** of emerging markets. As the term suggests, these characteristics reflect the constant state of transition in a nascent economy, which is for instance mirrored in the nature and depth of its economic and political institutions as well as in several demographic terms, including life expectancy and education status. Moreover, in an environment of increasing globalization, an increasing level of capital market liberalization plays a critical role in this macro risk dimension, given that the transition to a greater interaction with international financial trading floors often turns out to be long-drawn and, at times, disruptive.[75] In fact, various historical examples of emerging markets have unmistakably shown that the surges of capital (first into the country, and then out) imply tremendous costs that exercise cumulative adverse effects on the economy as a whole. This is because resources of all relevant economic agents have to be re-allocated in the event of an expected economic downturn. In particular, enterprises exposed to a higher risk of bankruptcy typically lower their level of indebtedness, with a decelerating effect on extent and pace of business expansion. Their entrepreneurial risks are spilled over to financial institutions, which are confronted with an increased risk of

72 Mody, Ashoka (2004), p. 5, 13.
73 In chapter 2, the term "development" is subsequently understood in the sense of sustained growth. Of course, the author is well aware that development accounts for more than just a matter of growth.
74 Kaminsky, Graciela L.; Reinhart, Carmen M.; Vegh, Carlos A. (2004), p. 31.
75 Mody, Ashoka (2004), p. 5, 13.

payment default and thus wary of granting new credits. All in all, governments place money into reserves to offset the anticipated macro risks, thereby accumulating higher amounts of opportunity costs, which, in turn, divert them from investments in key areas of economic growth.[76]

Against this background, a premature integration into the global financial markets is generally been seen as a source of increased macro risks in emerging markets. Given that the national governments of the emerging markets have time and again encountered difficulties in adapting to these risks, even the IMF nowadays concedes that it can only record a few emerging markets taking full advantage of it[77], whilst the greater part has fared poorly in a setting of free-flowing forces on international financial trading floors.[78]

II.1.3 Macroeconomic development of emerging markets in Asia and Latin America

Many emerging markets in East Asia – including China, Indonesia, and Malaysia – provide the strongest testimony in favor of positive growth effects owed to globalization in general and capital market liberalization in particular. Their recipe for economic success has been their emphasis on *pragmatic* policies enabling them to govern and regulate the process of capital market liberalization in a manner that saw them ultimately seize the opportunities it offered, whilst not being caught in vicious downward spirals.[79] The counterexamples to these successful emerging markets in East Asia are those in Latin America, including Argentina, Brazil, and Mexico, which have pursued more strictly *programmatic* policies of economic development, as codified in the so-called "Washington Consensus".[80] By following the precepts of this consensus, Latin American countries have partaken more of the costs emanating from the pro-cyclical surges of capital and therefore suffered from a particular adverse effect on overall economic development. As a result, the level of growth in Latin America in the 1980s was just over half of what it was in the pre-reform days between the 1950s and 1970s.[81]

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76 Stiglitz, Joseph E. (2003a), pp. 514 ff.
77 Mody, Ashoka (2004), p. 3.
78 Stiglitz, Joseph E. (2003a), p. 512.
79 Stiglitz, Joseph E. (2003a), p. 507 f.
80 Stiglitz, Joseph E. (2003b), pp. 20 ff.
81 Stiglitz, Joseph E. (2003a), pp. 506 f.

More decisively, the gap between emerging Asian[82] and Latin American countries diverged increasingly between 2000 and 2017, as can be seen in Figure II-3.

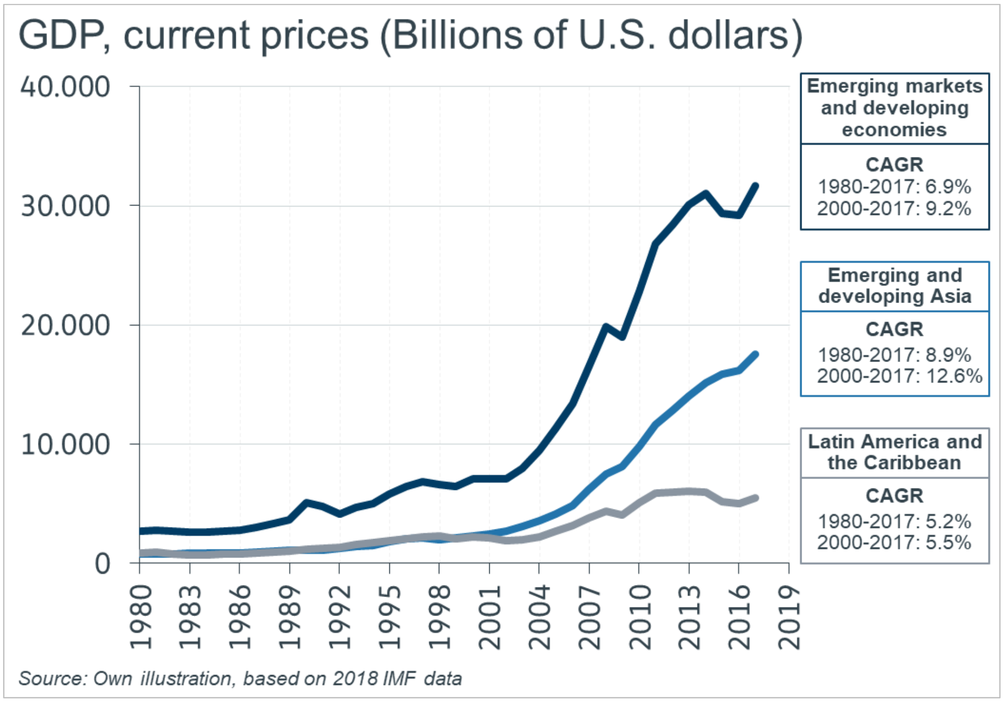

Figure II-3: Growth rates of emerging Asian and Latin American country clusters

Taking a politico-economic retrospective look at the structural evolvement of emerging markets in East Asia and Latin America, the next section dwells on inherently different magnitudes of macro risk in these clusters of emerging markets. In this context, a critical assessment of programmatic policymaking under the Washington Consensus, most notably concerning cross-border capital flows, concludes that the inherent volatility of economic development in Latin America has largely been the product of a self-inflicted wound.

II.2 The role of the state in emerging market development

The "Washington Consensus", a term coined by the British economist John Williamson in 1989, compiled a list of ten policies that captured the vision of Washington-based organizations, particularly the IMF, the World Bank, and the U.S. Treasury. The policies emerged in the attempt to bring about development in Latin America, which was engulfed in a severe

[82] A list of all countries belonging to the regional subgroups in "Emerging and developing Asia" and "Latin America and the Caribbean" can be found in Annex 2.

debt crisis in the 1980s.[83] At a later stage, the reform agenda was, to a varying degree, also applied to other emerging markets, including post-communist Russia[84] and countries in Sub-Saharan Africa[85].

The objectives of the Washington Consensus represent a shift from what had long been regarded as orthodox in Latin American countries, i.e. inflation tolerance, import substitution industrialization, and a leading role for the state, towards what had long been established in OECD (Organization for Economic Cooperation and Development) countries, i.e. macroeconomic discipline, outward orientation, and a market-based rather than state-directed economy. A particular emphasis was placed on the gains from liberalization, reflecting the fact that state intervention in the form of large state-owned enterprises and repressive regulation of private business was categorically considered a major obstacle for sustainable growth in emerging markets.[86]

II.2.1 The "lost decade" in Latin America

Throughout the 1980s, countries in Latin America were stagnating in terms of economic growth rates. Between 1980 and 1989, GNP average growth of Latin American[87] countries was only 1.7%. At the same time, countries in East Asia[88] enjoyed an average annual growth rate of 8% per year.[89]

The main reason why Latin American countries performed poorly in the 1980s was high budget deficits, many were as high as 5-10% of GDP. The spending underlying them was not used for productive purposes, but rather to subsidize the huge and inefficient state sector. With strong limitations on imports and a low focus on exports, enterprises had little incentive to increase their efficiency and to fulfil international quality standards, resulting in a huge gap between outflow of public spending and inflow of tax revenues. The problem was that this deficit was financed by borrowing, including heavy borrowing from abroad.[90] In concrete fig-

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83 Williamson, John (2000), p. 251.
84 Sanford, Jonathan E. Hardt, John P.; Nanto, Dick K. et al. (2003), p. 25; Kvintradze, Eteri (2010), p. 4.
85 Rodrik, Dani (2006), p. 974; Herr, Hansjörg et al. (2005), p. 72.
86 Williamson, John (2004), p. 197.
87 Including the Caribbean countries.
88 Including the Pacific countries.
89 Haynes, Jeffrey (2008), p. 71.
90 Stiglitz, Joseph E. (2001), p. 19 f.

ures, net external borrowing in Latin American countries grew sharply from $19.4 billion in 1977 to $62.3 billion in 1981, causing interest payments to rise dramatically.[91]

It is noteworthy that during and immediately after the Second World War, Latin American countries were actually able to reduce their defaults on U.S. dollar bond issues from over 1.5 billion to 127 million U.S. dollars. At that time, new inflows remained modest and were primarily from official sources or direct investments of U.S. enterprises in petroleum, mineral extraction, and public utilities. However, with the liberalization and deregulation of international capital markets in the mid-1970s, Latin American countries started to pile up larger amounts of debt, often using private bank lending and portfolio flows, which placed a heavy burden on their balance of payments. Indeed, many countries in Latin America became accustomed to relying on external borrowing in order to meet increasing debt service in a sort of "Ponzi scheme".[92] This scheme, which is inherently prone to collapse, only worked out until Paul Volcker, the former Chairman of the Federal Reserve, announced a rise in real interest rates in the United States in October 1979. Continued borrowing by Latin American countries had to come to an end as rising interest rates led to an appreciation of the U.S. dollar and thus increased the domestic debt burden of dollar-denominated loans.[93] To nonetheless finance their expenditures, most Latin American countries resorted to seigniorage[94] which, in turn, entailed high and extremely variable inflation and hence further exacerbated the crisis.[95] As a result, the majority of these countries declared inability to service their foreign debt in the year 1982, the official starting date of the Latin American debt crisis.[96]

The historical fact remains that the unforeseen and sudden shift from a superabundance of external financing to an abrupt severe shortage, triggered by the liberalization and deregulation of international capital markets in the mid-1970s, left deep scars on Latin American societies. It plunged a whole region into a serious crisis, that went on to last an entire decade. The resulting period of sluggish economic growth has commonly been dubbed as "lost decade". [97]

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91 Pastor, Manuel Jr. (1989), pp. 80 f.
92 A Ponzi scheme occurs when the deposits of current investors are used to pay returns on the deposits of previous investors. In fact, no real investment is happening.
See Johnstone, Karla; Gramling, Audrey; Rittenberg, Larry E. (2013), p. 35.
93 Kregel, Jan (2008), p. 548.
94 Seigniorage reflects the profit made by a government from the printing of money. It is the difference between the face value of the money minus the cost of physically making it.
See: Mankiw, N. Gregory (1987), p. 328.
95 Stiglitz, Joseph E. (2001), p. 19 f.
96 Marangos, John (2007), p. 198.
97 Devlin, Robert; Ffrench-Davis, Ricardo (1995), p. 118.

II.2.2 Washington Consensus: Emergence of neoliberal-style policymaking

The Brady Plan, which was devised in March 1989 by U.S. Treasury Secretary Nicholas F. Brady, addressed the adverse macroeconomic effects of the debt crisis and heralded a new era of policymaking in emerging markets – especially, but not exclusively, in Latin America.

As per this plan, Latin American countries had to abandon their existing economic model, which was based on inward-looking import substitution[98] and state intervention. It implied that defaulted bank debt was to be exchanged for new long-term bonds with a lower face value. Participating countries were granted very favorable exchange conditions, which amounted to a significant debt relief. Moreover, creditor banks and nations agreed to provide fresh funds under preferential terms in order to support eligible countries to jump-start their economies, with the ultimate objective to revert to a pre-crisis state of affairs.[99] In return, Latin American countries committed themselves to carry out policies that would attract private international capital flows sufficient to repaying the outstanding debts. In other words, they had little choice but to embark on the 19th century strategy of unrestricted open trade to build on comparative advantage, financed by external resources. These policy prescriptions, which are nowadays characterized as "neoliberal", were laid down by the Washington Consensus and portrayed as the ostensible solution to the problems of the lost decade.[100]

The remedy prescribed under the umbrella of the Washington Consensus revolved around the neoliberal paradigm[101] of weaning the economy from state intervention. Governments were called upon to liberalize domestic and international economic relations as well as privatize government assets and responsibilities. Tight monetary policy and a well-balanced state budget were favored so as to reinvigorate the economy as a whole.[102] However, having administered this kind of programmatic "medication", Williamson himself had to concede that some of the policies did not quite work out the way he and other advocates of the Washington Consensus had originally intended. Critics consider the policies of the Washington Consensus to be an "overtly ideological effort to impose neoliberalism" and "market fundamentalism" on

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98 The Great Depression of the 1930s resulted in a sharp decline of international trade and thus of imported products. As a consequence, Latin American countries started to pursue a "self-sufficiency" policy in manufactured goods so as to achieve greater economic independence.
See: Baer, Werner (1972), p. 97.

99 Edwards, Sebastian (2009), p. 21.

100 Kregel, Jan (2008), p. 542.

101 In the neoliberal paradigm, classical tasks of the state are providing law and order, a transparent and effective legal system, a stable macroeconomic framework as well as improving health services, education systems, and physical infrastructure.
See: Ahrens, Joachim (1999), p. 80 f.

102 Kotz, David M. (2004), p. 3; Stiglitz, Joseph E. (2003a), pp. 517 f.

emerging markets"[103] – the essence of what is visible in terms of economic performance in Latin American countries. While their economic recovery seemed to have been under way in the 1990s, with per capita GDP rising at a modest rate of 2.0% annually between 1990 and 1997, and thus almost as high as per capita GDP growth between 1950 and 1980 (+ 2.7%), shortly thereafter it turned out that this recovery proved to be short-lived. The region experienced a new "lost half-decade" between 1998 and 2002, when per capita GDP unexpectedly declined again by 0.3% annually[104], thereby testifying that Latin American countries did not manage to actually take off after all. As a case in point, **Argentina** was subjected to a substantial inflow of short-term capital after it had set the Argentinian Peso against the U.S. dollar at a fixed 1:1 parity in the 1990s. The idea was to pursue a more effective and sustainable price stabilization policy. In reality, the institutionalization of this so-called "currency board" entailed unjustifiable optimistic perspectives of investors, which led to a real overvaluation of the Peso and eventually culminated in high trade balance and current account deficits.[105] In a quest to finance these deficits, Argentina accumulated high external debt that destabilized the economy and made it vulnerable to even moderate shocks. Such a shock materialized precisely when Brazil, Argentina's main trading partner at that time, devaluated the Brazilian Real by around 50% against the U.S. dollar in 1999[106], leading to a situation in which Argentina's competitiveness deteriorated significantly and the currency board ultimately collapsed in 2002.[107] At that point, the Argentine economy was confronted with both the lenders, who suddenly refused to grant new credits[108], and the domestic economic agents, who decided to hold the greater part of their financial wealth in U.S dollar. The upshot was that all Latin American major countries[109], which were exposed to a comparatively high degree of dollarization[110],

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[103] Rodrik, Dani (2006), p. 974.
[104] Ocampo, Jose Antonio (2004), p. 67 f.
[105] Palley, Thomas I. (2003), p. 62, 74.
[106] Aschinger, Gerhard (2002), p. 112 f.
[107] Rodrik, Dani (2006), p. 975.
[108] Bresser-Pereira, Luiz Carlos; Nakano, Yoshiaki (2003), p.10 f.
[109] Medeiros, Carlos Aguiar de (2008), pp. 94 f.
[110] If agents move their wealth out of the country, it is capital flight; if they keep it inside the country, it is called dollarization. In this sense, dollarization is the use of a hard currency in an emerging market for holding wealth, giving credit or expressing the price of wages and goods. It is a sign that economic agents, due to an anticipated high inflation/depreciation, do not trust the domestic currency.
See: Herr, Hansjörg et al. (2005), p. 85.

suffered from the resulting strong depreciation of their domestic currency as their *real* debt burden increased respectively due to currency mismatch.[111]

The poor economic performance of Latin American countries like Argentina amply illustrates the failure of neoliberal policies imposed on nascent economies.[112] One argument for this disappointing outcome is that the local context of policy formulation was not sufficiently factored into the programmatic manifesto. Indeed, even though Williamson had addressed Latin American countries solely, his approach was rolled out to *all* emerging markets eligible and willing to accept the neoliberal path of development and reform, including those that were seeking to climb up the economic ladder as well as those states transitioning from socialism to capitalism.[113] Nonetheless, taking into account that Latin American economic recovery in the 1990s also could not be sustained, this line of reasoning does not appear to be exhaustively cogent. Rather, practitioners had to acknowledge over time that the policy reforms did not produce lasting effects, because many emerging markets lacked **adequate institutions** to deal with their inherent state of volatility within a system of unfettered market forces.[114] In response to that finding, the prior set of codified reforms was augmented in 2003 by a list of ten further policies (see Annex 3), most of them institutional in nature and hence a distinct improvement of the Washington Consensus in its original version.[115]

Despite certain programmatic rectifications under the Augmented Washington Consensus, the fundamental paradigm of neoliberal macroeconomic policy, i.e. requiring the state to withdraw from regulating and managing economic activities, nonetheless remained sacred for the Washington-based organizations.[116] In this context, the next sub-section particularizes two selected sources of macro risk and takes stock of the role that the state in Argentina and China has assumed to prevent systemic root causes of economic volatility.

II.2.3 The role of the Chinese state in economic development

Taking the standpoint of a MNE that is screening extensively for a portfolio of countries truly emerging by virtue of their fast- and consistent-evolving economy, it is fair to conclude that

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111 Currency mismatch means that the borrowers' assets are mainly denominated in domestic currency, but their liabilities are denominated in foreign currency.
See: Reinert, Kenneth A.; Rajan, Ramkishen S.; Glass, Amy Jocelyn (2009), p. 109.
112 Stiglitz, Joseph (2004a), p. 1.
113 Rodrik, Dani (2006), p. 975.
114 Stiglitz, Joseph E. (2003a), p. 512.
115 Rodrik, Dani (2006), p. 977 f.
116 Herr, Hansjörg et al. (2005), pp. 82 f.

Argentina, in the last 40 years, has been outperformed by economically more attractive East Asian countries. Above all, this statement holds particularly true for China, whose growth record has been outstanding, despite justified doubts on data and measurements of growth[117].

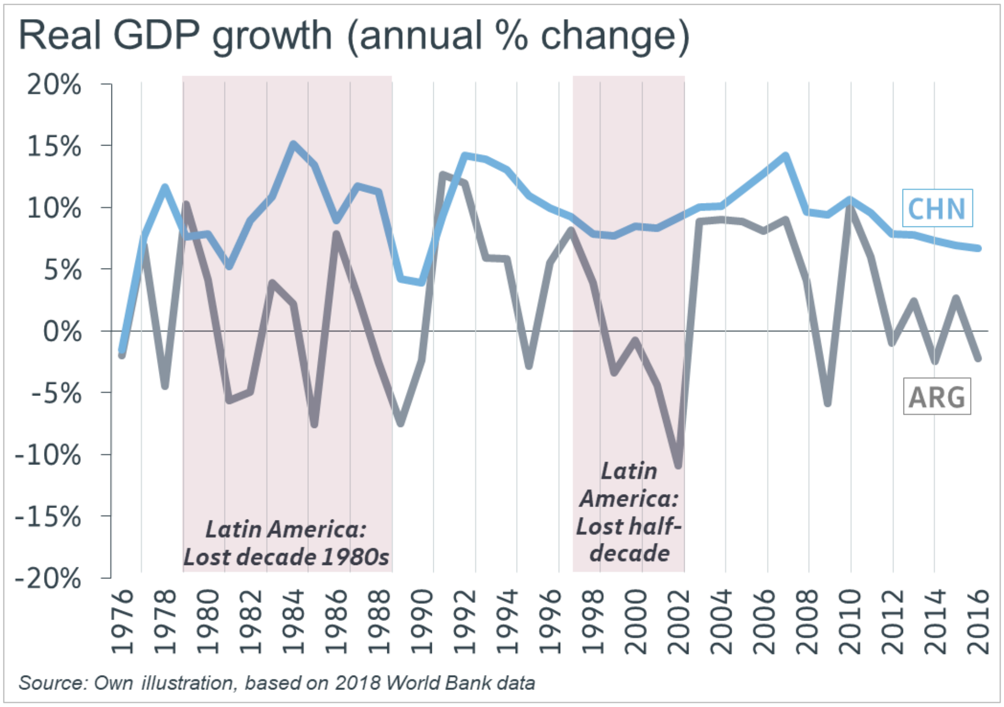

Figure II-4: Annual growth rates of China and Argentina 1976-2016

Exploring the different pathways of development in China and Argentina, with the latter being a showcase of neoliberal policy implementation, one has to acknowledge that China's unprecedented record of growth has been mainly accomplished through extensive but prudent **state intervention**.[118] The contrasting interpretations of state intervention in economic development are best pinpointed by the disparities in capital management policymaking, in particular with regard to **foreign exchange rates** and **cross-border capital controls**.[119]

First, while the Washington Consensus stipulates that a country must either "fix firmly" or "float cleanly" its exchange rate[120], the Chinese government eventually decided to deviate from this so-called "two-corner doctrine" shortly after the country's accession to the World Trade Organization (WTO): after almost a decade of firmly fixing the Renminbi (RMB) to the

[117] Naughton, Barry (2018), p. 442. Further elaboration in section V.1.
[118] Herr, Hansjörg; Ruoff, Bea (2018), pp. 3 ff.
[119] Epstein, Gerald; Grabel, Ilene; Jomo, K.S. (2008), pp. 158 f.; Naughton, Barry (2018), pp. 442 ff.
[120] Williamson, John (2008), p. 17; Bresser-Pereira, Luiz Carlos; Luiz Carlos; Gala, Paulo (2008), p. 318.

U.S. dollar at an exchange rate of 8.28[121], it abandoned the dollar peg in favor of a regime of "managed" floating exchange rates.[122] In this model, the nominal exchange rate is tied against a basket of hard currencies, but can be re-aligned in the foreign exchange market at any time on behalf of the Chinese central bank, the People's Bank of China (PBOC).[123] For instance, between 2003 and 2010, China recorded a comparatively large trade surplus and inflow of private capital. To re-balance the accounts and avoid domestic currency appreciation, the PBOC bought up extensive amounts of foreign exchange, resulting in a foreign-exchange accumulation that averaged 10% of GDP annually.[124] As such, the government assumed an intermediate but demonstrably active role in this process, because the PBOC is still predominantly guided by the government's industrial policies.[125] After all, this intervention-based exchange rate regime proved to be much less destabilizing than rigidly pre-determined exchange rates in the form of currency boards in Argentina or, to the other extreme, floating exchange rate regimes that entail a considerable potential of higher inflation and greater vulnerability to external debt shocks.[126]

Second, China, since the 1980s[127], emerged under the auspices of a strictly regulated domestic financial market.[128] Instead of rushing into full capital account convertibility[129], as observed in many other emerging markets[130], capital controls have been enacted to fend off risks from cross-border transactions, thereby keeping the dependency on foreign investors at comparatively low levels.[131] Efforts to ease capital controls have only been introduced on an incremental basis[132], recently pushed through the IMF's decision to include the RMB in the SDR[133] basket of hard currencies, which backed the PBOC's efforts to set agendas for further financial liberalization in China.[134] In fact, China has been one of the world's largest host countries for

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[121] Yu, Yongding (2018), p. 316.
[122] Du, Jiangze; Wang, Jying-Nan; Lai Kin Keung et al. (2018), p. 7.
[123] Herr, Hansjörg et al. (2005), p. 91 f.; Herr, Hansjörg et al. (2018), p. 20.
[124] Naughton, Barry (2018), p. 444.
[125] Li, He; Yu, Zhixiang; Zhang, Chuanjie et al. (2017), pp. 65 ff.; Chin, Gregory T. (2013), p. 526; Jiang, Dou (2016), p. 3940.
[126] Herr, Hansjörg et al. (2005), pp. 91 f.; Li, He et al. (2017), pp. 72 ff.
[127] Epstein, Gerald et al. (2008), p. 161.
[128] Herr, Hansjörg et al. (2018), p. 15.
[129] Naughton, Barry (2018), p. 444.
[130] Herr, Hansjörg et al. (2005), p. 93.
[131] Herr, Hansjörg et al. (2005), p. 80; Naughton, Barry (2018), p. 442.
[132] Wang, Jue (2018), p. 63.
[133] The SDRs (special drawing rights) are a special reserve asset allocated to IMF member countries. They may be used as a potential claim on the freely usable currencies of IMF members in that holders of SDRs can exchange their SDRs for these currencies.
See: Aryeetey, Ernest (2004), p. 92.
[134] Wang, Jue (2018), p. 74.

inward foreign direct investment (FDI)[135], the only form of capital inflow without any restrictions, except that it has to follow the "Catalogue of Industries for Guiding Foreign Investment"[136]. The advantage of FDI over short-term finance in an emerging market is that it implies less cyclical volatility[137], even in times of changing global market sentiments[138], because it shifts the exchange rate risk to the foreign investor[139] and also ensures a certain transfer of technology and management skills to the investment-receiving country.[140] This policy explicates why China has largely found itself in a position to keep its current account in equilibrium or surplus, whereas Argentina has had to face a long-lasting current account deficit (see Figure II-5). This deficit, to make matters worse, has been financed by foreign debt in the form of short-term and pro-cyclical portfolio investment.[141]

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135 The U.S. Department of Commerce, the IMF, and OECD regard a minimum of 10% equity ownership as a controlling interest, indicating a direct investment. A less than 10% equity ownership is considered a non-controlling interest, indicating a portfolio investment.
See: Cohn, Theodore H. (2016), p. 294.

136 The regulatory framework lists out those industries in which foreign investments are either "encouraged", "restricted", or "prohibited". Encouraged investment is the largest section, mainly consisting of industries in which either high-technology or foreign funding is needed.
See: Ministry of Commerce of the People`s Republic of China (n.d.).

137 Stiglitz, Joseph E. (2003a), p. 512.

138 Thomasberger, Claus (2012), p.153.

139 Herr, Hansjörg et al. (2005), p. 78.

140 Stiglitz, Joseph E. (2003a), p. 512.

141 Stiglitz, Joseph E. (2004b), p. 61; Herr, Hansjörg et al. (2005), p. 92; International Monetary Fund (2017), pp. 7 ff.

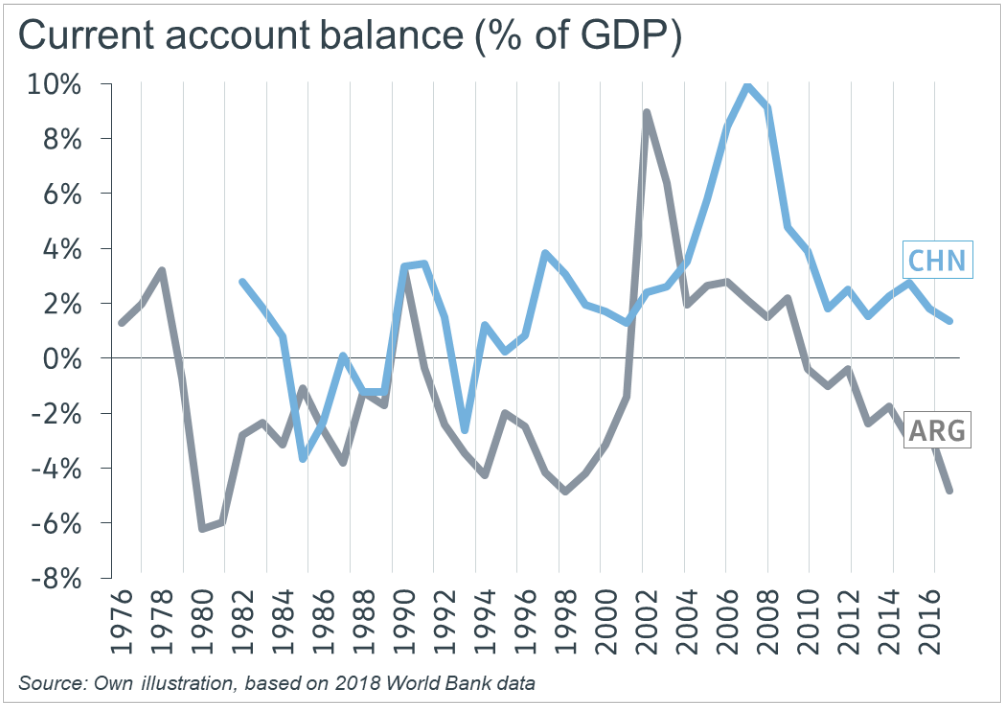

Figure II-5: Current account balance of Argentina and China 1976-2016

II.3 Institutional voids in emerging markets

Although there have been a few examples of governments in emerging markets that seem to have pursued prudent macroeconomic policies, one cannot deny that, beyond the surface of high economic growth rates, MNEs have often experienced poor soil for the conduct of profitable business there.[142] One decisive reason for this circumstance is that many MNEs originating from Western countries are accustomed to relying on a well-founded institutional framework[143] that facilitates the functioning of markets in more advanced economies. The absence of such institutions in emerging markets poses a critical source of micro-level risks and associated operational challenges for MNEs.[144]

Therefore, this section centers upon the concept of "institutional voids" in emerging markets, set in the frame of New Institutional Economics and transaction cost theory. It elaborates on the importance of institutions in NIE theory and illustrates the multifaceted nature of institutional void-related risk by citing selected mini-case examples in China and India, two emerging markets with a highly different level of economic openness.

[142] Khanna, Tarun et al. (2005), p. 63.
[143] Khanna, Tarun et al. (2010), p. 6, 17.
[144] Khanna, Tarun et al. (2010), p. 21, 28; Enderwick, Peter (2007), p. 82.

II.3.1 Institutions in the New Institutional Economics theory

The concept of “New Institutional Economics” (NIE) was coined by Oliver E. Williamson in his study on internal organizations of economic activity within and between markets and hierarchies in 1975.[145] The terminology itself has been pervasively used to distinguish the subject from orthodox economics, which argues that institutions only matter negligibly in economic performance, and older institutional economics, which is not amenable to orthodoxy, but subscribes to a more sociological framework instead.[146]

In NIE theory, the vital role of institutions is derived from the assumption that neoclassical theory has underestimated the importance of institutions in which markets operate and by which the costs of market transactions can be determined.[147] Along these lines, proponents of NIE hold the view that neoclassical economics fails to explain the discrepancies in growth levels between two countries.[148] In that sense, various definitions of the term “**institution**” are discussed in pertinent literature:

Eirik Furubotn and Rudolf Richter define, rather abstractly, an institution as “(…) a set of formal and informal rules, including their enforcement arrangement”.[149] In a similar manner, *Andrew Schotter* considers institutions as “regularities in behavior which are agreed to by all members of a society and which specify behavior in specific recurrent situations”[150]. Taking a more politico-economic standpoint, *Douglass C. North* contends that institutions “(…) are the key to understanding the interrelationship between the polity and the economy and the consequences of that interrelationship for economic growth (or stagnation and decline)”. He further illustrates that institutions “(…) provide the basic structure by which human beings throughout the history have created order and attempted to reduce uncertainty in exchange”.[151] As to uncertainty reduction, he states in a similar manner that “the (…) major role of institutions in a society is to reduce uncertainty by establishing a stable (…) structure to human interaction”.[152] *Ronald H. Coase* argues from a more economic point of view that “(…) it is the institutions that govern the performance of an economy (…)”.[153] He then later stated that “(…) a

[145] Williamson, Oliver E. (1975).
[146] Coase, Ronald (1998), p. 72.
[147] Cameron, John D. (2004), p. 98.
[148] Perry, Nathan; Schönerwald, Carlos (2012), p. 71.
[149] Furubotn, Eirik G.; Richter, Rudolf (2000), p. 6.
[150] Schotter, Andrew (1981), p. 9.
[151] North, Douglass C. (1990), p. 118.
[152] North, Douglass C. (1990), p. 6.
[153] Coase, Ronald (1998), p. 73.

modern market economy (…) requires an intricate web of social institutions to coordinate the working of markets and firms across boundaries”.[154] *Oliver E. Williamson* summarizes, also in light of the foregoing, that the distinguishing features of NIE can be expressed in an interdisciplinary combination of economics, law and organization, being different from, but not hostile to, orthodoxy. He sets forth that most of the provided definitions mainly operate at the level of institutional environment, referred to as the “rules of the game”. Williamson therefore introduced a complementary level to NIE called “institutions of governance” or “play of the game”, implying that institutions are susceptible to analysis, especially at the micro-analytical level of contract and organization.[155]

At precisely this micro-analytic level of organization, Williamson sheds a good bit of light on North’s key postulate of uncertainty reduction, which was firstly captured by *Tjalling C. Koopmans* who sketches that “(…) the core problem of the economic organization of society (is) that of facing and dealing with uncertainty”.[156] In this connection, Koopmans differentiates between primary and secondary uncertainty, pointing out that primary uncertainty is of rather state-contingent kind whereas secondary uncertainty arises from lack of communication, i.e. decision-makers being “uncertain” about plans and decisions concurrently made by other stakeholders. From his standpoint, state-contingent and communication-related uncertainty must be attributed equal quantitative significance[157], with both dimensions inevitably merging into a common source of statistical risk that needs to be addressed strategically at the micro level of business operations.[158]

A prerequisite for the underlying case study of PV sales in China is to place this sort of statistical risk into a proper risk management context. In this connection, the next sub-section explains how the absence of a strong institutional framework shapes the landscape of emerging markets and thereby ultimately contributes to the occurrence of micro risk and associated operational challenges on behalf of MNEs.

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[154] Coase, Ronald (2012), p. 2.
[155] Williamson, Oliver E. (1996), 326 ff.; Williamson, Oliver E. (2000), p. 597.
[156] Koopmans, Tjalling C. (1957), p. 147.
[157] Koopmans, Tjalling C. (1957), pp. 162 f.
[158] Simon, Herbert (1984), p. 40; Williamson, Oliver E. (1996), p. 60.

II.3.2 Sources of micro risk: The concept of institutional voids

MNEs are quick to acknowledge that, next to high and consistent levels of economic growth, the attractiveness of emerging markets is conditional on the presence and quality of existing local infrastructure.[159] Concerning this matter, one of the most decisive market entry decision parameters of MNEs refers to the adequacy of *physical* infrastructure in a given location. The Indian automotive industry, for example, recorded a considerable increase of investment by almost all global automotive market actors once the launch of industrial policies, enacted as part of the government's "Automotive Mission Plan 2006-2016", significantly improved the national road transportation system.[160]

By contrast, the importance of *institutional* infrastructure is less pronounced in MNEs' market entry decisions. This is the case even though it is of paramount relevance for an efficient functioning of markets, regardless of their geographic location or their contribution and position in the value chain. In this context, the term "**institutional voids**" is used to describe the lacunae of a transparent and trustworthy formal institutional framework that is either absent or not yet on par with its physical counterpart and/or remains stigmatized by historical legacies.[161] Of very important note here is that while MNEs can usually rely on a variety of formal institutions in their home markets[162], their (subjective) perception of institutional voids allows for more than just objective and measurable inter-market comparisons. Similar to a perceived arbitrariness in policymaking, which was found to be a key issue of high volatility in emerging markets, MNEs' "psychic[163] institutional distance" has an equally strong impact on the <u>perceived</u> attractiveness of an emerging market. This can be said of each case, depending on the degree to which a MNE's home market and the emerging market actually differ in their respective institutional profiles.[164]

Generally speaking, institutional voids in emerging markets cannot simply be dissolved through market liberalization and deregulation. This explains why MNEs are exposed to institutional voids in both closed and open economic contexts of emerging markets, albeit the

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159 Khanna, Tarun et al. (2010), p. 14; Chatterjee, Sheshadri; Kar, A.K. (2018), pp. 224 f.
160 Mani, Sunil (2017), pp. 93 f.
161 Khanna, Tarun et al. (2010), pp. 13 f.; Enderwick, Peter (2007), p. 82.
162 Khanna, Tarun et al. (2010), p. 15.
163 By definition, "institutional distance" may also refer to administrative aspects, i.e. the extent as to which regulatory measures implemented by domestic governments raise barriers to foreign competition. These aspects can be measured along six objective parameters: control of corruption; rule of law; voice and accountability; government effectiveness; political stability; and regulatory quality.
See: Magnani, Giovanna et al. (2018), pp. 2 ff.
164 Enderwick, Peter (2007), pp. 89 ff.

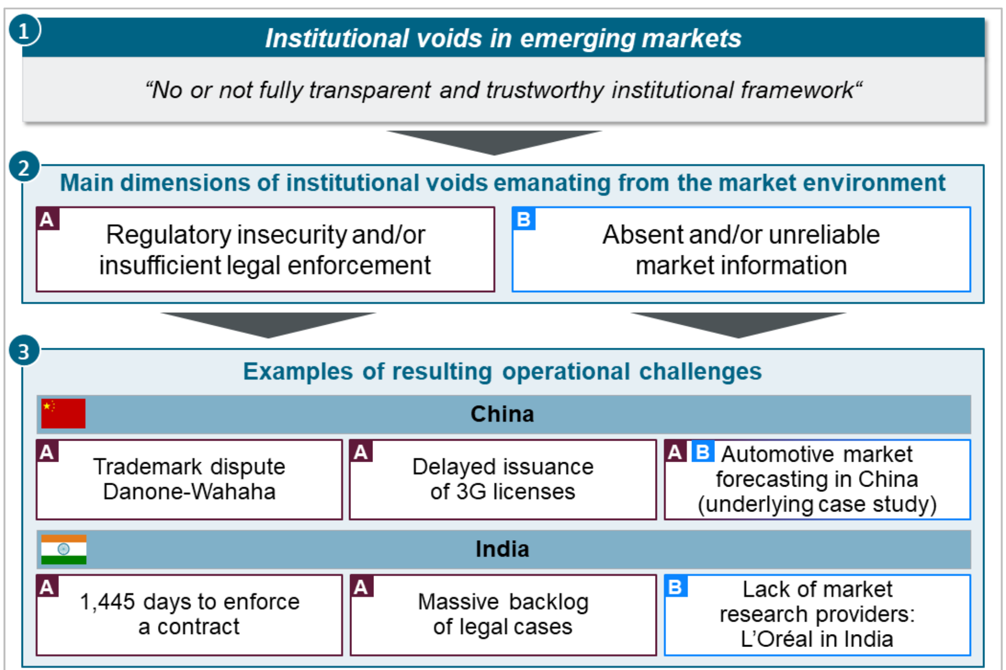
(perceived) dissemination and nature of institutional voids varies from market to market.[165] Surrogate instruments to bridge the institutional gap differ substantially, with informal institutions often acting in an intermediary function. However, as opposed to trustworthy and assertive formal institutions, informal institutions are seldom situated at the same institutional hierarchy level (law, judiciary)[166] and/or truly open to all market participants.[167]

That said, MNEs must necessarily cope with two intertwined dimensions of institutional voids in emerging markets:

i) regulatory insecurity and/or insufficient legal enforcement;

ii) absent and/or unreliable sources of market information.

Both dimensions are among the most daunting obstacles for MNEs to invest in emerging markets.[168] To undergird this point, a range of observed operational challenges that MNEs have encountered due to both dimensions of institutional voids in China and India is exemplified below. These examples are not meant to be exhaustive but do indeed illuminate the extent and diversity of business implication at a micro level of economic activity in emerging markets.



Source: Own illustration, based on Khanna, Tarun (2010)

Figure II-6: Examples of operational challenges for MNEs in emerging markets

165 Khanna, Tarun et al. (2010), p. 6, 26, 35.
166 Schrammel, Tine (2014), p. 203.
167 Khanna, Tarun et al. (2010), p. 15.
168 Khanna, Tarun et al. (2010), p. 16.

The institutional environment in emerging markets is the product of a country's underlying historical, political, economic, and cultural forces.[169] In this vein, it is not to be expected that, even with globalization and economic liberalization, Western achievements towards civil liberty and the associated "rule of law"[170] can be instantly and seamlessly translated into more "distanced" societies. That is mainly because institutions, which govern an efficient transacting in more advanced economies, underperform in markets with significant asymmetries of power resulting from the host country's sociopolitical heritage.[171]

An asymmetric use of regulatory institutions has been noticed in China to benefit domestic enterprises against foreign competitors by providing them a head start in responding to domestic market demand.[172] For instance, the formerly praised Danone-Wahaha "showcase" joint venture was eventually dissolved in 2009, after a three-year widely publicized trademark dispute. In this dispute, the French food Group Danone accused its Hangzhou-based partner Wahaha, the top beverage producer in China, of secretly operating parallel entrepreneurial activities that mirrored the joint venture's operations with virtually identical products. Given that the bilateral feud erupted into a public controversy, the conflict escalated to the point of political tensions between the French and the Chinese government. The upshot was that Danone's reputation in China suffered severely, leading to Danone's exit of the joint venture by selling its majority stake to Wahaha. This dispute has been cited by many scholars so as to make an example of Chinese authorities' perceived protectionist interpretation and application of regulations in favor of domestic enterprises.[173] Also, as another poignant example of perceived regulatory insecurity and/or insufficient legal enforcement, China's mobile telephone network operated a homegrown 3G standard, called TD-SCDMA (Time Division-Synchronous Code Division Multiple Access). This standard was incompatible with both international standards, namely European W-CDMA (Wideband-Code Division Multiplexing Access) and the U.S.-invented CDMA2000 (Code Division Multiple Access 2000). In effect, the government deliberately delayed the issuance of 3G licenses for several years until 2008/09, without any serious antitrust investigations in progress. It thereby gave the domestic

169 Khanna, Tarun et al. (2010), p. 13.
170 Carrithers, David W. (2001), p. 293.
171 Khanna, Tarun et al. (2010), p. 35.
172 Naughton, Barry (2018), p. 387.
173 Bu, Qingxiu (2011), p. 147; Li, Jieyin (2009), pp. 57 ff.

standard breathing space to catch up with both technologically more “advanced” foreign standards.[174]

Aside from the above-listed observations in China, institutional voids do not only refer to countries in which the state takes a very active role in economic development. In India, which is assumed to feature a lower degree of state intervention in economic development[175], the ability of MNEs to achieve profits may likewise be impaired by absent or unreliable information on customer tastes and purchase behavior.[176] For instance, the French enterprise “L’Oréal” successfully addressed Western mass markets in the 1990s. Later on, the enterprise used its Western-oriented product portfolio to target precisely the same market segment in India – but only gained little resonance among Indian domestic customers. Without adequate market research institutions or intermediaries in place, this was mainly attributable to faulty assumptions in the underlying marketing strategy. As a case in point, L’Oréal’s face powder and sunscreen were sold for 17 and 24 U.S. dollars respectively, whereas (local) competitors offered similar products for less than 1 U.S. dollar. The upshot was that, in 2007, L’Oréal shifted its organizational priorities towards the accumulation of local market knowledge by internalizing a greater part of its market research-related activities. Shortly thereafter, predicated upon its own and more profound research results, it managed to successfully re-launch a differentiated product portfolio in the (high-price) Indian luxury segment.[177]

Beyond that, the development of a transparent and efficient regulatory and judicial climate in India is, at least in part, hampered by the country’s upheld principles of democracy. To be sure, the to-and-fro of political debate in democracies generally caters to a balanced representation of individual needs and vested interests. Yet, in doing so, it also produces a rent-seeking and inefficient behavior by organized interest groups such as politicians, bureaucrats, and the organized working class[178] – a reason that has ultimately decelerated the necessary pace of institutional reform in India.[179] This is, for example, reflected by the comparatively long period of time that is needed to enforce a contract in India, i.e. 1,445 days[180] (see Fig-

[174] Dai, Xiudian (2013), p. 43; Naughton, Barry (2018), p. 387.
[175] Mishra, R.K., Zhou Shaopeng (2011), pp. 221 f.
[176] Khanna, Tarun et al. (2010), pp. 98 ff.
[177] Zhao, X. (2017), pp. 20 f.
[178] Nagaraj, R. (2012), p. 11.
[179] Khanna, Tarun et al. (2010), p. 35.
[180] Refers to the number of calendar days from the filing of the lawsuit in court until the final determination and, in appropriate cases, payment.
See: World Bank (n.d.; b).

ure II-7), and by the fact that lawsuit and arbitration resolutions can take up to fifteen years due to a massive backlog of cases[181].

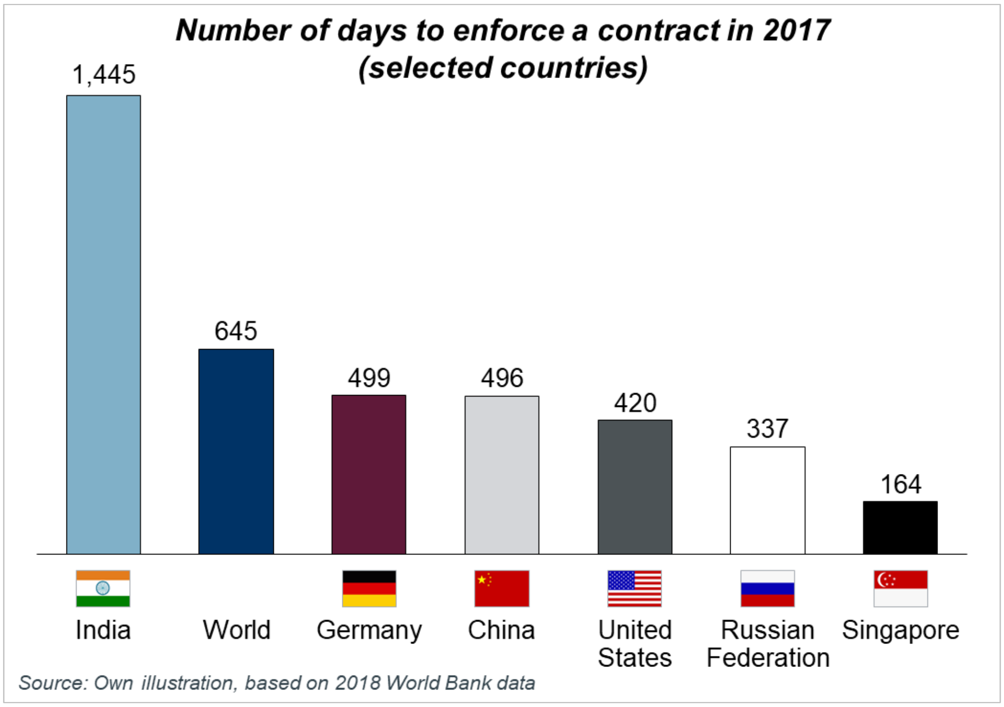


Figure II-7: Time required to enforce a contract in India vs. other selected countries

II.3.3 Transaction cost theory

As shown in the mini-case examples in China and India, emerging markets can be considered to function in a manner that is less than perfectly efficient. Even if countries manage to unleash domestic economic growth potentials through prudent macroeconomic policies, as observed in China, they do not necessarily produce well-functioning and thus highly attractive markets for MNEs. In fact, although the (perceived) dissemination and nature of institutional voids may differ considerably, institutional voids may constrain or even entirely inhibit the formation of markets with fair "rules of the game". Expecting the efficiency of advanced economies, MNEs have instead to reckon with entrepreneurial uncertainties, which manifests themselves in a time and resource-intensive process of transacting.[182] In this environment of inefficient business transactions, MNEs are well-advised to consider a more holistic and en-

[181] Khanna, Tarun et al. (2010), p. 14.
[182] Khanna, Tarun et al. (2010), p. 17.

terprise-specific perspective of institutional void-related risks – that of **transaction costs** – to obtain a firmer grasp of the derived operational challenges in emerging markets.[183]

The concept of transaction costs can be traced back, among others, to the writings of *Ronald H. Coase* who states that "in order to carry out a market transaction it is necessary to discover who it is that one wishes to deal with, to inform people that one wishes to deal and on what terms, to conduct negotiations leading up to bargain, to draw up the contract, to undertake the inspection needed to make sure that the terms of the contract are being observed (…)."[184] *Carl J. Dahlmann*, in a similar but more condensed manner, approaches the framework of transaction costs by ascribing to it all "search and information costs, bargaining and decision costs, policing and enforcement costs."[185] *Oliver E. Williamson*, in light of the previous definitions, aligns transaction costs with the institutions of governance at the micro-analytical level of organization, the "play of the game".[186] He states that the governance of contractual relations is prevailing at this level and therefore places a particular focus on contract management and dispute settlement directly between the transacting parties.[187]

The prevalent view in the neoclassical paradigm is that market transactions can be understood as an occasion in which "(…) faceless buyers and sellers (…) meet (…) for an instant to exchange standardized goods at equilibrium prices"[188]. In contrast to this orthodoxy of economic thinking, which assumes that transactions are consummated at zero costs, NIE makes express provision for market imperfection and, concurrently, the existence of transaction costs.[189] In this context, institutions in the aggregate can be considered a "(…) mixed bag composed of those that lower costs and those that raise them", thereby decisively determining market efficiency.[190] At an enterprise level, assuming that it costs something to enter into market transactions[191], **economizing on transaction costs** hence becomes the strategic engine of intra-firm analytics.[192] L'Oréal's retrospective decision to internalize market intelligence functions in the Indian market represents a good example of such an intra-firm analytical result – the outcome

[183] Arrow, Kenneth J. (1969), p. 48.
[184] Coase, Ronald H. (1960), p. 15.
[185] Dahlmann, Carl J. (1979), p. 148.
[186] Williamson, Oliver E. (1996), pp. 4 f.
[187] Williamson, Oliver E. (2000), p. 597 ff.
[188] Ben-Porath, Y. (1980), p. 4.
[189] Williamson, Oliver E. (2008a), p. 7.
[190] North, Douglass C. (1990), p. 63.
[191] Coase, R.H. (1988), p. 7.
[192] Williamson, Oliver E. (2008a), p. 7; Williamson, Oliver E (2008b), p. 8.

of which could have probably helped Danone to anticipate the protectionist interpretation and application of regulations in the Chinese market.

Regardless of L'Oréal's and Danone's specific market responses, both examples vividly illustrate that, due to the unavailability of market information (L'Oréal) and insufficient legal enforcement (Danone), the costliness of transacting in emerging markets tends to be higher than in more advanced economies in the Western world. Within such a setting, MNEs may predominantly have to make decisions on the basis of **information asymmetry** and thus apply subjectively-derived assumptions and premises as guides to their key strategic choices.[193]

The construct of higher transaction costs owed to information asymmetry is best captured by George Akerlof's example of a used car market, the so-called "market for lemons".

The basic premise of this example is that the seller of a used car, after several years of ownership, has an informational advantage towards the buyer who enters into the transaction with a somewhat higher level of skepticism and distrust. Hence, being uncertain about the actual working condition of the second-hand car, the buyer hesitates to pay the price demanded by the seller. The resulting stalemate raises the question as to how the transaction achieves an outcome that is satisfying for both interacting parties. On the assumption that the demand mainly hinges on the price and average quality of the used cars traded[194], one conceivable option would be to negotiate the seller's price in order to account for a range of product quality-related uncertainties. Under this circumstance, the buyer might suggest a counterproposal to the original offer which would, however, not contribute to both parties' mutual satisfaction. The reason for this is that the seller is very aware of the car's actual quality. He would accept the counterproposal only if it exceeded the car's genuine value. This, in turn, means that the buyer would have been overcharged for a car of low quality, a so-called "lemon". Conversely, if the demanded price should truly reflect the car's actual high quality, a so-called "peach", the seller would reject the (from his perspective) unattractive deal and search a for other prospective buyers. Either way, the only beneficiary in all described scenarios would be the seller of the lemon, who sells a malfunctioning car at an inflated price. Apparently, this sort of market is doomed to failure, because "peach" sellers will learn not to use it as a transaction platform and "lemon" buyers will regret their purchase decisions and avoid making that mistake again in future transactions.

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[193] North, Douglass C. (1990), pp. 8, 107 f.
[194] Akerlof, George A. (1970), p. 490.

To remedy institutional voids and prevent adverse selections on the used car market, a more viable option is to seek for expert advice, i.e. an independent intermediary organization assessing the car's real market value based on professional technical inspection. The intermediary's expertise alters the transaction in a way that the initial information asymmetry in favor of the seller is reduced and common ground for agreeing on a fair transaction price is attained. With an independent intermediary in place, the tide is turning for the lemon seller whose cars will then be priced for what they truly are, i.e. poor-quality products.[195]

In summary, there are at least three lessons learned from Akerlof's paper, which are thought to be of particular relevance:

i) Information asymmetry and incentive conflicts in the product market contribute to market inefficiency and increase transaction costs;
ii) Trustworthy institutions have the potential to reduce transaction costs, thereby creating a more equal playing field between the interacting parties;
iii) "Black sheep" – or in this case lemon sellers – having benefitted from institutional voids in the first place, are less likely to stay afloat in the market[196] once a transparent and trustworthy institutional framework is established.

II.3.4 Strategic implications for MNEs

From what is stated above, scanning for institutional voids constitutes a crucial factor in estimating the time and resources needed to consummate transactions. In this vein, one key task of MNEs is to formulate and implement strategies that allow for economizing on transaction costs and, on that basis, achieve sustained competitive advantage over domestic and international rivals.[197]

Given the importance of strategy formulation and implementation, the problem of many MNEs in emerging markets is principally twofold: First, executives often fail to distinguish between the conceptual dimensions of "strategy" and "operational effectiveness". While the essence of strategy is to create and preserve competitive advantage by deliberately choosing a different set of business activities than competitors in order to deliver a unique mix of value to

[195] Khanna, Tarun et al. (2010), pp. 19 ff.
[196] Khanna, Tarun et al. (2010), p. 20.
[197] Williamson, Oliver E. (2017), pp. 165 ff.

customers[198], operational effectiveness means performing the same or similar activities more efficiently than competitors do. To be sure, constant improvements in operational effectiveness strengthen a MNE's ability to economize on transaction costs in the near term. On the other hand, it is also true that few enterprises have managed to translate operational improvements into an extended period of profitability, mostly due to the fact that best practices diffuse rapidly amongst adapting competitors.[199] Second, even if the paramount significance of strategy is recognized, some MNEs are inclined to commit an inductive fallacy[200], misleadingly assuming that strategies deployed in more advanced economies would generally prove, after a few local twists, equally successful in emerging markets.[201] The case study of L'Oréal in its early years of business operations in India has been previously put forward to demonstrate precisely the opposite, exemplifying that MNEs struggle to customize their strategic approaches to fit the less matured institutional framework of emerging markets.

Seen as such, if there is a single overriding implication to derive from the L'Oréal and Danone mini-case examples described beforehand, it is that MNEs deciding to gain a foothold in emerging markets are inevitably exposed to institutional voids. Therefore, although there is no generally applicable formula for navigating emerging market-specific idiosyncrasies, a more subtle and sophisticated approach to institutional voids is postulated to outmaneuver any sort of operational challenges emanating from these voids or even capitalize on palpable opportunities to build businesses based on filling them.[202]

In addressing this issue, Khanna and Palepu conceptualized a set of four generic strategic choices (see Figure II-8) that represent an initial starting point for MNEs originating from more advanced economies[203]:

i) Replicate the business model, including products, services and processes, so as to exploit global capabilities <u>or</u> adapt this business model to institutional voids;

ii) Compete solely by internalizing basic market intermediary functions <u>or</u> forge partnerships to acquire local knowledge and capabilities;

iii) Accept <u>or</u> attempt to change the market context by filling institutional voids as part of an enterprise's core business proposition;

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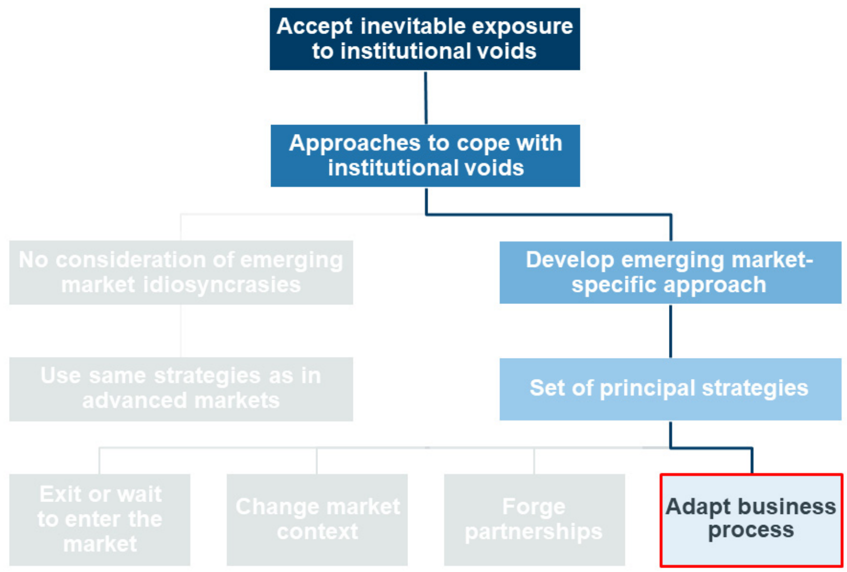
[198] Porter, Michael E. (2008), p. 43.
[199] Porter, Michael E. (2008), pp. 37 f.
[200] Godfrey, Richard (2016), p. 38.
[201] Khanna, Tarun et al. (2010), p. 61.
[202] Khanna, Tarun et al. (2010), p. 16, 44.
[203] Khanna, Tarun et al. (2010), pp. 40 ff.

iv) Enter or stay in the market despite institutional voids or exit it in favor of other markets with a more efficient institutional framework.



Source: Own illustration, based on Khanna, Tarun (2010)

Figure II-8: Principal strategies to deal with institutional voids

This thesis continues by concentrating upon a main branch of the first strategic choice, i.e. the **adaptation of internal business processes**, for the sake of improving the accuracy of sales forecasts in emerging markets. The decision in favor of this strategic choice can be attributed to the underlying Volkswagen case study, which assumes that an “exit” strategy is an illusory option given Volkswagen’s high degree of strategic dependence on the world’s largest single market. By the same token, it is expected that attempts to “change the market context” are most likely to be choked off by political decision-makers, because the automotive industry represents a key industrial sector of strategic development in China.

III Adaptation of sales forecasting process from the resource-based view

As determined in section II.3, institutional voids in emerging markets are inextricably linked to a comparatively high degree of entrepreneurial uncertainty. This uncertainty is chiefly rooted in regulatory insecurity and unreliable market information. Given these environmental forces, accurate sales forecasts serve as an effective instrument to reduce uncertainty by enabling corporate decision-makers to deflect or prepare for changing market development tendencies and adjust strategic and tactical planning premises prior to competition.[204]
With that in mind, this chapter introduces the fundamental importance and key challenges of sales forecasting in emerging markets. In the further course, a special emphasis is placed on how a RBV on an enterprise can contribute to a more dynamic forecasting process in the presence of institutional voids. Based on these research results, this chapter elucidates a set of methodological implications for the emerging market case study in general and the case study of PV sales in China in particular. As part of these implications, a key element of forecasting success is ascribed to the use of an ANN forecasting model, the concept of which is explained at the end of this chapter.

III.1 Importance and challenges of sales forecasting in emerging markets

The prevalence of regulatory insecurity and unreliable market information in emerging markets entails real and first-order implications on an enterprise's strategic and tactical business planning.[205] The key ingredient of entrepreneurial planning, in turn, is the business forecast. As such, business forecasting can be defined as a "prediction or estimate of an actual outcome expected at a future time period or for another situation"[206]. In product markets, such as the automotive industry, one of the most essential business forecasts refers to periodic total market sales.[207]

In fact, total market sales forecasts build the foundation for many entrepreneurial decisions; accurate forecasting results are thus considered to be a decisive prerequisite for well-founded planning assumptions.[208] At a minimum, sales forecasts for a specific period would reflect, first, any past trend in sales that is expected to carry through into the new period and, second,

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[204] Armstrong, J. Scott (2001), p. 2; Mahadevan, B. (2010), pp. 395 ff.
[205] Khanna, Tarun et al. (2010), p. 28; Enderwick, Peter (2007), p. 82.
[206] Ord, Keith et al. (2013), p. 2.
[207] Ord, Keith et al. (2013), p. 6.
[208] Shahabuddin, Syed (2009), p. 670.

the impact of any anticipated event that might materially affect that trend.[209] Technically, the aspect of sales forecasting and associated entrepreneurial planning is most commonly divided into short-term, medium-term, and long-term horizons. These different horizons are not necessarily represented in clear-cut distinctions. The prevailing view in literature holds that the short-term horizon is mainly concerned with tactical planning of (less than) three months, whereas medium-term horizons span decisions with strategic planning horizons of one to two years, and long-term horizons anything beyond that.[210]

In the short-term, accurate sales forecasts enable an organization to maintain an optimum inventory level in production planning. The overall goal is to run factories at full capacities[211] or, as another example, proactively adjust price positioning at dealerships to adequately respond to quickly changing market dynamics.[212] Opposed to this purely tactical decision-making, long-term sales forecasts are used for major strategic planning considerations. They might, for example, refer to costly fixed asset investments, the launch of new products in fast-growing segments, or the establishment of strategic alliances and partnerships for the sake of harnessing cutting-edge technologies.[213] Closely associated with both dimensions are medium-term sales forecasts that typically encompass minor strategic planning decisions. These decisions are related to both managerial accounting, which essentially deals with the expected operational performance within a functional area of an enterprise, and financial accounting, the function of which is to comply with international accounting standards by aggregating all functional performance reports into a consolidated external financial statement.[214]

Irrespective of the specified horizon, causal models theoretically represent an ideal basis for accurate results in sales forecasting. Such models assume that all key factors that determine the future values of the respective sales variable are known, quantifiable, and available in time for ex ante[215] forecasts. However, in real market applications, this assumption tends to be overly optimistic.[216] For that reason, non-causal models concentrate on substituting for causal input variables by selecting suitable **leading indicators** that precede significant changes in the

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[209] Petty, J. William; Titman, Sheridan; Keown, Arthur J. et al. (2012), p. 180.
[210] Mahadevan, B. (2010), p. 398; Gonzalez-Rivera, Gloria (2016), pp. 84 ff; George, Frank H. (1984), p. 52.
[211] Shahabuddin, Syed (2009), p. 670.
[212] Ord, Keith et al. (2013), p. 6.
[213] Fantazzini, Dean; Toktamysova, Zhamal (2015), p. 98; Faulkner, David (2006), p. 622.
[214] Rieg, Robert (2010), pp. 220 f.
[215] Ex ante forecasts only use the information that would have been available at the time the forecast was made. Ex post forecasts use the actual values of the explanatory variable, even if these would not have been known at the time the forecast was made.
[216] Ord, Keith et al. (2013), p. 206, 234.

sales variable of interest.[217] Sales forecasts based on leading indicators may yield quite decent results if selected carefully. At the same time, models based on leading indicators may not be as effective (in terms of forecasting accuracy) as models using causal variables.[218]

In other words, the use of leading indicators is associated with a higher probability of **inaccurate sales forecasts**. Inaccurate sales forecasts, in turn, may cause erratic assumptions of future development, with the ultimate effect being that management decisions could be seriously misguided[219] and inevitably result in unnecessarily high transaction costs.[220] The upshot is that enterprises have to reckon with unforeseen events that may have the potential to pull previously axiomatic planning assumptions into entirely different directions and affect an enterprise's relative position in the respective market.[221] It stands to reason that this sort of operational challenge is more serious in emerging markets than in advanced economies, due to higher levels of institutional void-related uncertainty.[222]

One of the main obstacles MNEs face in producing accurate sales predictions is their inability to deal with time series data. By definition, a time series is a "set of comparable measurements recorded on a single variable over multiple time periods ordered in time"[223]. The values may refer to either a point in time, e.g. "the exchange rate for the Euro against the Chinese Yuan is at a current level of 1 EUR / 7.816 RMB", or an aggregate over a period of time, e.g. "the total amount of crude steel production in China was about 76 million metric tons in the period between the 1st and 31st of December 2018".[224]

Regardless of the type of time series selected, several challenges may limit forecasting accuracy: First, incomplete time series data or data fractions due to scarcity of timely observations or restrictions imposed by the data owner.[225] Second, time series data inconsistencies, which may be the result of methodological shortcomings in data compilation or deliberate data manipulation. Third, a laic understanding of time series data. In this case, the forecaster may decide to eliminate an unexpected jump in sales from the raw data, classifying it as a non-

217 Ord, Keith et al. (2013), p. 206, 234.
218 Ord, Keith et al. (2013), p. 4, 234.
219 Rieg, Robert (2010), pp. 220 f., 234.
220 Fantazzini, Dean et al. (2015), p. 98.
221 Gilad, Ben (2004), pp. 69 f.
222 Mody, Ashoka (2004), p. 5, 13; Sakarya, Sema et al. (2007), p. 209.
223 Ord, Keith et al. (2013), p. 21.
224 Ord, Keith et al. (2013), p. 7.
225 Ord, Keith et al. (2013), p. 7, 206; Khanna, Tarun et al. (2010), pp. 60, 97 ff.

recurring outlier instead of (rightly) considering it to be an essential pattern of historical sales development.[226]

Even if time series data is complete, statistically sound, and the forecaster exhibits an in-depth understanding of the underlying market idiosyncrasies, the dynamism resulting from an ever-changing market environment leaves deep and permanent scars in the data to be analyzed. In such a setting, forecasting inaccuracies are also likely to materialize[227], because changing variances and changing parameters may affect pattern recognition in time series data.[228]

III.2 Model considerations for sales forecasting in emerging markets

From the illustrations provided above it can be inferred that the application of conventional models to forecasting in emerging markets is most likely to produce inaccurate and hardly trustworthy output results. This conclusion holds true even if the same forecasting models are successfully deployed in advanced economies. The rapid pace of change in emerging markets requires a more unconventional approach to sales forecasting. That said, the ultimate objective of this section is to conceptualize such an approach.

III.2.1 Resource-based view vis-à-vis institutional voids

In order to reconcile the principal challenges of sales forecasting in emerging markets with the underlying concept of institutional voids, two aspects are of fundamental relevance:

First, as found earlier, an ever-changing regulatory environment often implies a certain degree of structural change in emerging markets. In statistical terms, frequent structural changes manifest themselves in highly dynamic time series data for which, in MNEs, no suitable forecasting process exists. It follows that conceptualizing an equally **dynamic forecasting process** is considered an adequate response. Within this process, the most essential element refers to the development of a **quantitative model** that is capable of capturing changing variances and changing parameters in time series behavior.

Secondly, previous findings on sales forecasting in emerging markets have further revealed that the absence or unreliability of market information may entail a competitive disadvantage

[226] Shahabuddin, Syed (2009), pp. 671 f.
[227] Rieg, Robert (2010), p. 234; Shahabuddin, Syed (2009), p. 672; Sakarya, Sema et al. (2007), p. 209.
[228] Rieg, Robert (2010), p. 222; Konar, Amit; Bhattacharya, Diptendu (2017), pp. 3 f.

for MNEs. To compensate for this disadvantage, access to high-quality **local market expertise** is required in order to cultivate a more granular appreciation of an emerging market's distinctive peculiarities.

Tailored to the situation at hand, a RBV on enterprises offers an acknowledged framework. It suggests that an enterprise's potential to build and sustain competitive advantage is predominantly contingent upon its idiosyncratic bundle of resources and capabilities.[229] Decision-makers should therefore learn how to acquire and mobilize this bundle when examining their internal organization.[230] As such, the RBV centers upon the resources and capabilities that already reside within or are to be developed by an organization.[231] It explains why certain enterprises, ceteris paribus, have markedly lower costs or are able to offer better quality and more outstanding product performance than other market players.[232]

In this context, Toyota is often highlighted as a benchmark for efficiency levels achieved in the automotive industry. The high levels of efficiency have enabled the enterprise to attain vastly higher levels of profitability than its main global competitor, Volkswagen.[233] The divergence in profitability can be explained by Toyota's superior fast-cycle new-product development resources and outstanding manufacturing capabilities, the latter of which are commonly referred to as the "Toyota lean production system".[234] If one takes into account that Volkswagen's corporate brand portfolio extends to a series of higher-valued premium and luxury vehicle brands, which are usually associated with higher prices and higher profit potentials, Toyota's achievement becomes even more remarkable and underlines the importance ascribed to the RBV. This example illustrates that the RBV approaches strategy analysis from an enterprise's (internal) business environment, whereas the concept of institutional voids focuses on the (external) market environment.[235] The upshot is that both dimensions have to

[229] Glowik, Mario (2016), p. 72; Henry, Anthony E. (2018), p. 115.
[230] Hitt, Michael A. et al. (2016), p. 80.
[231] Henry, Anthony E. (2018), p. 116.
[232] Teece, David J.; Pisano, Gary; Shuen Amy (1997), p. 513.
[233] Volkswagen's profit margin accounted for 7.3% and 7.0% in 2015 and 2016 respectively, whereas Toyota's profit margin was 10.9% in both years. In 2017, both enterprises reported a profit margin of 8.3%.
At Volkswagen, the Audi and Porsche brands alone accounted for around 53.2% of the Group's operating profits in 2017 (excluding the results from both joint ventures in China).
Source: Moody's Investors Service (2018), p. 6, 9.
[234] Grant, Robert M. (2015), p. 99, 110.
[235] Henry, Anthony E. (2018), p. 115.

be aligned and converted into a unified approach of risk management in MNEs with the goal of ultimately suiting the surrounding institutional context of emerging markets.[236]

III.2.2 Resource-based view: The interplay of resources and capabilities

The RBV considers individual resources as the productive assets owned by an enterprise. These resources must supplement or complement each other to create organizational capabilities. On the other hand, capabilities lay the foundation for an enterprise's superior business performance in the long run. In other words, capabilities are what the enterprise can do.[237]

Resources can be thought of as "input factors" that enable an enterprise to carry out its business operations.[238] These input factors include both tangible and intangible assets that are tied (semi-) permanently to a given enterprise.[239] While tangible resources encompass all financial and physical assets, intangible resources comprise non-physical assets, such as brand names, patents and copyrights, the ability to innovate, and reputation.[240] For proponents of the RBV theory, considering enterprises as portfolios of tangible and intangible resources, rather than portfolios of products and services, is one essential step in building competitive advantage.[241] More specifically, there are four distinct attributes that measure the usefulness of an enterprise's resources:

First, the resource must be valuable. A resource is valuable when it allows decision-makers to conceive of or implement strategies that are aimed at increasing the enterprise's efficiency or effectiveness. In that sense, the traditional "strengths-weaknesses-opportunities-threats" framework helps tracking down valuable attributes in the enterprise, i.e. the strengths. Based on this pre-selection, the RBV framework then specifies what other attributes are needed in order to convert a valuable resource into a systematic source of competitive advantage.[242]

Second, the resources should be rare. The criterion of rareness is fulfilled when a resource is not widely held by a larger number of competing enterprises. If a particular valuable resource is owned simultaneously by a number of other enterprises, then each of these enterprises may also have the ability to exploit this resource, thereby conceiving and implementing similar

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236 Barney, Jay B.; Wright, Mike; Ketchen, David J. Jr. (2001), p. 629, 634.
237 Grant, Robert M. (2015), p. 89.
238 Henry, Anthony E. (2018), pp. 117 f.
239 Wernerfelt, Birger (1984), p. 172.
240 Henry, Anthony E. (2018), p. 117.
241 Wernerfelt, Birger (1984), p. 178.
242 Barney, Jay B. (1991), p. 106.

value-creating strategies. In this scenario, none of the enterprises can be expected to obtain a competitive advantage. The converse implication is that if a valuable resource is rare amongst competitors and other potential market entrants, the enterprise in possession of this unique resource will most likely generate competitive advantage. In capital and technology-intensive industries, enterprises with valuable and rare resources tend to be strategic pioneers benefitting from their first-mover advantage.[243] The purpose of early market entry is that the initial occupant of a strategic position or niche gains access to supplementary or complementary resources and capabilities that a follower will quite possibly not match. This is either because the market pioneer is able to preempt the best resources, or to use its early market entry to create superior resources and capabilities.[244]

A third attribute that makes resources relevant for enterprises' competitiveness is imperfect imitability. Resources are <u>imperfectly imitable</u> if a competitor's attempt to reproduce the resource will most likely fail due to implicit protective barriers set up by the resource-owning enterprise. Such barriers may refer the enterprise's intrinsic ability to acquire and exploit resources thanks to its *unique historical position in time and space*. For example, an early fixed-asset investment into a country that turns out to be a much more attractive location than originally predicted may endow enterprises with an imperfectly imitable resources, such as a well-entrenched brand image.[245] Likewise, the attribute of imperfect imitability is fulfilled when the link between a particular resource controlled by an enterprise and an enterprise's competitive advantage is *causally ambiguous*. In this case, competitors are uncertain which (or in which constellation) resources may provide a competitive advantage and thus are unable to take the necessary actions to imitate them. In fact, to become a systematic source of competitive advantage, the resource owner and its competitors must be confronted with the same degree of causal ambiguity. Otherwise, if the resource owner had a clear-cut comprehension of the exact interplay between its resource and the associated competitive advantage, competitors would have an incentive to extract and acquire the embedded expertise, thereby presumably closing the gap on the resource owner. Imperfect imitability can also occur if the resource is, per se, *socially complex*. Social complexity manifests itself in the corporate culture, brand reputation, and interpersonal relationships between managers, employees, and external stakeholders such as suppliers and customers. While it may be possible to identify the specific contribution that

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[243] Barney, Jay B. (1991), p. 107.
[244] Grant, Robert M. (2015), p. 131.
[245] Barney, Jay B. (1991), pp. 107 f; Ranchhod, Ashok (2007), p. 19.

such a resource has on an enterprise's competitive advantage, thereby implying that there is no or only little causal ambiguity, socially complex resources are often difficult to manage and reproduce. It follows that socially complex resources remain subject to imperfect imitation as long as they cannot be systematically influenced by the respective resource owner.[246]

The fourth and last criterion to measure the usefulness of an enterprise's resources is that the resource can be considered <u>non-substitutable</u>, meaning that there are no strategically equivalent substitutes in the marketplace. The criterion of non-substitution is met when two valuable resources can be exploited independent of each other. That is to say, if a specific resource is not rare or imitable, other market players might combine it with their unique portfolio of resources to build a competitive edge. In such a setting, the usefulness of the original resource is neutralized despite its valuable, rare, and imperfectly imitable attributes. If, for example, an enterprise's top management team represents a systematic source of competitive advantage in strategy formulation and execution, a competing enterprise would hardly be able to completely imitate the composition of the team. However, having recognized that the source of competitive advantage lies in, say, the team's clear strategic vision of corporate growth in a rapidly changing market environment, the substituting enterprise may be able to set up its own team, thereby creating a potentially equivalent resource.[247]

The four attributes of an enterprise's resources – valuable, rare, imperfectly imitable, and non-substitutable (VRIN) – constitute the very essence for building sustained competitive advantage. However, despite their proven usefulness, resources on their own do not necessarily create value for an enterprise. It is only when they are transformed into some productive use that superior business performance follows.[248] Along these lines, the RBV suggests that an enterprise must progressively pave the way for specific milestones of in-house capability development. This path not only determines what strategic options are available to the enterprise today, it also presents a roadmap as to what its internal repertoire must be like in the future so as to comply with the key challenges presented by market change. It is precisely at this point that the dynamic capabilities construct comes into play.[249]

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[246] Barney, Jay B. (1991), pp. 108 ff.
[247] Barney, Jay B. (1991), pp. 111 f.
[248] Henry, Anthony E. (2018), p. 116 ff; Teece, David J. (2018), p. 40.
[249] Teece, David J. et al. (1997), p. 515.

Dynamic capabilities are defined as an enterprise's ability to incorporate, build, and reconfigure internal competences[250] so as to achieve a high level of fit with changing market environments. Given a specific resource endowment, dynamic capabilities determine to which degree enterprises can craft innovative responses when "time-to-market" concerns are crucial, the pace and extent of technological change is disruptive, or the future trajectory of market development (including the behavior of rivals) is hard to ascertain. The ability to harness dynamic capabilities is particularly important in high-velocity emerging markets, where the level of change tends to be much faster than in rather saturated advanced economies.[251]

That said, it is important to distinguish between "dynamic capabilities" and "operational capabilities". Both types of capabilities are essential ingredients of an enterprise's business activities. Operational capabilities, also called "zero-order capabilities", relate to ongoing activities that allow an enterprise to make a living in the present. They ensure that the status quo within an enterprise is maintained by iteratively applying the same techniques to operate its daily business in the respective market. On the other hand, dynamic capabilities are concerned with the challenges presented by environmental change and concentrate on how to enable an enterprise to recalibrate its living in the present.

Dynamic capabilities can come in many shapes and forms. In the automotive industry, they may allow an enterprise to conduct mergers and acquisitions based on a well-founded due diligence process, learn from "best in the class" industry practices for agile software engineering, or adjust organizational processes and routines in an attempt to emphasize customer journeys and user experiences.[252] In broader terms, the most decisive capability in sustaining competitive advantage is found in an enterprise's "high-flex" mode of scanning and evaluating impelling forces of market development, thereby anticipating macro and micro risks in the environment as they arise. The subsequent organizational learning and transformation process is then intimately tied to the capability of accomplishing the necessary re-orchestration of resources. This re-orchestration has to occur in a timely and cost-efficient manner so as to ensure competitive levels of profitability.[253]

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250 In the RBV literature, the terms "capability" and "competence" are often used interchangeably. For the purpose of better understanding, only the term "capability" will be used throughout this chapter.
See: Henry, Anthony E. (2018), p. 118.

251 Teece, David J. (2018), p. 40; Henry, Anthony E. (2018), p. 131.

252 Henry, Anthony E. (2018), p. 131; Teece, David J. (2018), pp. 43 f.

253 Teece, David J. et al. (1997), pp. 520 f.

III.2.3 Methodological implications for the case study of PV sales in China

Up to this point, the specific terminology of an enterprise's resources and capabilities, as well as their general interplay in building sustained competitive advantage, have been outlined in detail. Applied to the emerging market case study, the first task now is to identify the type of resources that is expected to provide the best fit to the VRIN framework. The second task is to incorporate these resources into a dynamic forecasting process. This process shall also include a clear roadmap of how to proceed further in implementing the underlying research design and, ultimately, answering the research question of this thesis.

Drawing up the inventory of an enterprise`s resources can be astonishingly challenging.[254] That is because the source of sustained competitive advantage in many enterprises is no longer rooted in tangible assets. Instead, the ability to develop and leverage the value of intangible assets is becoming more and more a key capability for enterprises, especially in high-technology industries.[255]

In this regard, one of the most important intangible assets is knowledge.[256] As such, the term "knowledge" has to be distinguished from the less-specified terms "information" and "data". Whereas data consists of raw numbers and facts, a commonly held view is that information deals with the aspect of initial data processing, i.e. converting data into some form of broader context. Knowledge, in turn, pertains to a more complex level of contextualization. It refers to personalized information, which may or may not be new or unique and is typically based on facts, procedures, concepts, ideas, observations, and judgments. Thus, a mere stringing together of disconnected information resources does not create knowledge. Only the information that has been actively processed in the mind of an individual through a process of reflection, enlightenment, or learning can be considered as such.[257] In that sense, the existence of knowledge facilitates the decision about *which* data should be analyzed and *how* to process it so as to convert it into a useful element of quantitative forecasting applications.

In line with the RBV, knowledge can be sub-divided into two main taxonomies: explicit and tacit knowledge. Explicit knowledge refers to "knowing about facts and theories"[258] and comprises formally documented, codified knowledge, much like product specifications, scientific

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254 Grant, Robert M. (2015), p. 91.
255 Halawi, Leila A.; Aronson, Jay E.; McCarthy, Richard V. (2005), p. 78; Grant, Robert M. (2015), p. 91.
256 Henry, Anthony E. (2018), p. 117, 129.
257 Alavi, Maryam; Leidner, Dorthy E. (2001), pp. 109 f.
258 Glowik, Mario (2016), p. 72.

formulas, and manuals. This sort of knowledge is relatively objective and rational. It can be easily shared with other (groups of) individuals.[259] In contrast, **tacit knowledge** can be described as "knowing how"[260], referring to valuable skills, competencies, and/or previous lessons learned about collaboration. It has a highly cognitive and personalized dimension, as it is deeply embedded in the corporate culture, processes or minds of employees.[261] This type of knowledge is "path-dependent", because it is based on all the unique experiences an enterprise has acquired to date as a result of its tenure in business.[262] It is exactly this characteristic which makes tacit knowledge rather difficult to transfer among individuals and hence hard to imitate and substitute. In other words, enterprises that are seeking to accumulate local market expertise as a resource should preferably concentrate on the tacit dimension of knowledge creation.[263]

As stated before, a fine-grained understanding of local market idiosyncrasies is imperative to properly contextualizing the frequent ups and downs in an enterprise's market environment. For that matter, domestic enterprises, because of their legacy on their home turf, are said to have a competitive edge over MNEs.[264] Therefore, MNEs should strive to close the knowledge gap that separates them from local incumbents by, for example, supplementing and complementing their internal portfolio of knowledge resources with external expertise.[265] The extent to which an enterprise is able to do that hinges on its "absorptive capacity", a dynamic capability that considers the aspect of inter-organizational learning in three consecutive phases[266]:

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[259] Henry, Anthony E. (2018), p. 129.
[260] Glowik, Mario (2016), p. 72.
[261] Henry, Anthony E. (2018), p. 130.
[262] Henry, Anthony E. (2018), p. 117.
[263] Glowik, Mario (2016), p. 72; Henry, Anthony E. (2018), p. 130.
[264] Khanna, Tarun et al. (2010), p. 39, 42.
[265] Glowik, Mario et al. (2014), p. 179 f.
[266] Schildt, Henri; Keil, Thomas; Maula, Markku (2012), p. 1156.

i) Acquisition phase: Recognize and acquire potentially useful knowledge resources from external sources;[267]

ii) Assimilation phase: Extract all valuable parts of the acquired knowledge resources and assimilate them into organizational procedures;[268]

iii) Application phase: Apply the assimilated knowledge to build new and proprietary tacit knowledge within the own organization.[269]

The deployment of this so-called "triple-A" framework to the underlying case study of PV sales in China leads to the following roadmap of methodological implications:

First, in the **acquisition phase**, potentially useful knowledge has to be acquired through expert interviews. The interviews ought to provide profound insights into the unique experiences of an eclectic mix of automotive experts from the Chinese automotive industry. These insights must be articulated in a manner allowing the researcher to interpret them.[270] Therefore, special attention is placed on a semi-structured setup of interviewing, one that allows the researcher to elicit the tacit attributes of the interviewees' knowledge by asking further questions in response to what are seen as significant replies.[271] Moreover, to build longer-term competitive advantage, the interview setup has to be designed in a fashion to not only elicit know-how on a single occasion, but also grant access to post-interview longitudinal studies and data collection opportunities.[272]

Second, in the **assimilation phase**, the interview deliverables have to be processed in a manner to extract all valuable parts of the acquired knowledge resources and assimilate them into organizational procedures. The objective is to separate useful statements from less useful statements and, above all, to eventually select a set of leading indicators with sufficiently available and consistent time series data.

Third, in the **application phase**, all identified leading indicators are applied as "input factors" for the sales forecasting model. This model forms the centerpiece of the revised sales forecasting process, because it is expected to navigate through ever-changing conditions in the Chinese automotive market.

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267 Glowik, Mario et al. (2014), p. 218.
268 Carayannis, Elias G. (2012), p. 26.
269 Glowik, Mario (2016), p. 72.
270 Alavi, Maryam et al. (2001), p. 110.
271 Bryman, Alan et al. (2015), p. 213, 493.
272 Ryan, Paul; Dundon, Tony (2008), p. 448.

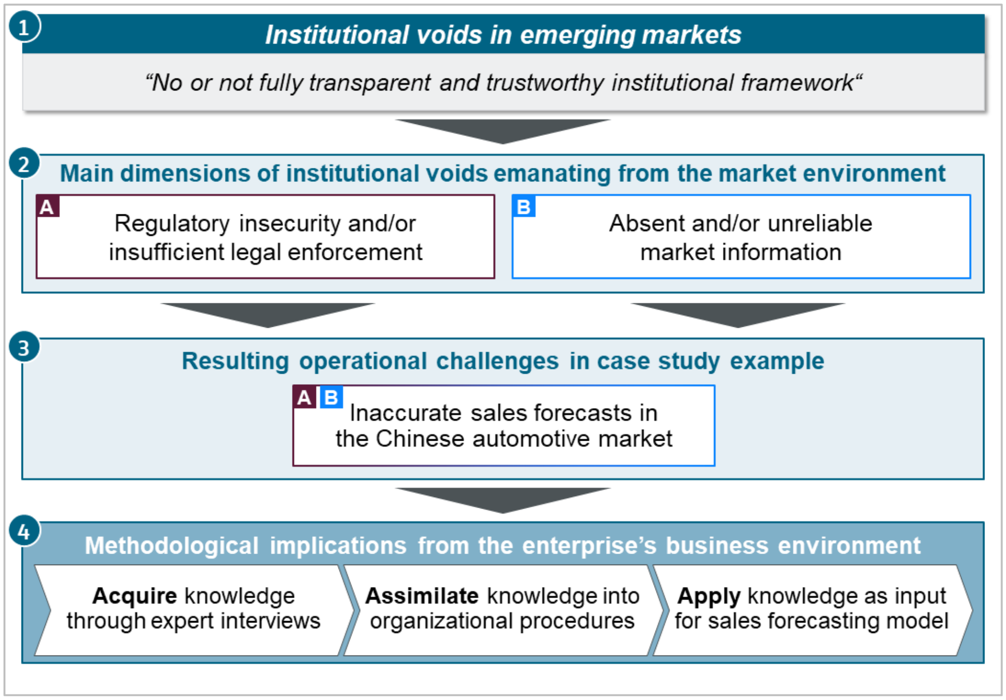

Figure III-1: Methodological implications from the resource-based view

The final selection of leading indicators in the assimilation phase is greatly influenced by the way in which data relationships are modelled. Therefore, the selection of the quantitative method to be applied to the underlying case study of PV sales in China had to be made at this early stage of research. It will be discussed in the following section.

III.3 The concept of Artificial Neural Network forecasting

As stated earlier, the overarching goal of this research is to devise an actionable process for more accurately forecasting PV sales in the Chinese automotive market. Previous findings from the RBV suggest that the most essential element in this process refers to the development of a dynamic forecasting model, one that features certain characteristics to handle the dynamics in time series data.

III.3.1 Comparative considerations in Artificial Neural Network forecasting

Conventional regression approaches that have long been dominant in the field of time series forecasting[273], most notably the Box-Jenkins ARMA[274] or VAR[275] models, are principally constrained by three fundamental limitations:

First, they are designed for linear statistical forecasting applications[276] and thus incapable of mapping any non-linear relationships in the data. As a result, the approximation of non-linear relationships with ARMA and VAR models has often failed to reliably identify patterns and produce satisfactory prediction results out of past observations.[277] Second, ARMA and VAR models are inappropriate for predicting "real-world" phenomena with non-stationary time series characteristics. One conceivable fallback solution consists of converting the non-stationary time series into a stationary series by using the difference(s) in consecutive data points. In univariate applications, this ultimately results in an Integrated ARMA model (i.e. "ARIMA"[278]).[279] Third, the reliability of prediction results in regressive models presupposes the presence of independent determinants. However, in real market applications, it can certainly be assumed that determinants are, at least to some degree, interconnected with each other. In statistical terms, this methodological limitation is expressed in the problem of multicollinearity, which occurs when a sample of at least one predictor is strongly correlated with other predictor values.[280]

In contrast to conventional regression-based methods of forecasting, ANNs represent a rather unconventional and versatile approach to forecasting in emerging markets. ANNs have a long history in research on finance and economic modeling[281] and thus been field-tested in both advanced economies and emerging markets[282]. Owed to their data-driven characteristic, ANNs

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273 Zhang, Peter G. (2004b), p. 2; Tong, Howell (2012), p. 6; Shahabuddin, Syed (2009), p. 672, 675; Hülsmann, Marco; Borscheid, Detlef; Friedrich, Christoph M. et al. (2012), p. 66.

274 ARMA models are univariate models combining an autoregressive (AR) part, which attempts to unveil the relationships between the values dependent on how far apart they are in time, and a moving average (MA) part smoothening out the "quirks" of time series data.
See: Kuvulmaz, Janset; Usanmaz, Serkan; Engin, Seref Naci (2005), p. 505.

275 Vector autoregressions (VAR) are multivariate models incorporating information from more than one time series into the forecasting process.
See: Hott, Christian; Kunkel, A.; Nerb, G. (2007), p. 238.

276 Kuvulmaz, Janset et al. (2005), p. 507; Hott, Christian et al. (2007), p. 233, 238.

277 Zhang, Peter G. (2004b), p. 2.

278 The distinction between ARMA and ARIMA models can be found in the "integrated" part, which represents the differencing of the original time series to achieve stationary.

279 Konar, Amit et al. (2017), p. 4; Gao, Junjie, Xie, Yanan; Cui, Xiaomin et al. (2018), p. 4.

280 Moosmayer, Dirk C.; Chong, Alain Yee-Loong; Liu, Martin J. (2013), p. 3029; Devore, Jay (2015), p. 606.

281 Huang, Wei et al. (2007), p. 114.

282 See for e.g. Maciel, Leandro S. et al. (2010); Zhang, Dabin et al. (2010); Chen, An-Sing et al. (2003).

excel at detecting non-linear relationships, even if there is no a priori knowledge concerning the process from which predictions are generated.[283] That is because ANNs belong to the category of structure-detecting multivariate methods, which are used to explore previously unknown data relationships – whereas (causal) regression-based models are classified as structure-testing multivariate methods, which merely check whether hypothesized data relationships can be confirmed empirically.[284] Furthermore, as a non-parametric method, ANNs are less vulnerable to the model specification problem and do not necessarily presuppose any sort of data transformation to achieve stationarity.[285] ANNs are also less sensitive to problems arising from multi-collinearity[286], because they tend to contain many parameters that are estimated to obtain model fits. This, in turn, means that ANNs are capable of processing contextual information fed into the network.[287]

Beyond these points, the unique distinguishing feature of ANNs is their mathematically proven universally functional approximation capability, which has turned out particularly useful for approximating any continuously differentiable function at any arbitrary degree of accuracy.[288] This capability enables ANNs to bridge across topological gaps – whereas a single missing observation in regression-based forecasting models may lead the forecaster to drop the entire sample or discard the variable from all observations. The result is that ANNs are comparatively fault-tolerant models, which are robust in terms of prediction performance, even if data is partially unavailable, entirely missing, or affected by outliers[289].

A downside of ANN forecasting is the large variety of parameter settings, because it involves a lot of trial and error on behalf of the forecaster and it varies depending on the nature of the underlying dataset.[290] That is to say, the versatility of ANNs comes at the cost of experimenting with a sheer unlimited number of layers and neurons for which there is no blueprint configuration.[291] Furthermore, it can be argued that superior ANN performance hinges on the

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[283] Zhang, Peter G. (2004b), pp. 2 f; Du, Ke-Lin et al. (2014), p. 108; Adamowski, Jan; Karapataki, Christina (2010), p. 730; Haykin, Simon (2009), p. 3.
[284] Backhaus, Klaus et al. (2018), p. 15; Ord, Keith et al. (2013), p. 459.
[285] Konar, Amit et al. (2017), p. 4; Haykin, Simon (2009), p. 3; Yim, Juliana (2002), p. 25; Ord, Keith et al. (2013), p. 331.
[286] De Veaux, Richard D.; Ungar, Lyle H. (1994), p. 394; Moosmayer, Dirk C. et al. (2013), p. 3033.
[287] Haykin, Simon (2009), p. 4.
[288] Kuvulmaz, Janset et al. (2005), p. 505; Kaastra, Iebeling et al. (1996), p. 216; Armstrong, J. Scott (2001), p. 246.
[289] Venugopal, Venkataraman; Baets, Walter (1994), p. 34; Du, Ke-Lin et al. (2014), pp. 10 f; Haykin, Simon (2009), p. 4,10.
[290] Kaastra, Iebeling. et al. (1996), p. 217; Du, Ke-Lin et al. (2014), p. 96.
[291] Kuvulmaz, Janset et al. (2005), p. 505; Kruse, Rudolf et al. (2016), pp. 79 ff.

availability of a large amount of training data, which is particularly true for non-linear applications with complex yet revolving patterns of extreme input conditions.[292] This is opposed to most other (traditional) time series forecasting models for which far fewer parameters have to be estimated.[293] In effect, there is no appropriate sample size specified to determine ex ante whether ANNs produce superior prediction results. A “guesstimate” would be around 300 observations[294], although other economic models indicate equally successful outcomes with smaller sample quantities employed.[295] Compared with linear models, critics also suggest that the knowledge learned from the ANN training process is encrypted in a matrix of real-valued numbers, the so-called connection weights, which appear to be a “black box” rather than straightforward and easily interpretable.[296]

At the bottom line, despite certain objections raised about their configuration, performance, and transparency, ANNs are considered to be a promising solution to forecasting in a highly dynamic emerging market context. For that reason, the following sub-sections are devoted to explaining the concept of ANN forecasting in the field of machine learning. These sub-sections illustrate, metaphorically and technically, how ANNs are usually trained to recall and apply their “knowledge” in business forecasting applications.

III.3.2 Artificial Neural Networks in the field of machine learning applications

Although the concept of ANN forecasting has a history of more than 50 years, its today’s widespread acceptance is owed to the increasing computer power[297] that has become available in recent years.[298] Right from its inception, the application of ANNs has been inspired by the awareness and recognition that the human brain processes information in a fundamentally different and faster way from the conventional digital computer.[299] That is why the focus of Artificial Intelligence (AI) has been to render machines intelligent by enabling them to emulate human problem-solving behavior. Taking into consideration that intelligence cannot be

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[292] Tarassenko, Lionel (1998), p. 54.
[293] Armstrong, J. Scott (2001), p. 248.
[294] Tkacz, Greg et al. (1999), p. 13.
[295] See for e.g.: Zhang, Dabin et al. (2010).
[296] Kruse, Rudolf et al. (2016), p. 89.
[297] Rieg, Robert (2010), p. 222; Hülsmann, Marco et al. (2012), pp. 65 ff.
[298] Ord, Keith et al. (2013), p. 327.
[299] Haykin, Simon (2009), p. 1.

attained without some kind of learning capabilities, research efforts on different forms of machine learning have come to occupy an important place in pertinent AI literature.[300]

Generally, machine learning occurs when a machine is able to accumulate experience and, based on that experience, generate new knowledge so as to enhance its performance on specific tasks over time.[301] It is customary to distinguish between two different types of machine learning methods, namely the supervised and unsupervised learning methods. While both methods seek to uncover data relationships by undergoing an iterative learning process, an important distinction between them is in the role of "teacher" supervision:

Supervised learning, or learning with a teacher, denotes a method in which the learning algorithm of an ANN receives a composition of continuous or categorical input variables in an effort to produce the correct "answers" to a learning problem in a completely unknown environment.[302] The solutions to this problem are reflected by the output variable, which may either be continuous for forecasting or categorical for classification[303] applications.[304] The solutions are made available by an explicit teacher who, by virtue of built-in knowledge, knows exactly what the environment looks like. Assuming that both the ANN and the teacher are presented with certain input/output training samples, which are extracted randomly from the surrounding environment, the teacher is in a position to evaluate the ANN's response and, if necessary, correct it. Any such correction is conducted iteratively and done step-by-step with the ultimate goal of making the ANN emulate the teacher. In other words, the ANN learns from the teacher's feedback by creating an input/output mapping for the problem at hand.[305] That way, a certain transfer of knowledge under the tutelage of the "omniscient" teacher to the initially "naïve" ANN is accomplished, with the knowledge being stored in its long-term memory. Once this sort of error-correction learning within a closed-loop feedback system has been accomplished sufficiently, the ANN is able to dispense with the teacher and ready to handle new tasks from the surrounding environment entirely on its own accord.[306]

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300 Chen, Zhiyuan; Liu, Bing (2018), p. 2.
301 Izenman, Alan J. (2008), p. 9.
302 Rojas, Raul (2013), p. 78; Du, Ke-Lin et al. (2014), p. 15.
303 Categorical output variables are used, for instance, in image or character recognition. In these fields of classification applications, the task of ANNs is to assign new inputs representing a pattern to one of a number of discrete pattern classes (categories), which, in turn, share common features and usually originate from the same source.
See: Bishop, Christopher M. (1996), p. 5; Theodoridis, Sergios; Koutroumbas, Konstantinos (2008), pp. 4 f.
304 Izenman, Alan J. (2009), p. 10.
305 Haykin, Simon (2009), p. 3.
306 Haykin, Simon (2009), pp. 34 f.

On the other hand, unsupervised learning, or learning without a teacher, means that no teacher is supervising the learning process. It follows that, for a specific input, the "correct" answer in the form of a corresponding output variable is not known a priori. While a set of labeled – or pre-classified – training samples is provided in supervised classifications, the challenge in unsupervised learning is to develop a self-organizing capability that encodes statistical regularities of newly encountered, yet unlabeled, input data into new clusters with similar features.[307] To this end, the ANN auto-associates information from the correlations among the input variables by reducing either data dimensionality or the total amount of input data.[308] By virtue of its exploratory discovery capabilities, this type of machine learning is particularly useful for, say, the early detection of cancer in that it improves the clustering of benign and malignant tumors based on gene expression patterns.[309]

With regard to forecasting (of automotive sales development in emerging markets), the commonality between ANN and regression models is that both approaches attempt to minimize the sum of squared errors over the input/output training samples. In that sense, a linear regression model resembles a feedforward ANN topology with no hidden layer (i.e. a so-called "single-layer perceptron" (SLP)), in which the connection weights between the input variables and single output variable correspond to the coefficients in a linear least squares regression model.[310] Logically, the source of the distinctive universal function approximation capability in ANNs can then be explained via non-linear information processing in the hidden layer(s) of a "multi-layer perceptron" (MLP).[311]

[307] Roohi, Farhat (2013), p. 35; Rojas, Raul (2013), p. 78; Haykin, Simon (2009), p. 37.
[308] Du, Ke-Lin et al. (2014), pp. 10 ff.
[309] See for e.g. Yu, Zhiwen; Chen, Hantao; You, Jane et al. (2015).
[310] Kaastra, Iebeling. et al. (1996), p. 217.
[311] An MLP qualifies as such if the ANN contains at least one hidden layer.
See: Du, Ke-Lin et al. (2014), p. 83.

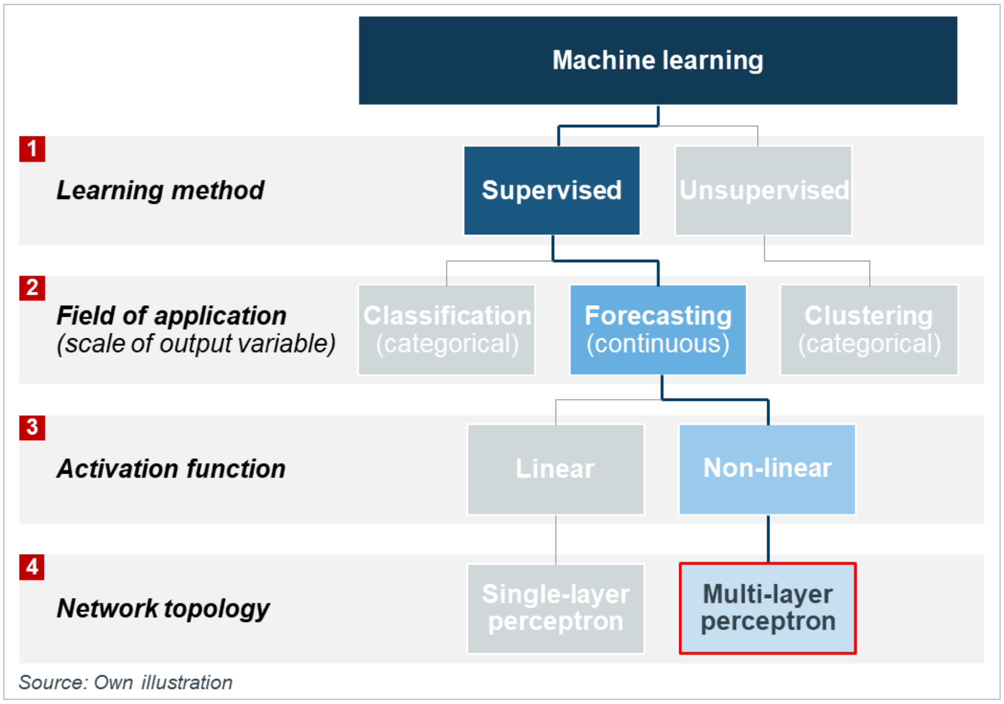

Figure III-2: Multi-layer perceptrons in machine learning

III.3.3 Topology and training of a MLP with gradient-descent algorithm

In the field of ANN forecasting, the most popular and successfully implemented model refers to a three-layered feedforward MLP with error backpropagation.[312]

Figure III-3 depicts the topology of such an ANN, which is organized in input, output, and hidden layers. It consists of many simple computing units collecting and transmitting electrical activity, the so-called "neurons".[313] The input and output neurons are directly connected with the external environment of the ANN, whereas the neurons in the hidden layer are interconnected to all other neurons, but do not possess any link to the ANN periphery.[314] The information is passed through in a one-directional feedforward manner, i.e. from the input to the output layer, without any feedback loop between the layers.[315]

312 Kruse, Rudolf et al. (2016), p. 47.
313 Rojas, Raul (2013), p. 123; Kruse, Rudolf et al. (2016), p. 11.
314 Kruse, Rudolf et al. (2016), p. 38.
315 Zhang, Peter G. (2004b), pp. 3 f; Du, Ke-Lin et al. (2014), p. 9.

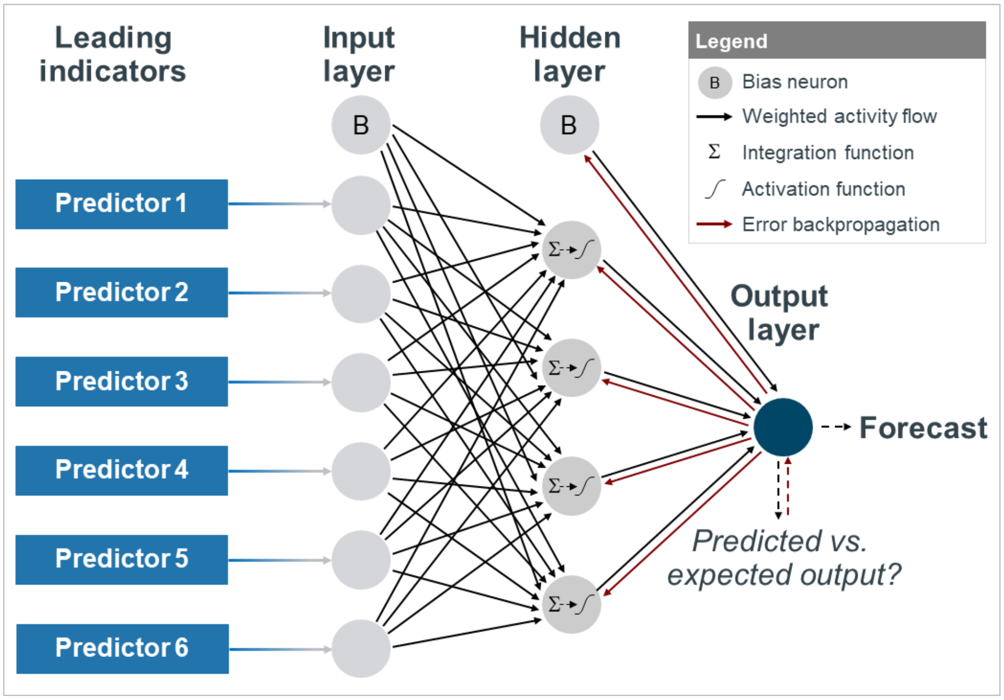

Figure III-3: Typical topology of a feedforward MLP with error backpropagation

As for the topological components, the entry points listed on the left-hand side of Figure III-3 represent the interface of the ANN to its external environment, which is used to feed data into the ANN without running any computational processing.[316] As such, the input neurons equate to the number of all pre-identified predictors that are assumed to "lead" the variable of interest in the output neuron for a respective length of time.[317]

In each layer, the neurons assume the task of translating received inputs into processed outputs. The weights between the hidden neurons and their equivalents in the upstream and downstream layers indicate the strength of connection and are the key to learning input and output data patterns.[318] Adjacent to the information processing neurons, an additional column of bias neurons complements the topology of ANNs. With a value that is always set to positive one, bias neurons are linked to each processing neuron in the hidden and output layers, performing functions analogous to the intercept term in regression models.[319] As for the signal processing within the neurons, the sum of inputs is aggregated by means of an integration function[320], before – as a second step – the aggregated values are converted into a probability

[316] Rojas, Raul (2013), p. 123.
[317] Koch-Weser, Iacob N. (2013), p. 28.
[318] Zhang, Peter G. (2004b), pp. 3 f.
[319] Kaastra, Iebeling. et al. (1996), p. 217.
[320] Rojas, Raul (2013), p. 123.

value whose exact value depends on the selected activation function. In this context, the logistic and hyperbolic activation functions are most commonly utilized in multi-layered ANNs. That is because both functions display continuously differentiable properties[321], which are required to introduce non-linearity to the ANN training procedure.[322]

In essence, training ANNs can be considered a non-linear optimization problem. The key task chiefly consists of learning patterns by iteratively providing ANNs with training samples of the correct known values. A pre-specified learning algorithm tries to achieve convergence, i.e. locating a global minimum of the error function in weight space for a given set of training samples.[323] For that purpose, the continuously differentiable properties of the sigmoidal activation function are transferred to the error function, allowing the ANN to repeatedly "optimize" the present constellation of connection weights.

In ANN forecasting, the most influential learning algorithm is based on a backpropagation training method.[324] In backpropagation, each sample of training observations is fed through the network with the connection weights initialized at random values. The result of this data pass-through produces an estimated value in the output layer, which is compared with the expected value. The resulting discrepancy for every training sample is represented by an individual error function, which is ultimately integrated into a total error function for the entire training set.[325] The total discrepancy is then minimized by computing the gradient of the error function by means of gradient descent. As such, the gradient depicts the slope (direction and steepness) of the error function and is computed at its given location of weights. The main purpose for applying the gradient descent method is to constantly modify weights so as to learn how significant the change in weights must be in order to minimize the error function.[326] To this end, the error signal emanating from the discrepancy between the estimated and expected output is recursively "propagated" from the output to the precedent hidden layer.[327] It constitutes the baseline for gradient re-computations with the ultimate goal of reaching a global minimum of the error function as part of the ANN training process.[328]

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321 Du, Ke-Lin et al. (2014), pp. 85 f.
322 Kaastra, Iebeling. et al. (1996), p. 227.
323 Du, Ke-Lin et al. (2014), p. 15.
324 Zhang, Peter G. (2004b), p. 5; Du, Ke-Lin et al. (2014), p. 85.
325 Law, Rob; Pine, Ray (2004), p. 128.
326 Kruse, Rudolf et al. (2016), p. 61 f.
327 Du, Ke-Lin et al. (2014), p. 85.
328 Kruse, Rudolf et al. (2016), p. 62, 67.

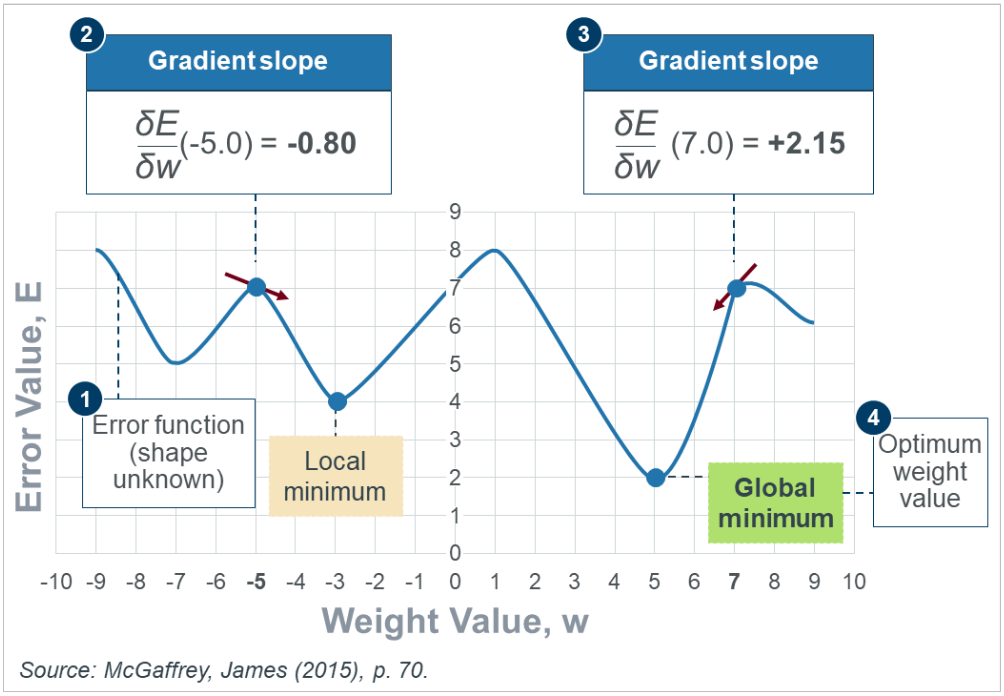

Figure III-4: Method of gradient descent using an exemplary error function

Stated differently, the backpropagation algorithm utilizes the method of gradient descent to adjust the weights by moving down the steepest slope of the error surface. In general, there are two variations of gradient descent that may come in question: batch/mini-batch (offline) and online learning. In the offline mode, weight adjustments are performed on an epoch-by-epoch basis, i.e. after the presentation of *all* training samples. This type of learning allows for an accurate estimation of the gradient, which may imply finding a local minimum – but also getting stuck in it. In the online mode, weight adjustments are performed on an iteration-by-iteration basis, i.e. after the presentation of *one* training example. The training samples in online learning are randomly presented to the ANN, making the multidimensional weight space stochastic in nature. This characteristic has the desirable effect of being able to escape local minima, which is a considerable advantage over offline learning. On the downside, the frequent iterations in online learning may result in a noisy gradient signal, which may cause the model error to oscillate.[329]

In other words, both types of gradient descent – online and offline – have advantages and disadvantages. Based on a process of trial and error undertaken by the researcher, the overall goal is to find the optimum combination of weights that minimizes the error function to the

[329] Haykin, Simon (2009), p. 127 ff.

greatest possible extent. This can then be considered the best approximate solution for the present learning problem.[330]

III.3.4 Practical implications for accurate forecasts

Finally, the assessment of predictive model performance typically differentiates between two distinct kinds of forecasts: in-sample and out-of-sample.

In-sample forecasts are those generated for the same set of time series data as that used to estimate each model's parameters.[331] It stands to reason that in-sample forecasting models exhibit a relatively strong performance, because they seek to provide the best fit to historical data. However, fixating on the best reconstruction of data to achieve high in-sample forecasting accuracy includes the risk of "overfitting".[332] Overfitting has a detrimental effect on predictive models, because it is not only the relationships inherent in data that are mapped, but also the existing noise.[333] This circumstance would mean that the model is inclined to memorize specifics about the data presented to it, instead of learning and generalizing the data's basic structures. The consequence is a high error rate when testing the model with patterns not used in the training process.[334]

For that reason, out-of-sample forecasts cross-validate the generalization ability of in-sample models by using "hold-out" data, i.e. a reasonable number of unseen observations that have intentionally been held back from the original records of available time series data.[335] In machine learning terminology, the out-of-sample dataset is often referred to as "validation"[336], whereas all in-sample observations belong to a so-called "training" set.[337] Unlike traditional approaches to forecasting, model fitting during ANN training contains an additional "testing"[338] stage, the function of which is to verify the generalization ability of a supposedly trained model and the possibly subsequent re-consideration of a model's configuration choices. The testing stage provides a valuable indication as to whether a training sample tends to be

330 Rojas, Raul (2013), p. 149, 167.
331 Brooks, Chris (2014), p. 286 f.
332 Camm, Jeffrey D. (2015), p. 179.
333 Thawornwong, Suraphan; Enke, David (2004), p. 60.
334 Priddy, Kevin L.; Keller, Paul E. (2005), p. 148.
335 Brooks, Chris (2014), p. 286 f.
336 In machine learning vocabulary, there is no uniform usage of the term "validation". In some scientific publications, the validation set is called "testing" set.
See for e.g. Zhang, Peter G. (2004a); Priddy, Kevin L. et al. (2005).
337 Kaastra, Iebeling. et al. (1996), p. 223.
338 In some scientific publications, the testing set is called "validation" set.

over-fitted.[339] This is likely to occur when the testing error grows whereas the training error falls – an unequivocal sign that the training process should be terminated.[340]

To summarize, the operation of an ANN for forecasting applications consists of two essential stages: learning and generalization. In the learning stage, the ANN is equipped with a set of input/output training samples and a learning algorithm, which can either be used in an offline or online mode. Once the ANN accomplishes the desired in-sample forecasting accuracy, the researcher validates the model by testing its ability to generalize on unseen data. If the model still exhibits accurate forecasting performance, it may have learned (all) relevant patterns inherent in the data and can then be utilized for actual business forecasting applications.[341]

[339] Kaastra, Iebeling. et al. (1996), p. 223.
[340] Peterson, Gerald E. et al. (1995), p. 953.
[341] Du, Ke-Lin et al. (2014), p. 10.

IV Knowledge acquisition in the Chinese automotive industry

As outlined in chapter III, the RBV on enterprises holds that a MNE's absorptive capacity is one of the key dynamic capabilities to acquire, assimilate, and apply other enterprises' expertise. This so-called "triple-A" framework helps MNEs supplement and complement their internal portfolio of knowledge resources, thereby building and sustaining a competitive advantage in the presence of institutional voids in emerging markets.

That said, the following three chapters are meant to implement the triple-A framework in the underlying case study of PV sales in China. It begins with *this* chapter, which elaborates on acquiring knowledge from ten market forecasting experts in the Chinese automotive industry. To adequately address all experts' (controversial) views on indicator selection, the key results of each interview are summarized separately. Chapter V then assimilates the interviewees' statements as part of a multi-level indicator selection process. The outcome of this process is a set of leading indicators with superior predictive power. Chapter VI applies the selected indicators as part of an ANN model to forecast monthly PV sales in the Chinese automotive market. The ultimate objective of ANN modelling is to figure out whether or not ANNs are capable of improving the accuracy of forecasts in a highly dynamic emerging market environment.

Serving as the outset of this case study, the following section dwells on the key milestones of automotive development in China. These milestones provide an initial insight into how government policies have shaped the historical evolution of the Chinese automotive industry and, in this way, undoubtedly "contributed" to its present-day transitional characteristics and associated regulatory insecurities.

IV.1 The role of government policies in the Chinese automotive industry

During the central planning stage between 1949 and 1978, the Chinese automotive industry was considered to be a national blueprint for the institutional arrangements of China's planned economy. The Chinese government had emphasized the relevance of automotive production, taking into account the rising need for mechanized transport and associated manufacturing capabilities so as to effectuate national industrialization. In doing so, enterprises were established as factories that were owned and run by local or central governments, with only little space for entrepreneurial autonomy.[342] Within this macro governance structure, volumes and variety of vehicles were centrally planned, rather than determined by market forces.[343] The production output was predominately composed of commercial vehicles and, to a smaller degree, motorized two-wheelers. Passenger vehicles, in contrast, accounted for less than 1% of total national output and were the exclusive prerogative of a few high-level government bureaucrats. Taxis for personal transport were virtually not present at all.[344]

Circumstances began to change once China transitioned from a planned into a market economy between 1978 and 1994. During this era of reform, and especially in the second half of it, there were initial signs that the government would soon refrain from prescriptive commands and instead exert its influence by means of industrial policies. Provincial and municipal governments and ministries gradually assumed more autonomy in the emerging market environment without being afraid of having supposedly taken the "capitalist road"[345]. The resulting diffusion of automotive manufacturing in China led to a marked increase of total market output volumes and a simultaneous increase in the product range.[346]

In 1994, the Chinese government started designating the automotive industry as a "pillar industry", expecting it to stir overall economic growth by creating new employment opportunities.[347] The rationale behind this decision was that a conventionally-powered vehicle typically comprises more than 10,000 components. The sourcing of these components extends to a wide range of suppliers and sub-suppliers from different industries, such as metallurgy, petroleum, and electronics. In an effort to push and coordinate all activities surrounding automotive production more effectively, the government pledged considerable political and financial support in "China's 1994 Automotive Industry Policy"[348]. By this point, it was increasingly clear that the central government had no intention of leaving the market to complete self-regulation. Instead, the automotive policy was to be understood as a "visible hand" for a government-initiated growth plan that formulated four distinct regulatory objectives, namely:

i) Establishing large-scale producers of sedans and light commercial vehicles;

ii) Enhancing the supply of components;

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342 Feng, Qiushi (2018), p. 5.
343 Holweg, Oliver N.; Luo, Jianxi; Oliver, Nick (2009), p. 80.
344 Feng, Qiushi (2018), p. 2; Holweg, Oliver N. et al. (2009), p. 80.
345 Holweg, Oliver N. et al. (2009), p. 80.
346 Feng, Qiushi (2018), pp. 5 f; Holweg, Oliver N. et al. (2009), p. 80.
347 Colton, Luke S.; Morrison, Wayne M. (1997), p. 296.
348 For the complete text, see Ministry of Commerce of the People's Republic of China (1994).

iii) Developing automotive product development capabilities;

iv) Boosting individual passenger vehicle ownership.[349]

With that policy in effect, domestic automotive consumption started to take off and the share of passenger vehicle output increased to about 30% of total market production in the late 1990s.[350]

At that time, a legacy of the planned economy was that vehicles were still sold at a price determined by the government. The absence of a self-regulating market mechanism secured the survival of small-scale local enterprises and was the chief reason for persisting protectionist tariff and non-tariff barriers to trade. However, in the course of China's WTO entry in December of 2001, the increasing presence of foreign automotive enterprises placed growing pressure on the central government to comply with its own industrial policy.[351] In an effort to gain international competitiveness in automotive production and exploit the potential of the domestic market for passenger vehicles, the government therefore announced (and enforced) the incremental dismantling of some of its most important trade barriers (see Figure IV-1). The immediate effect of this measure was that production output increased by 38.8% in 2002 and 36.7% in 2003 respectively[352].

[349] Holweg, Oliver N. et al. (2009), p. 81 f; Colton, Luke S. et al. (1997), pp. 296 f.
[350] Feng, Qiushi (2018), p. 2.
[351] Holweg, Oliver N. et al. (2009), pp. 80 f.
[352] Holweg, Oliver N. et al. (2009), p. 82.

	Before entry into WTO	After entry into WTO
Tariff rates	– 200% in 1980s – 80%-100% in 1990s	– 25% for fully-built units by 2006 – 10% for components by 2006
Import quotas	– 30,000 vehicles p.a. for foreign MNE	– Quota increased by 20% p.a. since 2002 and phased out by 2006
Local content	– 40% in first year of production, 60% in second year, and 80% in third year	– No official requirements after 2002
Foreign ownership	– Limited to two joint ventures per segment (stake ≤ 50%) – Wholesaling and retail only through joint ventures	– No change in joint venture obligations, but wholesaling and retail ownership allowed by 2006

Source: Holweg, Oliver N. et al. (2009), p. 80.

Figure IV-1: Ease of trade restrictions announced after China's entry into the WTO

Unfortunately, one of the side effects following China's WTO entry was that the production capacities for automotive manufacturing started to exceed customer demand. This resulted in excess capacity, increasing the already fierce competition in the market. In response, the government introduced a series of cooling-down policies at the macro level in 2004, which encompassed a curb in bank lending and slowed down approvals for investments. At the micro level, extensive price discounting induced customers to delay their vehicle purchasing decision, because they were expecting even lower prices.

In the same year, the National Development and Reform Commission (NDRC) issued the "2004 Automotive Industry Policy"[353], a comprehensive amendment to the policy enacted ten years earlier. The new version represented a shift in the role of the government in that guidance and encouragement of enterprises ought to determine the fate of the automotive industry's future, rather than rigid policy prescriptions. For instance, self-reliant research, development, and production at a large scale for key components was encouraged in the 2004 guidelines. A particular focus was placed on intellectual property created by Chinese brands

[353] For the complete text, see National Development and Reform Commission (2004).

so as to spawn a few famous domestic manufacturers and suppliers in expectation that they would become globally competitive by 2010.[354]

This key issue was picked up again under the heading of "indigenous brands" in China's 11th Five-Year Plan (FYP), which was released in 2006. The purpose of developing this plan was to create large-scale automotive enterprises with a production capacity of at least two million passenger and/or light commercial vehicles; 50% of these enterprises were to be manufacturing Chinese indigenous brands, while only 10% were to be exported to other countries.[355] At that time, 70% of Chinese automobile output was accounted for by passenger vehicles.[356]

In 2009, amid the global economic slowdown, the government formulated several development objectives under the umbrella of the three-year "Automotive Readjustment and Revitalization Plan"[357]. Subsidies and incentives were granted to promote indigenous innovation in new technologies and to stir the consumption of vehicles with small engine capacities and new technology installed.[358] For instance, the Chinese government has been particularly supportive of vehicle connectivity, one of the disruptive mega trends currently transforming the global automotive industry in that it enables a seamless interaction between the driver and the "connected" transportation environment, thereby paving the way for fully autonomous driving.[359]

Beyond that – and along with the commitment to decarbonize the domestic economy – a hike in oil prices and air pollution levels has strengthened the government's intention to encourage research, development, and production of "New Energy Vehicles" (NEVs[360]).[361] This intention has been backed in both the 12th (2011-2015) and 13th (2016-2020) editions of the FYP[362] and, most recently, resulted in the implementation of the so-called "NEV cap-and-trade policy", effective as of January 2019. This policy actually implied a minimum requirement for the production of NEVs in China for both domestic and foreign manufacturers. As such, all manufacturers exceeding a production or import threshold of 30,000 passenger vehicles are mandated to obtain NEV credits that amount to at least 10% of their vehicle fleet. This de facto

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354 Holweg, Oliver N. et al. (2009), p. 82 f.
355 Guo, Grace Chun; Jiang, Crystal X.; Yang, Qin (2017), pp. 11 f.
356 Data sources: Volkswagen Group of China; Chinese Association of Automobile Manufacturers.
357 For the complete text, see The Central People's Government of the People's Republic of China (2009).
358 Tang, Rachel (2012), pp. 18 f; United States International Trade Commission (2011), p. 5-36.
359 Herrmann, Andreas; Brenner, Walter; Stadler, Rupert (2018), p. 372.
360 These vehicles are powered by new drive technologies, i.e. battery electric, plug-in hybrid, fuel-cell, and hydrogen.
361 Guo, Grace Chun et al. (2017), pp. 11 f.
362 Chang, Crystal (2016), p. 7.

electric vehicle quota has been altered several times and eventually postponed from 2018 to 2019 as part of a major concession to German Chancellor Angela Merkel. It will be elevated to at least 12% in 2020, thereby raising the pressure for enterprises to comply with the ever-tightening environmental regulatory requirements.[363]

The NEV cap-and-trade policy ultimately represents the latest of a long list of industrial policies that is expected to once again initiate structural transformation in the Chinese automotive industry. As outlined above, viewed from the standpoint of a PV sales forecaster, the back-and-forth involved in the implementation of this policy is assumed to leave deep and permanent scars in the set of leading indicators to be analyzed. These scars, in turn, constitute one decisive reason for inaccurate predictions. To better understand how well-established market experts in the Chinese automotive industry deal with this sort of regulatory insecurity in their quantitative models, the author interviewed a total of ten experts from different Chinese automotive organizations. The overall setup and analysis of these expert interviews will be discussed in the subsequent sections.

IV.2 Setup of expert interviews in a business context

In business research, the interview is probably one of the most widely utilized methods of extracting all manner of knowledge from different organizations' experts.[364] One can distinguish between three main types of interviewing: structured, unstructured, and semi-structured interviewing.

In a structured interview, which is most commonly used in quantitative business research, the interviewer uses a standardized interview schedule to ask questions that were planned and formulated ahead of the actual interview time. With this type of interview, all interviewees are given exactly the same order of questioning. The overall goal is to maximize the reliability and validity of measurement so that the answers provided by the interviewees can be coded and processed quickly. Typically, the questions asked by the interviewer are rather formal and closed-ended. They are specifically related to the research objective(s) and often equip the interviewee with a fixed and pre-coded range of answer categories.[365]

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363 International Energy Agency (2018), pp. 23 ff.
364 Bryman, Alan et al. (2015), p. 210, 479.
365 Bryman, Alan et al. (2015), p. 211, 481.

By contrast, unstructured interviews, which are most commonly used in qualitative business research, allow the interviewer to depart significantly from any sort of pre-prepared interview schedule. The overall goal in unstructured interviewing is to obtain rich and detailed answers from the interviewee in an effort to understand the big picture context of the underlying research item. To this end, interviewers may introduce a great deal of flexibility into the interview process by responding to the situation at hand and even adjusting the emphases in the research as a result of particular relevant issues raised by the interviewees. The style of questioning in unstructured interviews is usually informal and open-ended and will vary from interview to interview.[366]

Between the two extremes of structured and unstructured interviewing lies a wide range of conceivable variations, commonly referred to as semi-structured interviews. As stated before, this type of interviewing was used for the case study of PV sales in China. Structured interview elements were incorporated into the interview strategy, because the author, who conducted all interviews, has had a fairly clear focus on the research objectives and also the way how the collected data should be analyzed subsequently.[367] Nonetheless, for the most part of the expert interviews, a more unstructured investigation constituted the preferred research method. The flexibility in the conduct of interviews seemed to be particularly important to explore the "big picture context" of institutional voids in the Chinese automotive market and how it shapes the matter of PV sales forecasting in the same. From this point of view, rather than rigidly adhering to a standardized interview schedule with very specific questions in a pre-determined order, a list of somewhat more general questions along certain focus areas was conceptualized in an interview guideline. This guideline served as a non-binding script[368] for all of the ten expert interviews, which were either conducted in English or Chinese language (see Annexes 4 and 5).

Framed within a broader process of knowledge acquisition, the basic elements of expert interviewing in the case study of PV sales in China can be summarized as follows:

[366] Bryman, Alan et al. (2015), pp. 214, 480 f.
[367] Bryman, Alan et al. (2015), pp. 483 f.
[368] Bryman, Alan et al. (2015), p. 213, 481, 486.

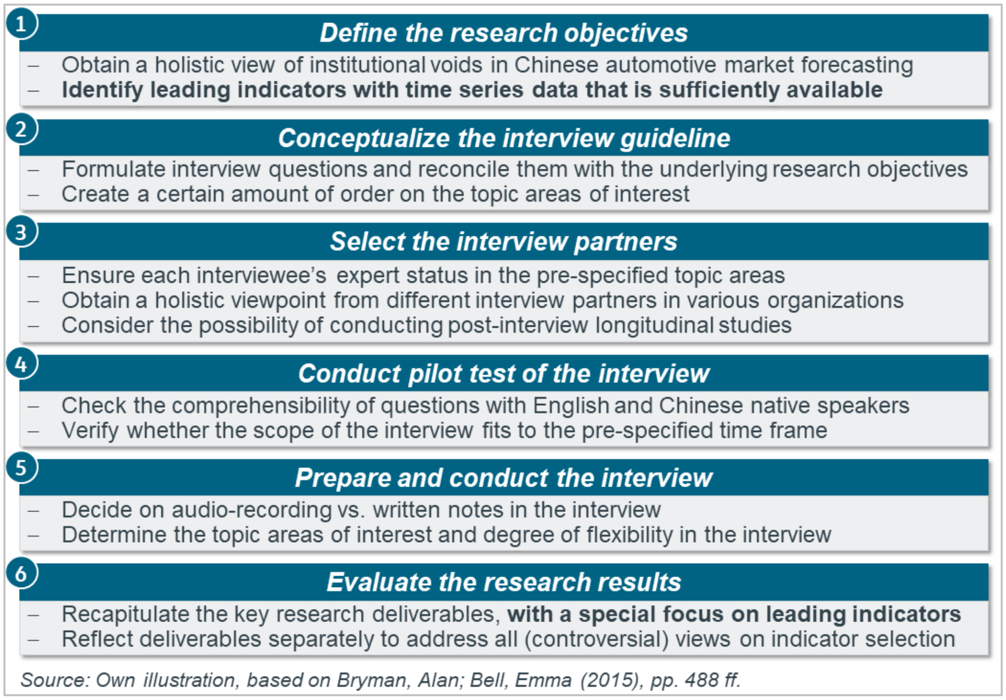

Figure IV-2: Process of knowledge acquisition through expert interviews in China

As can be seen in Figure IV-2, the primary research objective for the expert interviews was to identify a set of leading indicators with time series data that is sufficiently available and thus suitable for the subsequent ANN forecasting application. The availability of time series data was considered a crucial issue, because the success of ANN modeling largely depends on the (multitude of) patterns represented by the input variables.[369]

All interviewees were presented a list of potential leading indicators, which were pre-selected by the author. The list contained a total of 32 indicators[370] that were clustered into three broader categories, i.e. traditional economy, new economy, and automotive industry-specific indicators (see Annexes 6 and 7). The pre-selected indicators originated from both primary and secondary sources. The vast majority of indicators, especially in the new economy and automotive industry-specific cluster, stemmed from primary research. It was the result of the author's continued presence during his seven months-long participant observation at Volkswagen's market intelligence department for sales forecasting in the Chinese automotive market. As for the secondary sources, besides the most traditional leading indicators to signal changes in economic condi-

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369 Zhang, Peter G. (2004b), p. 4.

370 At this juncture, there will be no detailed discussion of the supposed relevance of all 32 indicators. Instead, this research only elaborates on those indicators that manage to "pass" the indicator selection process as specified in section V.2.

tions, such as a closing levels of a major domestic stock market index or a survey of consumer confidence[371], the author referred to indicators used in studies of comparable investigation scope in the German and U.S.-American automotive markets[372].

Based on this list of pre-selected leading indicators, the task for each of the ten interviewees (see Figure IV-3) was to select the most promising ones in terms of superior predictive power for automotive sales forecasting in China. To avoid situations in which a particular answer was actually encouraged, the key requisite was that all interviewees were given some time to reflect the list of pre-selected indicators without any additional prompting by the author.[373] The timing at which the list was brought up was dependent on the order of priority that the author had attached to the selection of leading indicators in the respective interview.

	Date/ Duration	Organization	Function	Language	Topic areas (in order of priority)
1	– Nov. 7th – 45 min.	Chinese state association A	Secretary General	Chinese	– Leading indicators – Access to time series data
2	– Nov. 7th – 65 min.	Chinese state association B	Deputy Secretary General	Chinese	– Used car business and data – Impact of government policies – Leading indicators
3	– Nov. 9th – 125 min.	Chinese state association C	Director automotive market research	English	– Forecasting methodologies – Leading indicators – Access to time series data
4	– Nov. 10th – 45 min.	Multinational automotive enterprise A	Senior management consultant for market intelligence activities	English	– Automotive mega trends – Leading indicators – Quantitative impact of policies
5	– Nov. 10th – 50 min.	Chinese state association D	Secretary General	Chinese	– Leading indicators – Impact of government policies – Access to time series data
6	– Nov. 11th – 60 min.	Multinational automotive consulting	Manager provincial light vehicles sales forecasting	English	– Provincial market forecasting – Forecasting methodologies – Leading indicators
7	– Nov. 11th – 55 min.	Multinational automotive enterprise B	Director powertrain strategy and planning in Asia-Pacific region	English	– Consumer behavior – Impact of government policies – Leading indicators
8	– Nov. 12th – 60 min.	Multinational automotive enterprise C	Senior manager market intelligence and research	English	– Leading indicators – Data pre-processing – Quantitative impact of policies
9	– Nov. 14th – 50 min.	Multinational automotive enterprise A	Senior manager market intelligence and analysis	English	– Total market forecasting – Leading indicators – Quantitative impact of policies
10	– Nov. 14th – 40 min.	Multinational automotive enterprise A	Director market intelligence and analysis	English	– Quantitative impact of policies – Leading indicators – Data pre-processing

Figure IV-3: Overview of interviews in the Chinese automotive industry in 2016

[371] Ord, Keith et al. (2013), p. 4, 236.
[372] Shahabuddin, Syed (2009), pp. 674 f.; Hülsmann, Marco et al. (2012), p. 68.
[373] Bryman, Alan et al. (2015), p. 224.

IV.3 Interview results

In this section, the author provides an in-depth analysis of all ten expert interviews. The first interview reflects the author's interview analysis in detail by describing the following:

i) The reasons for selecting the respective expert to be interviewed;

ii) the degree of flexibility in conducting qualitative interviewing;

iii) the interview setting and recording;

iv) the key (research) deliverables;

v) interview impressions.

For the sake of readability, Interviews 2-10 only focus on the reasons for selecting the respective expert to be interviewed (i.) and the key research deliverables (iv.). The remaining aspects for each interview are provided in detail in the Appendix of this thesis.

Interview 1: State association A | Secretary General

<u>a) Reasons for selecting this expert as an interviewee</u>

The interviewee holds the position of Executive Vice Chairman and General Secretary for state association A. Registered under the Chinese Ministry of Civil Affairs, the state association A is a social organization that was founded in Beijing in 1987. It is engaged in the production and management of automobiles, auto parts, and vehicle-related industries within the boundaries of the People's Republic of China. The state association A provides a scientific-based decision-making foundation for the related state department, the latter of which promulgates automotive policies to ultimately ensure a sound and rapid development in the Chinese automotive industry.

The interviewee has been selected as an interview partner due to his extensive experience in Chinese automotive development, which he obtained in his participation in the WTO's accession negotiations, in his position as General Manager and Deputy Party Secretary at a Chinese state-owned automotive enterprise, and through his scientific contributions to the technological development program for the automotive industry, the latter of which were incorporated into the national science and technology White Paper. Considering the interviewee's long-standing professional background, the focal interest of the interview was placed on identifying the most promising leading indicators for the ANN forecasting model. In conjunction with this, another key motivational factor for conducting this expert interview was to benefit from the interviewee's deeply integrated business network by eliciting information on key institutions and organizations for the subsequent retrieval of time series data.

b) Degree of flexibility in the conduct of qualitative interviewing

The selected interview strategy was coined by strict adherence to the interview schedule. The reasons for this decision were twofold:
First, one of the necessary preconditions for an approval of the interview appointment had been to brief one of the interviewee's assistants with a detailed set of information about the chief areas of interest in the research. The author reasoned that the interviewee's assistants had to prepare a preliminary script of answers to the questions, inducing the author to stick to the pre-discussed questions in the actual expert interview.

Second, the depth of exploration during an interview is conditional upon the interviewer's ability to express his/her thoughts and ideas verbally. In this vein, oral articulateness can be regarded as an indispensable ingredient of qualitative interviewing.[374] In the present case, the interview was conducted in Chinese. Despite the author's Chinese language skills being at the HSK 5-level, enabling him to read Chinese newspapers and magazines and give a full-length speech in Chinese[375], the complexity of the research subject prevented the researcher, to a certain extent, to depart from his interview schedule. Nonetheless, the rationale behind the decision to conduct the interview in Chinese followed a meticulous and explicit consideration of merits and limitations of interpersonal sensitivities: Admittedly, using English would have facilitated the departure from the schedule in favor of alternative avenues of agenda-focused conversation that might have arisen in the course of a more unstructured interview. Still, having been previously aware of the interviewee's poor English language skills, a need for the services of a translator would have been necessary to ensure a seamless in-depth enquiry. However, the author surmised that the need for a translator would have put the interviewee in an uncomfortable situation of inferiority, unveiling his poor English language skills in the presence of one or more of his employees. In addition, this kind of interview conduct might have also created a more formal atmosphere, akin to a more standardized survey research pattern that centers upon a one-way information outflow process in which the interviewer seeks

374 Bryman, Alan et al. (2015), p. 488 f.
375 For more information on the respective Chinese language proficiency levels, see Confucius Institute Headquarter 国家汉办 (n.d.).

out information without offering any equivalent return for the extraction.[376] This approach would have been inconsistent with the actually intended evolution and subsequent embedding of a sound interviewee-researcher relationship. As mentioned earlier, the development of such a relationship has been fundamental to not only elicit valuable knowledge on a single occasion, but also pave the way for post-interview longitudinal studies and data collection opportunities.[377] Seen in this light, especially at the onset of a bilateral partnership, the initial meeting must underscore the significance of a direct communication channel between the interviewer and the interviewee. Therefore, a face-to-face interview in Chinese, albeit at a less sophisticated expressive level, seemed to be a more convincing and rigorous approach in placing research acumen towards qualitative interviewing into established practice.

c) Interview setting and recording

The expert interview took place on November 7th of 2016 at the interviewee's office in Beijing, starting at 1:10 p.m. and ending at 1:55 p.m. One of the interviewee's assistants documented the greater part of the interview upon the interviewee's request.

The decision not to audio-record and transcribe the interview had been made in concert with the author's mentor (interviewee 4), who had not only arranged the initial contact between the author and the interviewee, but also has decade-long experience in Chinese business practices. The author's mentor set forth that elder generations of Chinese managers without an international academic background are generally less-sensitized to scientific research practices. An audio-recording of the interview might have caused an emotional discomfort, hampering the interviewees' willingness to candidly share information. In recognition of this circumstance, the author decided to forego audio recording in lieu of jotted notes. The key shortcoming of verbatims from memory can be traced back to the possibility of bias introduced by context distortions and memory lapses.[378] In an effort to reduce this adverse effect on the subsequent interview analysis, a preliminary draft of the jotted notes and the context in which they were intended to be utilized was shown to and evaluated by the interviewee right after the interview.[379] To this end, given the anticipated complexity and density of information involved in the interview, the author visualized all indicator-related statements in a mind map software

376 Bryman, Alan et al. (2015), p. 503.
377 Ryan, Paul et al. (2008), p. 448.
378 Bryman, Alan et al. (2015), p. 493.
379 Bryman, Alan et al. (2015), p. 495.

program. The final write-up of the minutes started immediately upon conclusion of the interview session, finalizing it at the end of the interview day, whilst the essential facts and wording of key phrases were still fresh in mind.[380]

d) Key research deliverables

After a brief introduction into the author's dissertation project, the interviewee raised two general issues:

First, he confirmed that since China's accession to the WTO, the Chinese automotive market can be characterized as a very dynamic market, shaped by a multitude of driving forces ranging from micro to macroeconomic factors. He outlined the significant impact of government-initiated policies towards automotive sales. As a concrete example, he elucidated that, amid weak automotive sales, the government cut the levy on purchases of small-engine vehicles with 1.6-liter engines or below in half to 5% in October of 2015. He ascertained that the initiation of this policy exemplifies the government's endeavor to maintain stable growth of passenger cars and prevent sharp short-term fluctuations in one of China's backbones of overall economic development. The interviewee also illustrated that the implementation of such policies represents an impulse that is directly passed through to enterprises, which, in turn, have to adjust their planning premises in light of changed circumstances. Second, he pointed out that although the state association A may yield adequately accurate forecasts in normal periods, no apt statistical model could thus far be identified to capture drastic changes in customer demand.

Based on the existing list of pre-selected indicators provided by the author, the interviewee pinpointed the most relevant indicators that might serve as an effective leading indicator of an emerging risk. These indicators follow the same chronological sequence as mentioned in the expert interview.

aa) Disposable income per capita

The interviewee pointed out that each statistical model should incorporate a good mix of industry-specific as well as macroeconomic data. According to his understanding, disposable income per capita, which is defined as a macroeconomic indicator, constitutes one of the key indicators used to assess the overall state of the Chinese economy. Transferred to the automo-

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[380] Patton, Michael Q. (2015), p. 387 f.

tive industry, disposable income per capita reflects the amount of money that people have available for purchasing a car. Indeed, the affordability of a car constitutes a particularly salient factor in low-income regions.

bb) Fixed asset investment

The interviewee illuminated that fixed asset investment data has no immediate link to the automotive industry. Even so, it depicts another important dimension of macroeconomic "early warning" by measuring the overall economic health and activity. In concrete terms, fixed asset investments gauge how much investment is occurring in various industries and regions, such as machinery and real-estate. Overall, it suits the purpose of medium to long-term market forecasts as it relates to any investments being held for more than one year.

cc) Urban public transport

The interviewee put forward that urban public transport has a huge and measurable impact on total automotive market development and thus should be captured in the ANN forecasting model. He explained that the expansion of public transport infrastructure in tier 1-2 cities may reduce the consumers' willingness to purchase a car. This effect may, above all, apply to consumers who are not first-time car buyers, highly educated, and are pessimistic about intended measures to relieve traffic congestion in cities.

dd) Used car market

According to the interviewee, the market for used cars will become one of the key driving forces for future automotive development in China. He outlined that private ownership of cars began to accelerate in the early 2000s. In the past few years, he said, the accelerated growth of passenger cars has given rise to the concurrent advent of a used car market which has, to a certain extent, the potential to substitute the sales of new cars. This aspect has emerged more significantly in the case of tier 3-5 cities, bearing in mind that the majority of customers in these cities are first-time car buyers and rather price-sensitive. Thus, a well-preserved or restored used vehicle may serve as a serious alternative for those customers considering a future automotive.

ee) Dealer showroom traffic

Based on the interviewee's experience in automotive sales forecasting, dealer showroom traffic has always been a relevant leading indicator for short-term market forecasting. This applies not only to China and the automotive industry, but also to more mature markets in the United States and other industries, such as mall-based retailers for food. There were nonetheless a few caveats as to the use of dealer showroom traffic. First, the interviewee's employees have experienced that data for the dealer showroom is often imprecise and not sufficiently available due to discontinuous compilations at the dealers' site. Second, the interviewee sowed seeds of doubt on whether there is sufficient data available for the late 1990s and early 2000s to be analyzed in the ANN forecasting model.

In answering the question as to whether any additional indicators ought to be considered on top of the existing list of pre-selected indicators, the interviewee recommended that the following be included:

ff) Automobile financing

The interviewee pointed out that automobile financing has already become a salient feature of customer behavior that facilitates car ownership in terms of affordability and convenience. As he believes that automobile financing will become even more important in the future, this aspect should be considered in any future statistical model. Yet at the same time, the interviewee conceded that the present paucity of data for automobile financing constitutes a problem for statistical modelling.

The interviewee recommended referring to the following institutions for the sake of retrieving time series data for his suggested indicators:

i) National Bureau of Statistics (NBS) for disposable income per capita and fixed asset investment data;
ii) Chinese Automobile Dealer Association for used car market- as well as dealer showroom traffic-related data.

With regard to the question as to which year exactly this data was made readily available on a monthly basis, he replied that there

i) is a sufficient amount of data available for disposable income per capita and fixed asset investment;

ii) may not be enough data available for dealer showroom traffic;

iii) most likely is not a sufficient amount of data available for used car market and automobile financing-related data.

e) Interview impressions

Taking a retrospective look at the course of the interview, the strict schedule adherence sought out a wealth of information that could most probably not be achieved using another interviewing strategy. With the application of an interview guideline, the author was able to provide content-related prompts, which enabled the interviewee to reflect more about the specific questions, yielding further consideration for a more elaborated response.

During the interview, the author was particularly concerned with building empathy and rapport in the relationship between the interviewee and himself. The endeavor at this stage was to overcome the interviewee's perceived suspicion of the author's motives, which made him obviously less amenable to interviewing. The common ground was found in the mutual search for a statistical model that facilitates dealing with ad hoc changes in the Chinese automotive market environment. In this context, the interviewee concluded that in this case "a problem shared is a problem halved"[381], indicating that he expects the author's research results to be shared with him. In return, he offered the provision of assistance throughout the data collection phase as well as further networking opportunities, for example with one of the state association's closest automotive partners, namely Toyota.

Interview 2: State association B | Deputy Secretary General

a) Reasons for selecting this expert as an interviewee

The interviewee holds the position as Deputy Secretary General for state association B. The state association B is the only national organization in the field of automobile distribution that is registered under the Chinese Ministry of Civil Affairs. In 2015, the state association B had more than 6,300 new car dealerships that sold a total of 24 million new cars and 8 million

[381] In Chinese: "有人分担，忧愁减半".

used cars. Member dealers employ some two million people. Its members encompass not only domestic and international sales companies of vehicle manufacturers (including used vehicles), but also automotive suppliers, traders, and leasing companies. The main task of the association is to stir and modernize automotive circulation in China and equip its members with first-hand statistics on automotive development in China.

The interviewee is one of the most recognized experts on Chinese and international used car businesses. He has undertaken numerous research projects commissioned by the government. These research projects encompassed studies on China's used car circulation system (including identification and evaluation of used cars), used car-related trading norms, and other research mandates that are linked to industrial policies. The results of the interviewee's research were published by domestic mainstream media, including China Central Television (CCTV) and China National Radio (CNR), which invited him to discuss the key findings of his work. In addition, since 2003, he has been regularly requested by the Chinese Ministry of Commerce to carry out examinations of future courses on domestic and European used car market development. In light of his multifaceted scientific work, the goal of the interview was to explore the role of industrial policies in the Chinese automotive industry and gain a more profound glimpse into central courses of automotive development in China. Moreover, there was an intrinsic motivation to obtain better access to used car-related market data via the interviewee's wide-ranging business network.

b) Key research deliverables

Right at the outset of the interview, the interviewee expressed that not even the most acknowledged market experts had the faintest notion of the extent and speed at which the Chinese stock market collapsed in mid-2015. Based on that, the interviewee inferred that the Chinese stock market has been a poignant example of a highly dynamic market landscape, the volatility of which usually spills over to other sectors. He further explained that the stock market collapse entailed negative expectations with regard to the overall Chinese economic performance and, ultimately, resulted in a dramatic contraction of total automotive sales volumes in the higher (and more expensive) vehicle segments. In light of this explanation, the interviewee agreed that the compiled capitalization-weighted stock market index *CSI 300* could be a valuable contributor to quantify the correlation between Chinese stock markets and the automotive industry.

Aside from CSI 300 as the first suggested leading indicator, the interviewee stressed the relevance of the following indicators from the existing list of pre-selected indicators. These indicators follow the same chronological sequence as mentioned in the expert interview.

aa) Disposable income per capita

The interviewee underscored the heterogeneity of the Chinese economy, stating that the widening income gaps between different cities in China will be a key determinant for future economic growth. From the perspective of an international automotive manufacturer, his advice is to enter the untapped rural part of China at the earliest possible stage so as to cover the rising needs of resident inhabitants. In these areas, he further pointed out that perceptible tendencies towards mass consumption will become apparent in the near future. He nonetheless stated that vehicle affordability remains the chief impediment to a car purchase at the moment. In his opinion, the stepwise nature of this emerging consumption trend can be best observed and gauged by tracking disposable income per capita development.

bb) Consumer confidence

Considering the previous explanations concerning the documented relationship between economic expectations (e.g. based on stock market performance) and automotive consumption patterns, the interviewee suggested that consumer confidence also be incorporated as a leading indicator.

cc) Urban public transport

Taking into account China’s increasing level of urbanization, the interviewee emphasized that urban public transport may become the most important medium of transportation for “ordinary” people. He assumes that a more extensive urban public transport infrastructure will significantly abate the peoples’ need for a privately-owned car. He further argued that people in cities do not use their car 95% of the time, implying that a privately-owned car is not economically viable. Also, during the time they have available to drive, people are encountered with an ever-increasing traffic congestion that deprives them of any driving enjoyment.

dd) Air pollution index

The interviewee pointed out that the air pollution index does not have an immediate connection to automotive consumption. However, he outlined that automotive pollution is responsible for more than one-third of Beijing and other Chinese cities' devastating smog, triggering government-initiated restrictions on vehicle registrations for petrol-powered cars. Against this backdrop, he further explained that the situation is completely different in the case of NEVs. The rapid growth of NEV sales over the past few years is owed to the fact that many cities offer not only free license plates for NEVs, but also free parking spots and generous subsidies from the central and local governments to stir the consumption of emission-free electric vehicles.

ee) Gasoline prices

The interviewee indicated that the price of gasoline in China is comparatively low. Nonetheless, in view of the fact that a greater part of future customers might come from lesser developed regions in China, the total cost of ownership constitutes an essential determinant for the selection of mobility offers. A possible counterargument for the inclusion of the gasoline price as a leading indicator could be the increasing figure of fully electric motors that do not require conventional fuels to propel a vehicle. In response to this argument, the interviewee assumed that the present stage of battery-charging infrastructural development in tier 3-5 cities will prevent the resident inhabitants from purchasing a fully electric-powered car. Coupled with a dissatisfying attainable range of current battery electric vehicle (BEV) models, the interviewee believed that even tier 1-2 city inhabitants might prefer to purchase a hybrid electric vehicle (HEV) that combines the conventional internal combustion engine (ICE) with an electric propulsion system. Following this notion, the importance of gasoline prices remains a crucial factor for total market forecast or might even matter more in the near to mid-term future.

When asked whether any additional indicators ought to be considered for the ANN forecasting model, the interviewee recommended incorporating the following:

ff) Interest rates

The interviewee denoted that the development of interest rates might serve as a resilient precursor for peoples' buying decisions, reflecting their purchase affordability and willingness. Without any concrete statistical evidence at hand, he reported that a one percentage point increase from the central bank in more advanced economies in Europe and the U.S. has had a similar impact on automobile financing rates with a six-month time lag. Yet at the same time, he conceded that only slight increases or decreases of interest rates figure negligibly in peoples' purchase consideration criteria.

gg) Used car market

According to the interviewee, the used car market and new automotive sales are closely intertwined. In the past few years, the state association B has observed an accelerating course towards used car development entailing a substitution effect for new car sales. It is assumed that – to a certain extent – the availability of used cars prevents customers from purchasing a new one. This trend has recently emerged in the whole Chinese automotive industry and is forecasted to accelerate in tier 3-5 cities where price sensitivity is still exceptionally high.

In addition, the interviewee recommended that the aspect of *dealer profit-making capability* be included into the ANN forecasting model. This figure is provided by the state association B and indicates the overall health of the automotive industry which, he assumes, is also a good short-term indicator for future automotive sales. Referring to data availability, the interviewee admitted that other interview partners were possibly more familiar with the question as to whether sufficient data for the selected indicators is available and from which institutions this data could possibly be retrieved.

Interview 3: State association C | Director automotive market research

<u>a) Reasons for selecting this expert as an interviewee</u>

The interviewee is a principal investigator and automotive industry market research division director for state association C. The state association C is an institution directly under the jurisdiction of the NDRC. Its mission is to provide comprehensive and basic economic information at a national and local level to government bodies and society. In addition, the state association C undertakes consulting services for sound political decision-making at the governmental level.

Specifically, the state association C comprises several functional departments that mainly perform the following activities:

i) Operating specialized network service platforms such as the NDRC e-government and national economic information network;

ii) Macro and microeconomic monitoring and forecasting as well as policy simulations, based on qualitative and quantitative modeling;

iii) Providing societal information services at a national and local level;

iv) Coordinating and administrating a global price information system;

v) Conducting research on national information economics and technologies.

Joining the state association C in 1991, the interviewee worked in the department of economic forecasting, mainly engaged in agricultural product markets, household appliances, and automotive market research. Since 2000, he has been working in the economic information center, specializing in the research of the Chinese automotive industry. In his function as market research division director, he has managed several automotive market-related research projects and developed numerous statistical models for automotive market forecasts.

In light of the interviewee's extensive experience towards the Chinese automotive market forecasting, the main research purpose was to elucidate some knowledge with regard to the total market forecasting methodology used at the state association C and, correspondingly, the identification of suitable leading indicators. Moreover, as the central platform for Chinese economic and automotive data-affiliated data distribution, the focus of research was to lay the cornerstone for a long-term relationship, based on a reciprocal exchange of data and market research deliverables.

b) Key research deliverables

As for the selection of leading indicators, the interviewee stressed the need for a good mix of macro and microeconomic indicators for both mid to long-term and short-term forecasts. For short-term forecasts, he underscored that there are several key driving forces of automotive development in China, which ought to be considered in the author's ANN forecasting model: The interviewee suggested that one best considers the statistical model from the customers' purchase power and purchase willingness. In that sense, quantifiable elements that directly impinge on the customers' purchase power and purchase willingness include indicators related to the economy, measured by *money supply*, *disposable income per capita*, *stock market development*, and *consumer prices*, and the consumption environment, measured by *gasoline prices*. The state association C assumes that a gasoline increase of more than 10% may affect the customers willingness to purchase a new car. That is because customers, on the basis of the information they have available, predicate the time of purchase on a permanent evaluation of their future personal income versus expenditure expectations. Along these lines, the interviewee underscored the importance of *consumer confidence*, which has proven to be the most relevant yardstick to measure the customers' willingness to purchase a new car.

In addition to these demand-related influencing variables, the state association C also analyzes the upcoming *supply of car model launches*, which have to be previously announced by all car manufacturers operating in China. Nonetheless, this indicator, the interviewee explained, is more likely used for segment-based and provincial/city-based PV sales forecasts. In the case of certain city-based forecasts, the state association C has observed that the launch of NEVs, such as Tesla's Model X in 2016, contributed to a short-term stimulus effect on Beijing's regional automotive demand. That is because NEVs are exempted from driving bans and license restrictions, enticing customers to buy electric cars in order to deal with the notorious air pollution in major Chinese cities. Besides, the state association C has proven that a higher supply of car model launches is usually accompanied by an increase in customer demand. The reasons for this are twofold. First, the likelihood that interested customers turn into real customers is higher if customers can select between a greater variety of products. Second, a greater supply of car models in the respective vehicle segments accentuates competition among car manufacturers, which, in turn, increases pressure on car prices, enabling a greater set of price-sensitive customers to purchase a car.

Moreover, so-called "**unexpected factors**" are added into the state association's quantitative model for short-term forecasts. The interviewee illustrated that, usually immediately prior to and during large-scale events that place a worldwide spotlight on China, i.e. the 2008 Olympic Games or international political convenes, a massive contraction of automotive sales can be observed. He attributes this decline to two reasons. First, and this particularly applies to the peoples' great excitement about big sports events, people tend to shift their private investments into goods that have a close relation to the forthcoming event. The second and more prominent rationale emanates from the fact that, in advance of and during political convenes hosted in China, such as the G-20 summit in Hangzhou in September of 2016, local governments take temporarily restrictive measures, such as road closures, traffic controls, and increased security presence at popular public squares so as to guarantee the event's success. The interviewee reasoned that these measures possess their legitimacy when maintaining face for the Chinese government is an aspect of particular importance in times of intensified global media focus. The flipside of the coin is that such measures also impinge on automotive dealership operations to the effect that the customers' mood for shopping diminishes a significant amount, thereby preventing them to execute a purchase on such days or at such times.

In addition to the quantifiable metrics of short-term market forecasts, the interviewee underscored the importance of inherently non-quantifiable factors. These factors may include announced or anticipated **automotive industry-related policies**, such as the purchase tax cut for small-engine passenger vehicles in 2015 as well as "other incidents" that stir the emotions of potential customers, such as media reports on the natural disaster in Japan in 2011. These factors are indeed less foreseeable in nature, but may also wield a sweeping influence on customer behavior and thus have a considerable impact on PV sales development.

Interview 4: Automotive enterprise A | Senior management consultant

a) Reasons for selecting this expert as an interviewee

The interviewee currently holds the position as a senior management consultant for market intelligence-related activities for automotive enterprise A. He joined the automotive enterprise A in 2008. He served as a strategic project manager and was responsible for improving the operational efficiency of a multinational automotive enterprise in China. After eight months of service, he switched to the automotive enterprise A, where his task was to establish an efficient market forecasting process by allocating internal and external resources to track key indicators for early warning on automotive market-related risks.

With regards to the allocation of external resources, he also obtained the position as chief negotiator for the selection of market agencies, which have provided several forecasting methodologies to the automotive enterprise A. In addition, the interviewee also organized the enterprise's annual long-term planning workshop for the China region and thus was the main interface for the its joint ventures and subsidies in terms of market planning activities. In 2012, the interviewee was assigned to a market intelligence function at a German automotive enterprise in Germany, a role he assumed for four years. In this function, the interviewee represented the German division of the enterprise's short-term and long-term total market and segment trend forecasts for China and other (East) Asian countries.

The author's primary goal in this interview was to obtain a big picture overview of socio-demographic mega trends and their impact on automotive market development in China. Another focus was placed on the quantitative impact of policies for ANN forecasting, an issue that the interviewee had raised several times during the author's participant observation stage.

b) Key research deliverables

Right from the outset of the interview, the interviewee referred to the particular significance of socio-demographic changes that have already taken effect in contemporary China. Along these lines, he illustrated that the demographic change in China has already reached a turning point of sustained economic slowdown, which needs to be considered in forecasting automotive market development. He expressed his conviction that the government will not be able to fully avert the social consequences of the one-child policy. The one-child policy, which was initiated in the late 1970s and early 1980s to reduce the growth rate of China's enormous population, implied an ageing Chinese population and thus a decreasing size of labor population. A decreasing *size of labor population*, the interviewee illustrated, is strongly correlated with a decline of private domestic consumption, including the consumption of passenger cars.

This correlation can be traced back to an increasing number of dependents, i.e. people of non-working age, compared to the number of non-dependents who have the potential to earn their own income. The interviewee outlined that the aspect of greater social dependency represents a serious problem for the Chinese society as it involves a greater burden for the young population in supporting the aging population – a phenomenon that is already deeply rooted as part of the Chinese culture. Closely connected to this, the interviewee argues that the financial burden for the one-child policy generation will significantly rise as a result of an increasing dependency ratio in their own family. The interviewee therefore strongly recommended including the *income per household* indicator rather than the per capita indicator.

Furthermore, the interviewee highlighted the increasing urbanization trend. He pointed out that this aspect is also reflected in a rising potential for car sales as an increasing urbanization ratio is usually accompanied with increasing disposable income figures. He put forward that this is particularly true for China, given the huge income gap between rural and urban areas. He set forth that the urbanization trend can be best observed with the expansion of public transportation systems, which allows residents a more efficient access to mobility in highly congested areas. As a result, he outlined that this medium of transport may well serve as a substitute for traditional automotive demand, depending on the availability and convenience of urban public transport. Viewed from this perspective, he recommended considering the *length of the subway divided by urban area* into the ANN forecasting model. By taking Hong Kong as an example, the interviewee also scrutinized the motive of potential automotive customers to purchase and own a car. He explained that the diversity of mobility needs may offer a sufficient scope for automotive demand. However, this demand may no longer be satisfied by car ownership, but by an increasing *number of car sharing* offers, for example, those provided by Didi Chuxing, which enjoys a growing rate of popularity in China.

Moreover, the interviewee has held the view that it is very challenging, if not impossible, to constantly achieve accurate short-term automotive market forecasts. He explained that the Chinese economy, especially the car market, is highly influenced by **government policies**, which are decided upon by top government officials on an ad hoc basis and in a non-transparent process of codification. He cited the purchase tax cut in 2015 as one example of industry-wide uncertainty, which materialized in high forecasting inaccuracies. Indeed, the interviewee disclosed that the automotive enterprise A has not been capable of quantitatively anticipating the market's behavior when automotive policies are in effect. For instance, he indicated that automotive dealers often tend to mislead customers by circulating rumors about alleged announcements on imminent policy termination dates, thereby inducing customers to engage in panic-based purchases. These market behavior patterns, the interviewee argues, can only be captured if **data outliers remain a part of the ANN forecasting model**.

Interview 5: State association D | Secretary General

a) Reasons for selecting this expert as an interviewee

The interviewee currently holds the position as Secretary General for state association D. The state association D was established in 1994 and is an organizational unit of China's Automobile Dealers Association. Co-sponsored by the major domestic and Sino-foreign passenger car manufacturers, the state association D is geared towards passenger car market research-related issues. More specifically, it gathers market-relevant production and sales data shared by its members and synthesizes this information to grasp considerable future trends and developmental tendencies in the Chinese passenger car market. The research results are distributed to its members and affiliated associations on both a daily and periodic basis.

The interviewee is a dedicated consultant for automotive sales statistics with sound managerial experience in the area of market intelligence at a Chinese state-owned automotive manufacturer. In 2008, the state association D appointed the interviewee as chief expert for small displacement vehicle market research. In the same year, owing to the rapid changes in the market and policy environment, the interviewee promoted the conception and implementation of an industrial policy analysis system, which traces all relevant industrial policies in the automotive sector. In light of the interviewee's professional background, one focal point of the interview was to participate from the interviewee's knowledge towards key success factors of accurate short-term market forecasts. In addition, the intention was to delve deeply into the role of Chinese automotive policies and their penetrating effect on overall automotive development. Considering the interviewee is a highly renowned publisher of many automotive statistics, the author also had a keen interest in capitalizing on new sources of data to be harnessed in his ANN forecasting model.

b) Key research deliverables

The interviewee elaborately argued that the Chinese state has always performed its responsibilities and obligations within its business relationships with international car manufacturers. This even applies to economically challenging times such as when the state unleashed a huge stimulus program in the aftermath of the global financial crisis in 2008 (which, in turn, bolstered sales of passenger vehicles) or the stock market crash in June of 2015, when the state intervened with huge investments to stabilize the economy, thereby allowing the automotive industry to deflect an irreversible downward trend. The interviewee referred to these examples to underscore the need for **automotive industry policy-related analyses** as a key determinant to unveil the direction of change intended by the state.

As for the author's presented list of leading indicators, the interviewee considered the following one to be particularly important:

aa) CSI 300

The interviewee illustrated that, from mid-2014 onwards, the number of new stock accounts in China has grown exponentially. He traced this phenomenon back to an increasing number of ordinary people who have invested much of their savings and loans for the first time into a, at that time, booming stock market. Referring to a large-scale China Household Finance Survey issued by Southwestern University of Finance and Economics in Chengdu in 2015, the interviewee laid out that two-thirds of new investors in the Chinese stock market have a comparatively low level of education. He argued that the government had encouraged particularly these people to move money from their savings in favor of financial market investments, consequently stimulating an increasingly sluggish Chinese economy.

He concluded that the disappointing stock market performance in mid-2015 has left deep scars in its wake, casting serious doubts on overall economic stability – not only with regard to uncertain investors, but also their inner circle consisting of relatives, friends, and neighbors. The resulting negative expectations across the entire Chinese society, the interviewee sketched out, caused a sweeping spillover effect on new car sales. Viewed from this perspective, he assumed a strong correlation between stock market development (as a quantified metric of negative societal expectations) and automotive sales.

bb) Urban public transport

The interviewee emphasized the role of urbanization as probably being the most significant mega trend in contemporary China. In this context, the interviewee regards urban public transport as an important yardstick, which reflects various dimensions of future automotive development. First, he explained that a higher level of urbanization usually goes hand in hand with higher levels of disposable income. This, in turn, has a favorable impact on car affordability. At the same time, the interviewee contested whether the future demand for privately-owned cars will achieve the same magnitude as it did in the past. On the assumption that a higher population density will trigger or exacerbate traffic congestion, he argued that Chinese people might switch to urban public transport given that it can equally fulfill the need to transport people from remote locations to other destinations within the city. In addition, the interviewee has observed a growing environmental awareness of urban people, which might reinforce the trend towards alternative mobility services – such as urban public transport. The interviewee concluded that both mediums of transport, urban public and automotive, interrelate with each other and thus should be considered in the ANN forecasting model.

cc) Gasoline prices

The interviewee considered gasoline prices to be a relevant dimension of the total cost of car ownership. According to several customer purchase decision analyses conducted by the state association D, the total cost of ownership still represents a crucial criterion for car affordability, especially in low-income regions. Moreover, in close connection to an expanding public transport infrastructure, the interviewee learned that even a moderate increase in gasoline prices will induce people to make use of alternative mediums of transport, if available and convenient. If people are apt to use their car less often, the interviewee reasoned, the lifecycle of a car will be prolonged, leading to a situation in which the demand for a new car will plummet accordingly.

dd) Automobile financing

Lastly, the interviewee noticed that automotive enterprises have long searched for a way to boost their revenues and defend their margins in an increasingly competitive automotive market. As he sees it, these enterprises recognized that finance-related business models for cost-intensive big-ticket items, such as cars, grant access to a broader set of interested customers, which would have been previously excluded by traditional automotive business models.

The interviewee explained that the well-established use of financial services reflects a pervasive change of consumption behavior in the Chinese automotive market, in which only seven to ten years ago a car was usually purchased using cash. Given that there is still a huge amount of untapped potential customers who are not able to allocate their entire financial resources to purchase a car, the interviewee has been convinced that automobile financing will become even more significant in the future.

Interview 6: Consulting enterprise A | Manager provincial vehicles sales forecasting

<u>a) Reasons for selecting this expert as an interviewee</u>

The interviewee currently holds a managerial position for China's light vehicles sales forecast and China's provincial and city-level light vehicles sales forecast at consulting enterprise A. The consulting enterprise A is one of the most renowned global automotive consulting enterprises, offering its clients predictive qualitative-quantitative solutions along the entire automotive value chain. Its mission is to enable automotive enterprises to capitalize on business opportunities emanating from a highly complex and competitive industry by serving as a source of critical market research.

The interviewee is in charge of long-term sales forecasts for automotive enterprises and national sales companies, covering automotive sales in all of China's 31 provinces. He has gathered more than eleven years of experience in the automotive industry and is considered to be one of very few market intelligence analysts with a deep understanding of province and city-based data relationships and how they are modelled using different forecasting methodologies.

b) Key research deliverables

The interviewee laid out that automotive forecasts at the consulting enterprise A can be separated into two distinct elements: First, the national forecast, also referred to as top-down approach, is comprised of several indicators that are processed in a non-linear regression model. This approach aims at forecasting the long-term dimension of total market development, incorporating "traditional" macroeconomic indicators such as GDP per capita and household income. In addition to these macroeconomic indicators, which indicate potential customers' overall demand, the interviewee set forth that the level of car parc density and scrappage rate is suggestive of possible saturation effects from the automotive supply side. Second, to complement the top-down approach findings, the consulting enterprise A also conducts sub-national forecasts referred to as **bottom-up models**. For this purpose, the interviewee uses **non-linear regression models** to forecast the automotive growth trajectories of all 31 of China's provinces. The imperative of such an elaborate bottom-up approach, the interviewee said, results from the heterogeneity of automotive development in China. In an effort to capture these regionally different growth dynamics, the interviewee disaggregates his analyses into extensive province-level models and then adds them up to arrive at a composite picture of total market sales, which, at best, corresponds to the research deliverables of the top-down model.

As for the selection of short-term leading indicators, the interviewee suggested incorporating the following indicators into the ANN forecasting model:

aa) Retail price trend

Retail prices, the interviewee said, reflect market realities at the automotive dealers' site. In fact, the interviewee outlined that premium car brands, such as Audi and BMW, have granted massive discounts of 20 to 30% over the past few years in cities like Beijing and Shanghai. Given the fact that more people have been able to afford a discounted premium branded car, this development has had an ultimate effect on the overall penetration of premium brands in the automotive market. He denoted that the retail price trend may be classified as leading indicator for short-term forecasts. Yet at the same time, the interviewee admitted that time series data for future retail prices is very difficult to obtain.

bb) Automobile financing

The interviewee declared himself in favor of using automobile financing as an important factor driving automotive market growth. He mentioned that in terms of correlation coefficients, this indicator mattered significantly in various statistical models at the consulting enterprise A, despite certain multi-collinearity effects with economy and income-related indicators. He is also convinced that with younger people "coming on board", customer behavior will change from paying for one's car in cash to using financing models to purchase a car.

The interviewee also made a few remarks as to which indicators should <u>not</u> be used in the author's ANN forecasting model.

First of all, the interviewee indicated that *gasoline prices* do not indicate a big impact on vehicle demand in China. As a result of massive government interventions, the prices on the gasoline market have recorded a lot of ups and downs over the past three years. However, in none of the consulting enterprise's models any correlation effect with automotive demand could be noticed. As a principal reason, the interviewee argued that the annual mileage of cars in China is rather low, averaging below 10,000 kilometers per year. For this reason, he concluded that even a tremendous price increase of 20 to 30% does not truly constitute a huge cost add-on.

Second, the interviewee cast strong doubt on the relevance of *car sharing* as a leading indicator for total automotive sales forecasting. Aside from insufficient data availability for time series analyses, the consulting enterprise A will not be assuming a significant impact of car sharing in the next seven to eight years. As a reason, he stated that in contrast to Western countries, cars in China still embody a strong symbol of status. He set forth that in a market that is still in the initial stage of car ownership, car-sharing business models may not replace the desire of Chinese people to possess a privately-owned car. A further matter is that Chinese car sharing service providers have not managed to deliver market-oriented product portfolio offers. For instance, in reference to one service provider, the interviewee found that the share of SUVs – by far the most important body style in the Chinese automotive market – only accounted for 10% of vehicles that could be rented out on the respective online platform.

Third, although the consulting enterprise A has not yet considered *CSI 300* as a potential leading indicator for previous total automotive market forecasts, the interviewee noted that this indicator may not be relevant either. He conceded that in the aftermath of both stock market crashes in 2008 and 2015, customers delayed their purchases for several months due to prevailing negative economic performance expectations. However, he underlined that, as opposed to in Western countries, the household investment rate in Chinese stock markets is comparatively low, ranging at a lower single-digit rate. Thus, he concluded that the small percentage of potential household wealth losses in Chinese stock markets does not serve as the kind of representative figure necessary to assume a precipitous decline in vehicle demand. Moreover, to substantiate his argument, the interviewee argued that the government has always quickly taken action to restore stability on stock markets in China, thereby also promoting automotive growth.

Lastly, the interviewee argued that *used car market development* may speed up the overall vehicle replacement cycle, consequently accelerating customer demand for new cars. Nonetheless, he also underpinned that with a rising market for used cars, a large part of customers might opt for used as opposed to new cars. These interaction effects, he said, are crucial to automotive forecasting and should theoretically be considered part of any forecasting effort. However, he unmistakably set out that, from his observation, the poor quality of used car market data may distort analytical results to a significant degree. He noted that for a number of years, used car market statistics for the same year may differ depending on the edition of the respective publication in which the data appears. As a concrete example for this data inconsistency, he stated that the nationwide trading volume in 2012 may range between five and seven million used cars sold.

Moreover, the interviewee hinted at two fundamental drawbacks of regression models as they are deployed for top-down and bottom-up forecasting models at the consulting enterprise A.

First, he explained that **government policies** are the principal reason for most of the statistical outliers in short-term market forecasts. Using the 2008 and 2015 tax cuts for vehicles with 1.6-liter engines or smaller as an example, he illustrated that these policies create so-called “payback effects” in periods with the corresponding policy in place. These special effects generate additional sales volumes by fueling artificial instead of organic demand for incentivized vehicle segments, eventually leading to deviations in the equally unconstrained statistical model. The resulting constrained demand, he said, is very difficult to quantify in regression models. To capture this shift in demand, the interviewee stated that forecasters require a subjective estimation of vehicle frontloading for the period with the policy in effect. In addition, forecasters also have to account for the typically lower sales volumes immediately following the expiration of the corresponding incentive policy. To address the issue of resulting data outliers accordingly, the interviewee refers to a **dummy variable** for his statistical models.

Second, at several points in the interview, the interviewee indicated that the aspect of **multi-collinearity** in regression models represents a serious problem for accurate forecasting deliverables. He argued that, in cases in which two or more indicators might be useful for the subsequent statistical modelling, the consulting enterprise's analysts had to select just one indicator in order to prevent undermining the necessary statistical properties of regression models. A further aspect he mentioned is that the use of panel data, a combination of cross-sectional and time series data, is deemed imperative to solve the problem of multi-collinearity in his statistical models. As the interviewee sees it, this workaround implicates a strong limitation with regards to the best possible selection of leading indicators for statistical modeling.

In the forecasting process-related questions at the end of the interview, the interviewee revealed that the validity of the consulting enterprise's market intelligence-process is usually reviewed on a <u>monthly</u> basis. The purport of this process review is to minimize the **out-of-sample forecasting error of 10%** to the greatest possible extent.

Interview 7: Automotive enterprise B | Director powertrain strategy Asia

<u>a) Reasons for selecting this expert as an interviewee</u>

The interviewee worked in the field of automotive consulting for seven years, responsible for the enterprise's Asia automotive operation and global powertrain forecast and analysis. In 2010, he switched over to an U.S. American automotive supplier, where he held the position as Asia-Pacific strategic marketing director. Since 2013, the interviewee has been responsible for the Asia-Pacific powertrain strategy and planning division for automotive enterprise B. On the whole, the interviewee has gathered almost fifteen years of extensive consulting and market research experience within the automotive industry. He can be seen as an expert for automotive market and business development in the Asian-Pacific region, including China and India. In his work, he has centered upon new automotive business models, powertrain and components development, technology trends, and consumer behavior as well as the impact of government policies on automotive development. That is to say, the interview was supposed to help the author familiarize with the key plans of future automotive development in China, also in comparison to other emerging and developed markets in the Asian-Pacific region.

b) Key research deliverables

At the very beginning of the interview, the interviewee accentuated that one peculiarity of emerging markets can be found in the fact that the communication between the regulatory body and the industry is much less transparent than in more advanced economies in North America and Europe. What he has experienced is that **regulatory uncertainty** poses a significant problem for automotive enterprises conducting business in emerging markets. He exemplified the "beauty of a one-party government" in China as one of the key operational risks, meaning that policies may be enacted without granting automotive enterprises sufficient time to respond to the changing conditions. In concrete terms, the interviewee set forth that the Chinese emission standard C6b was supposed to be introduced by the end of 2017. At the time of the interview, which was thirteen months before the envisaged enactment, the codification process was still far from being finalized. Automotive enterprises, he said, were left with uncertainty as to what extent cars had to be modified technically in order to satisfy the mandatory emission standard requirements. However, he further stated that automotive enterprises will require at least two years of research and development to find a technical solution to address emission standard-related issues. He concluded that these kinds of "last minute" policies put automotive enterprises under great pressure, thereby impinging upon their business performance.

As per this argument, the interviewee distinguished policies along two principal dimensions. First, **"direct policies"**, such as the enactment of an emission standard, entail an immediate effect on the automotive business. As another example, he indicated that policies in the Chinese NEV segment, which, by definition, include BEVs, plug-in HEVs (PHEVs), and fuel-cell vehicles) are more aggressive than those of other markets. He stressed that special incentives are provided by both local and central governments, including financial subsidies for a car purchase, no license plate and driving ban restrictions, and free parking zones in downtown areas. The interviewee explained that granting these incentives is subject to industrial policy objectives, i.e. to promote alternative powertrain technologies. Second, the interviewee mentioned that **"indirect policies"** exert a mediate effect on the automotive business. For example, the phase-out of the one-child policy in 2015 has had a huge impact on automotive body style trends. A strong growth in the multi-purpose vehicle (MPV) and sport utility vehicle (SUV) body style segments has been observed, favoring automotive enterprises with a high coverage of these body styles in their respective product portfolio.

Furthermore, the interviewee emphasized the importance of geographic differences in China. First, he illustrated that consumer behavior in China is heterogeneous in nature and mainly dependent upon the residents' different income levels. This implies that the mindset of customers in coastal areas is similar to those in Western countries, whereas customers in more rural regions behave similarly to those in emerging markets, such as in India. Although tier 1 and tier 2 cities have often served as domestic trendsetters for certain body styles and car models, the interviewee underlined that "value for money" still constitutes the key purchase reason for customers in lower-tier cities. Second, he reasoned that the penetration of BEVs and PHEVs can be viewed and described as a tier 1 and tier 2 city phenomena. He set forth that in the past few years, battery-charging facilities have successively gained currency in the customers' daily life, being set up around all important customer touchpoints i.e. in shopping malls or residential compounds. The interviewee therefore advised incorporating the ever-rising amount of *battery-charging stations* into the ANN forecasting model, because these stations embody the gradual setup of viable e-mobility mobility solutions in China.

Moreover, the interviewee elucidated that the launch of new business models from non-automotive IT companies, such as Didi Chuxing and LeTV, poses a serious threat to traditional car ownership-based business models. He explicated that customers and the society are encountered with certain problems that can directly emanate from traditional automotive business models. These problems have an effect on traffic congestion and the associated poor air quality in the surrounding environment, license plate and driving ban restrictions, high car purchase costs, and a limited availability of public transport mediums. In response to that, entrepreneurial newcomers to the automotive industry are pushing for new mobility services, placing their focus on sharing in lieu of owning a car. According to the interviewee, there are two main customer segments in which car-sharing-based companies will most likely target in the future, namely commuters with a limited access to public transport and young people who are no longer willing to purchase a privately-owned car or simply cannot afford a new one. In an effort to map the composition of future automotive sales, the interviewee therefore suggested incorporating *Didi Chuxing's total mileage* figures into the ANN forecasting model.

Given the fact that the rise of alternative mobility solutions will ease traffic congestion and improve air quality in metropolitan areas, the interviewee additionally stressed the significance of urban public transport. He mentioned that the Chinese government has been investing into a massive extension of public transportation infrastructure, including a denser network of metro and bus stations. He unveiled that this development will have a huge impact not only on car ownership, but also on car usage. People may still decide to purchase a new car but tend to use it less often, for example, only on the weekends, which will ultimately prolong the car-holding period and postpone possible replacement needs. Hence, the interviewee also recommended including *urban public transport* as a leading indicator.

Interview 8: Automotive enterprise C | Senior manager market research

a) Reasons for selecting this expert as an interviewee

The interviewee currently holds the position of senior manager in the field of automotive market intelligence and research for automotive enterprise C. In her actual position, she represented her division in the enterprise's 2016 regional planning round workshop in Beijing, which aimed to discuss total market, segment, and e-mobility trends until 2027 for the Chinese market. The interviewee was praised by the author's colleagues for her profound understanding of leading indicators with different forecasting horizons and her experience concerning the impact of policies in quantitative modelling.

b) Key research deliverables

After a brief introduction into the author's dissertation project, the interviewee approved the author's proposal of clustering all relevant leading indicators into three different taxonomies, i.e. old economy, new economy, and automotive industry-related indicators. Based on these taxonomies, the interviewee further suggested dividing all selected indicators into items of short-term and/or long-term market forecast relevance.

<u>*Indicators with short-term market forecast relevance:*</u>

aa) M2

At first, the interviewee specifically outlined the importance of M2 due to its very high relationship towards automotive growth. She explained that the overall objective of M2 is to gauge the size of the money supply in an economy, thereby, inter alia, mirroring market agents' near-term prospects towards future consumption intentions. The interviewee reported that if M2 growth can be sustained for two or three months, automotive growth will follow suit. Indeed, in the course of the interview, the interviewee evinced a bivariate correlation analysis of the automotive enterprise C, unveiling a strong correlation between M2 and passenger vehicle growth of r= 0.81 from 2013 to 2015. Between 2002 and 2015, the correlation coefficient was recorded at a notably lower level with r= 0.58.[382] She explained that the difference between both time horizons can be traced back the Chinese peoples' enthusiasm about Western cars in the aftermath of China's entry into the WTO. This enthusiasm, she said, led to artificially-generated development dynamics, which outpaced the growth of money liquidity to a considerable degree. In the past three years, however, the interviewee believed that the automotive market has leveled off to a more organic growth development, which can be reflected more closely by M2. She also indicated that M2 data is usually reported on a monthly basis, providing sufficiently frequented data for in-depth analyses.

bb) Consumer confidence

As a general notion, the interviewee set forth that customer purchase intentions and consumer confidence can be regarded as an essential yardstick for short-term-related automotive market forecasts. While data on concrete customer car purchase intentions is rather difficult to obtain in a frequent sequence, the interviewee outlined that consumer confidence can be measured with two different indicators. First, issued by the NBS, consumer confidence can be used as a gauge to provide a current snapshot of the overall macroeconomic situation. Second, published by the State Information Center (SIC), consumer confidence can also be applied specifically to the automotive industry, indicating to what extent customers are principally willing to purchase a car. Whilst the interviewee uses both indicators in her forecasts, she set out that the automotive-specific indicator possesses a closer relation to the industry and hence should be used in the ANN forecasting model.

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[382] In both analyses, the measurement was taken by referring to annual M2 data.

cc) Fixed asset investment

The interviewee affirmed that fixed asset investment can be seen as a key governmental instrument for sustaining economic growth in China. She holds the view that fixed asset investment has been a substantial contributor to economic flourishing, serving as an impulse generator for strategic policies in pillar industries. The interviewee pointed out that the easiest way to stimulate economic growth could be found in investments into the real-estate sector, which, at the time of the interview, enjoyed strong growth despite overall low investment figures. However, as the interviewee sees it, the problem is that the real-estate sector is quickly prone to overheating and bubbles, which might then affect the entire economy. In this case, the government must resort to alternative economic growth levers in the form of domestic consumption tools in other key industries, such as the three-year readjustment and revitalization plan in 2009 for the automotive industry. At a later stage of the interview, she accentuated the effect of such incentive policies without which the automotive industry would have seen negative growth and massive price erosion in 2015.

dd) Air pollution index

With respect to the air pollution index, the interviewee outlined that her market intelligence team has undertaken an analysis in which the degrees of air pollution and traffic congestion were set in relation to one another. The ultimate goal of this analysis has been to examine the likelihood of driving bans and license plate restrictions on a city-by-city comparison in China. The examination involved between twenty and thirty Chinese cities that share the characteristic of being very well-developed, but also densely populated. According to the interviewee, the analysis proved to be successful as the results corresponded to actual restrictions implemented by regional governments.

The interviewee explained the success of this analysis by taking the position of regional government officials who may decide to adopt countermeasures against deteriorating environment and traffic conditions, especially during the winter time. When asked about which of the two indicators to choose, the interviewee dissuaded from using traffic congestion as leading indicator given the lack of data availability and relevance for *total* market forecasts. In turn, she suggested that the air pollution index be incorporated into the ANN forecasting model, because it measures the environmental challenge that is prevalent *throughout* China and thus more apt for nationwide market forecasts. However, from the interviewee's statements, it remained unclear whether sufficient data is available for the air pollution index.

ee) Dealer showroom traffic

The interviewee emphasized a close relationship between the dealers' showroom traffic and automotive sales. From her experience, she said that showroom traffic has always been a leading indicator for car sales, because potential customers have physically visited dealer showrooms before their actual purchase one to three months later. In times of fewer showroom visits, the interviewee disclosed that the number of cars sold plummeted with a one or two-month delay. Yet at the same time, she admitted that data from physical showroom visits must be complemented by website traffic data, because an increasing number of customers have become online shopping customers who refrain from physical visits in favor or online showroom visits.

ff) Dealer confidence

In addition to the author's list of pre-selected indicators, the interviewee underscored the relevance of dealer confidence as an additional short-term market forecast indicator. She referred to the achievement of dealers, which is assessed in a joint project with two other multinational automotive enterprises in China, as well as to an external agency supporting in the acquisition of weekly or monthly dealer performance data. Specifically, the dealers are asked how confident they are that they can achieve the current or next month's sales target. Based on her experience, the interviewee reported that any confidence level figure lower than 80%, or even 70%, might be suggestive of a cool-down of automotive sales.

Indicators with long-term market forecast relevance:

gg) GDP per household

The interviewee signified that GDP development has a very high correlation with automotive growth. However, unlike M2, which has the closest short-term relationship to automotive sales, GDP has to be considered as a long-term indicator for which data is available on a quarterly basis. The interviewee advocates the use of the GDP per household over GDP per capita figures, because she considers a car purchase in China to be a household rather than an individual's decision.

hh) Disposable income

Similar to GDP per household, disposable income can be regarded as a long-term leading indicator. Disposable income figures provide a clue as to whether interested customers can turn into real customers, depending on their ability to move up from the bottom of the income pyramid to a level at which they can actually afford purchasing a car.

Finally, the interviewee unveiled that she has been investigating the impact of **automotive policies** on total market sales. From her point of view, these policies constitute the predominant cause of unexpected data outliers. Therefore, the interviewee strongly recommended the **inclusion of data outliers** in the ANN forecasting model, because these outliers represent an imperative ingredient of Chinese automotive growth and will continue to do so in the coming years. From her experience, any attempt to replace these outliers by a dummy variable have not proven successful, especially if there is more than just one automotive policy in effect.

Interview 9: Automotive enterprise A | Senior manager market analysis

<u>a) Reasons for selecting this expert as an interviewee</u>

The interviewee has held the position as a senior manager in the strategy and planning division, department of China economic insights and automotive strategy for automotive enterprise A. He has been in the lead for the first pillar of automotive forecasts, i.e. quantitative analysis of automotive customer demand development. His tasks range from annual and quarterly total market and vehicle segment-related forecasts, which he quantifies by means of **regression models** that use **economic and industry-related indicators** as an underlying dataset. Complementary to this, he has also been involved in the analysis process of automotive supply factors, which seek to adjust the output of the interviewee's quantitative forecasting models and thus form the second cornerstone of quarterly and annual market forecasts at the automotive enterprise A.

<u>b) Key research deliverables</u>

Right from the outset of the interview, the interviewee expounded on the fact that the Chinese automotive sector is a highly regulated market. The regulation manifests itself in **restriction and purchase tax policies**, which both have had strong impact on total market development.

Based on his experience, the interviewee reported that it is almost impossible to forecast policy changes in the automotive sector. Following on from this, the interviewee said that a forecaster's inability to anticipate policy changes directly translates into errors in the respective forecasting model. In addition, the interviewee set out that a purely quantitative approach does not denote the ultima ratio of automotive market modelling. He explained that, at the automotive enterprise A, quarterly and annual forecasting models of potential customer demand are always in tandem with accompanying supply-side factors. These supply-side factors include *upcoming product launches* and seasonal influencing factors, both of which adjust the quantitative dimension of forecast on a short to mid-term basis and are chiefly based on expert experience.

With regards to the selection of indicators, the interviewee revealed that he has been using **coincident indicators** for his statistical models. He admitted that the inherent problem of his approach results from the fact that he is dependent on the reliable forecasts of each indicator to keep the forecast error as small as possible. Despite his different analytical approach, he confirmed that he has accumulated knowledge towards meaningful antecedents of development in the Chinese automotive market. His statements are rendered in the same chronological sequence as mentioned in the expert interview.

aa) M2

The interviewee summarized that M2 money supply in China has increased tremendously over the past few years. He explained that this development has had an ultimate effect on automotive growth. Unlike the housing sector, in which the demand for houses outpaced the supply quantities leading to a sharp rise of housing prices, prices in the automotive industry have remained stable or even abated. As a result, the interviewee said that the proliferation of automotive transaction volumes has kept pace with the associated growth in M2. This explains why there is a strong correlation between M2 and automotive sales.

bb) CSI 300

The interviewee noticed that the stock market crash in 2015 caused a significant drop in the premium market segment, which is why he was able to prove a strong correlation between CSI 300 and automotive sales in the same. However, he pointed out that CSI 300 might not have a considerable impact on total automotive development, as the premium segment merely constitutes a relatively small part of automotive sales in China. Nevertheless, the interviewee subscribed to the notion that the stock market will play an even greater role in the future. He argued that the stock market in China has sequentially become an investing platform for individual investors whose overall investment decisions are closely tied to stock market performance. On the assumption that the amount of individual investors will rise along with a more mature stock market environment, the interviewee set forth that the inclusion of a stock market indicator appears to be consistent. He also noted that stock market data should be sufficiently available.

cc) Automobile financing

The interviewee raised the issue of automobile financing, which has increased sharply in recent years. He assumed that this trend will continue to grow in the future, referring to more advanced economies in which this kind of consumption pattern has found its way into society. On the other hand, the interviewee argued that time series data for automobile financing is, most probably, not sufficiently available to trace back the emergence of this consumption pattern in China.

dd) Growth of mobile Internet sales

The interviewee repeatedly emphasized the importance of new economy indicators, especially stemming from the <u>t</u>elecommunication, (social) <u>m</u>edia, and I<u>T</u> (TMT) business. Above all, he stressed the significance of mobile Internet, gauged by the growth of mobile Internet sales, as the most important factor of the digitalizing Chinese economy. Indeed, he explained that automotive customers are increasingly apt to buying their cars without visiting the dealers' stores. Thus, the *physical dealer showroom traffic* has been gradually shifted to online customer touchpoints of automotive enterprises. At the same time, the interviewee indicated that the availability of data for all new economy indicators, including the growth of mobile Internet sales, is very limited. In the case of TMT businesses, he pointed out that data might only be available from 2010, sometimes on an annual and regional basis only.

ee) Used car market

As for the impact of the used car market development in China, the interviewee inferred that, in 2016, the automotive enterprise A allocated a 0.5% contribution from the used car market segment to total automotive market development in China. Despite this rather low contribution to total market growth, the interviewee indicated a rising significance of this indicator owed to the fact that the State Council cancelled the purchase limit of used cars in Western provinces in April of 2016. Specifically, he pointed out that the restrictions had originally been imposed to protect regional interests by limiting the import of used cars from other Chinese provinces. With the cancellation of these restrictions in place, the government aimed at achieving two goals. The first goal is to supply the Western provinces with cars that have to fulfill the same higher emission standards as those in the Eastern provinces. The second goal is to push the sales of new cars in Eastern provinces, thereby increasing the dealers' financial clout and thus raising local tax revenues in order to safeguard the national target of 6.5% in GDP growth.

ff) Car parc

Lastly, the interviewee underscored that the car parc constitutes a key variable of market forecasts at the automotive enterprise A. He explained that this indicator measures the density and saturation level of the automotive market, which, in turn, is particularly meaningful for the sake of differentiating the heterogeneous level of automotive sales development in China. Still, the interviewee admitted that this indicator may be of even greater significance for long-term and/or regional forecasts. As for the regional forecasts, he pointed out that the potential for car sales in lower-tier regions is expected to rise tremendously over the next few years, providing enough reason to incorporate this indicator into the ANN forecasting model. Moreover, the interviewee mentioned that the automotive enterprise A does have sufficient data on car parc development.

Aside from his statements concerning the selection of leading indicators, the interviewee espoused the **inclusion of data outliers** as an integral part of the ANN forecasting model. The interviewee unveiled that he usually uses a **dummy variable** in his regression analyses to account for data deviations resulting from government policies. He conceded that this approach does not provide a satisfactory solution, which is expressed in comparably high out-of-sample forecasting errors.

The interviewee concluded by pointing out that his selection of indicators has not involved any consideration of **new economy-related variables**. That is because the availability of time series data is scarce for most of this data. As for his regression analyses, the interviewee necessitated at least two-digit samples of data to effectuate significant forecasting results.

Interview 10: Automotive enterprise A | Director market intelligence & analysis

a) Reasons for selecting this expert as an interviewee

The interviewee has been head of market intelligence and analysis for automotive enterprise A. Before that, she worked for more than seven years as an automotive consultant in an international consulting company.

The initial contact between the author and interviewee was established during the interviewee's business trip to Germany in March of 2016. At that point of time, the expert from Interview 4 organized a one-hour meeting, which was spent explaining the key premises of the underlying Ph.D. project. In the run-up to this meeting, the expert from Interview 4 substantiated the relevance of the interviewee by virtue of her executive position in China and the associated extensive business network of market intelligence experts and data suppliers.

During the initial meeting, the interviewee showed a strong affinity for the quantitative dimension of Chinese automotive market forecasting. She asked various questions concerning the selected ANN methodology and how it could help in improving forecasting accuracy in the Chinese automotive market. Immediately following the very first meeting in Wolfsburg, the interviewee signaled her readiness to provide the author with data input that could be used for his ANN forecasting model.
For all these reasons, the focus of the interview in China was placed on the quantitative impact of policies in China as well as the selection of suitable short-term leading indicators and their use in time series data pre-processing and multivariate modelling.

b) Key research deliverables

At the outset of the interview, the interviewee provided profound insight into the imponderables of short-term automotive market forecasting that the automotive enterprise A has encountered in the past few years. She sketched out that the root challenge can be chiefly attributed to the endemic characteristic of **systematic structural change in the Chinese economy**, which is rather difficult to quantify in statistical models. The pace of this change, she said, has vastly accelerated since President Xi's inauguration in 2012.

First, the interviewee outlined that the formerly prevailing investment-driven economic growth pattern involved constantly recurring state investment. This sort of state investment caused artificially generated demand, which, after the expiration of the respective investment package, created overcapacities in certain pillar industries. As a prime example, the interviewee illustrated the 4-trillion RMB stimulus plan in 2009. This stimulus plan had produced speculative price bubbles in the real-estate sector, which emanated from an excessive supply of newly built-up houses, especially in tier 3 to tier 5 cities. It was in light of this misleading development that President Xi decided to overhaul the economic structure by decreasing the abundance of state investment into key industrial sectors in favor of an intensified domestic consumption-driven growth pattern.

Second, along with the change in government leadership, the interviewee also pinpointed President Xi's campaign against corruption and extravagant spending as another source of structural change. This campaign had an immediate impact on the automotive industry in China, which was initially underestimated by the automotive enterprise A. The interviewee explained that this campaign was originally launched for the sake of improving the public's perception of the government. By implementation, it affected the global luxury goods markets, including the sales of premium-branded vehicles. This was due to an overall more pessimistic outlook of premium brand buyers. As a result, the automotive industry has observed a considerable shift of customer demand from higher-end to middle and lower-end vehicle segments, which has been tantamount to decreasing margins per vehicle sold.

Third, the interviewee pointed to the relevance of policies directly and indirectly linked to the automotive market. She mentioned the tax cut on 1.6-liter vehicles as a directly-linked policy and the associated rumors of dealers about the uncertain expiration date of this policy. The rumors, she stated, created a source of panic-based car purchases, the frontloading effects of which are, per se, very difficult to ascertain. When it comes to the impact of indirectly-linked policies, the interviewee pointed out the example of China's dispute with Japan on the so-called "Diaoyu island", which renewed the flare-up of anti-Japanese sentiments in mainland China followed by a significant drop of Japanese-branded cars. In fact, especially at the peak of the conflict in 2012/2013, some of the customers were choosing German or U.S. car brands. Nonetheless, the souring of ties between China and Japan entailed an overall decrease of total market development. This decrease could not be adequately anticipated by analysts across the entire automotive industry.

With respect to the selection of suitable leading indicators, the interviewee noted that time series data of short-term leading indicators needs to exhibit a **certain degree of change within the envisioned forecasting period**. She stated that time series data of long-term indicators, such as the *size of labor population*, is rather stable within the short-term observation horizon and therefore inappropriate to reflect automotive development dynamics. According to the interviewee's experience and understanding, indicators that are particularly designed for the short-term dimension of total automotive market forecast include the following:

aa) M2

Serving as the first "really important" leading indicator for short-term automotive market forecast, the interviewee mentioned M2 as a variable for measuring the overall amount of money supply in the economy. She further stated that previous correlation analyses at the automotive enterprise A had shown that there is a strong connection to both the premium market and total market development.

bb) Producer Price Index (PPI)

The interviewee argued that the Producer Price Index goes towards gauging the profit of an entire industry, depending on the average change in price of commodities sold. Similar to M2, she pointed out that PPI also has indicated a strong statistical correlation to the premium and luxury vehicle segment.

cc) Automobile financing

The interviewee explained that, in the past, most Chinese car customers were accustomed to relying on their cash savings to purchase a car. However, what has been discovered by the automotive enterprise A is that in recent years, the proportion of younger generation first-time car buyers has increased significantly in comparison to elder generations that are purchasing their second or third car. Along these lines, the interviewee firmly believes that the trend towards a rising rejuvenating customer segment will be reflected by the manner in which financial transactions will be conducted in the future.

In general, the interviewee suggested that younger car customers are apt to be more open to the idea of mobile payments methods, such as the WeChat payment, to conduct their financial transactions. She is convinced that this kind of purchasing behavior will also penetrate into the automotive industry if two basic conditions are met. First, she said that it must continue to be easy to gain a loan approval. This, in turn, primarily depends on the waiting time widely involved with the loan approval process, which is decisive in determining when exactly loan-requiring customers can actually acquire their newly-purchased car. As the interviewee sees it, the overall framework of loan approval has improved in recent years. Second, she feels that interest rates for auto financing must be kept at a low level. In fact, she reported that a lot of automotive enterprises have recently refinanced their auto financing companies so as to optimize their ratio of auto financing.

She further revealed that the automotive enterprise A closely monitors the development of automobile financing in China. At the same time, she conceded that only a minimal amount of official data is available.

dd) Interest rates

The interviewee suggested analyzing interest rates as a potential metric for short-term automotive market forecasts. She explained that the interest rate, as part of the Chinese government's monetary policy[383], has proven to signal whether it is inclined to stimulate the economy by loan-financed investments. She also indicated that interest rate developments are closely connected to the automobile financing trend and should therefore be viewed as a leading indicator.

ee) Stock market-related indicator

The interviewee used times of very sudden and dramatic economic dynamics to establish how the fluctuating stock market performance has been tightly linked to automotive development. She explained that in 2015, when the stock market swung both upwards and downwards, many customers were very reluctant to purchase a new car. The associated negative expectations towards overall economic development could thus be recorded in the amount of new car sales, a number that dropped considerably in the second quarter of 2015.

ff) Transaction price

For short-term market forecasts, the interviewee emphasized the role of transaction price development. Unlike the manufacturer's suggested retail price (MSRP), which merely indicates the car models' strategic positioning determined by the respective automotive enterprises, the transaction price mirrors what customers are willing to pay for a car. Using the following as a principal rule of thumb, she outlined that if the industry-wide transaction price should de-

[383] The People`s Bank of China (PBOC) holds the exclusive authority to formulate monetary policies in China. Nonetheless, it is acknowledged that the PBOC does not represent an independent central bank as commonly understood but functions instead as transmission belt for industrial policies formulated by the State Council. See: Chin, Gregory T. (2013), p. 526.

crease, for example due to dealer incentives provided to the customer, the absolute amount of sales tends to increase. However, she also acknowledged that a sufficient amount of data may not be available, because each automotive enterprise gleans this data on its own.

With regards the pre-processing of data, the interviewee disclosed that **data outliers** constitute an integral part of short-term market forecasts within a three-month moving average model used at the automotive enterprise A. She suggested adopting a very high tolerance level in the selection of data outliers that should *not* become part of the ANN forecasting model. In an effort to map all relevant patterns that might explicate the market's up and downs, she recommended including all data outliers except for those that can be traced back to the earthquake in Japan in 2011. In addition, for the sake of minimizing data distortions around the Chinese New Year, a point of time when businesses often cut back their operations or close them completely, she proposed to **merge January and February's data together**, a practice often used for publishing official economic data as well.

Lastly, in answering the question as to how close it will be able to approximate market realities for the short-term market forecasting model, the interviewee suggested a 3-5% forecasted error-objective for <u>quarterly</u> forecasts. She insinuated that the automotive enterprise A has not been able to achieve this objective recently. For some quarterly periods, in which certain policies came into effect, she reported that the forecasting target was missed by 10-20%.

IV.4 Executive summary of expert interviews

The expert interviews epitomize the persisting difficulties that even the savviest forecasters face with near-term predictions of automotive sales development in China. In fact, while almost all market experts claimed to cope reasonably well with longer forecasting horizons, in some cases a deviation to actual sales of only 3-5% was ascertained, the vulnerability to monthly fluctuations has presented a more intricate and as yet unresolved challenge across the entire industry. In this respect, the interviewees involved in short-term sales forecasting reported that their established quantitative models may have yielded adequately accurate forecasts at normal times, yet often missed the mark at times of drastic changes in supply and/or demand.

The interviewees traced back the principal roots of these changes to the frequent ups and downs in the Chinese automotive market environment. More specifically, the deficiency of dealing with government policies was seen as the main inhibitor of accurate total market sales predictions. The ad hoc initiation of restriction and purchase tax policies, which often act as a corrective action in response to increasing air pollution levels or subsiding economic growth momentum, was described as a pervasive phenomenon of **regulatory insecurity** in the Chinese automotive industry. Looking ahead, the majority of interviewees also articulated their doubts that government officials will wean the economy from that sort of state interference in the years to come. On the contrary, the interviewees thought it reasonable to assert that the policy dimension will continue to play a cardinal role in the automotive industry.

In this context, the interviewees confirmed the author's previous findings that a robust short-term forecasting model for the underlying case study of PV sales in China must handle the confluence of

i) **non-linear relationships** in time series data, which mostly represent the inherent state of flux in the Chinese economy;
ii) **outliers**, which mostly represent artificially-generated customer demand fueled by elusive government-initiated policies;
iii) **multi-collinearity effects**, which were considered another major drawback of regression-based forecasting methodologies because they, quite unrealistically, assume all predictors to be independent of each other.

As we have seen at some length in section III.3, ANNs, as structure-detecting non-parametric methods, possess certain dynamic characteristics that capture the resulting complexity in time series data. It is these characteristics that are said to differentiate ANNs from more conventional, regression-based approaches to business forecasting. Therefore, the author's expectation that ANNs can help improve the accuracy of short-term sales forecasts in a highly dynamic Chinese automotive market environment was even higher after the expert interviews.

Aside from a set of technical modelling requirements to adequately respond to the described regulatory insecurity in the Chinese automotive market, the expert interviews also indicated somewhat **unreliable sources of market information**, the second main dimension of institutional voids in emerging markets. This problem was particularly specified by the expert in Interview 6 who set out the poor quality of the used car market time series data, which may differ vastly for the same year depending on the edition of the respective publication in which the data appears. Exactly this type of unreliable data in the Chinese automotive market is what the next chapter investigates as part of a multi-level indicator selection process for the ANN forecasting model to be developed.

V Knowledge assimilation: Selection of superior leading indicators

As outlined in the section IV.2, the expert interviews served two principal research objectives. First, the author sought to obtain a holistic view on the extent of regulatory insecurity in the Chinese automotive industry. In this respect, the experts illustrated the extent as to which the ad hoc initiation of government policies have affected the accuracy of PV sales forecasts. Second, the author also aimed to identify leading indicators with time series data that is sufficiently available to be exploited in the ANN forecasting model. In this vein, a wealth of knowledge concerning the selection of leading indicators with presumed superior predictive power could be acquired.

In conjunction with the second research objective, the focus of this chapter is to assimilate the acquired knowledge as part of a multi-leveled indicator selection process. For that purpose, the first section of this chapter entails a comprehensive literature review on the credibility of Chinese economic indicators, some of which were explicitly stressed in the expert interviews. Based on these findings, the author then critically reflects upon the interviewees' statements by eliminating all indicators that are either unreliable or not sufficiently available for the subsequent ANN forecasting application.

V.1 Indicator selection in the presence of unreliable market information

Since the late 1990s, the quality of Chinese official statistics has come under increasing scrutiny.[384] Critics suggest that official economic data has not proven to be as reliable as data equivalents in more advanced economies in Europe or the United States, because it tends to overstate nominal GDP growth and understate inflation in China's economy.[385] Suspicions about China's statistical work have been expressed by outside economists and even within the inner circle of the Chinese government itself[386], which is said to be interfering by means of a systematic and persistent process of data manipulation.[387] This sort of politically motivated interference manifests itself not only in a less independent[388] and assertive institutional setting

[384] Holz, Carsten A. (2014), pp. 309 f.
[385] Koch-Weser, Iacob N. (2013), p. 4.
[386] In the late 2000s, China`s premier disclosed that China`s official GDP statistics, other than electricity consumption, rail cargo volume, and bank lending, were "man-made", "unreliable" and "for reference" only. See: Rosen, Daniel; Bao, Beibei (2015), p. 4, 47.
[387] Koch-Weser, Iacob N. (2013), p. 20.
[388] Liu, Fang; Zhang, Jun; Zhu, Tian (2016), pp. 223 f.

of data compilation under an extraordinarily weak regulatory framework[389], but also in the methods deployed to measure and present GDP statistics.[390]

In view of possibly distorting quantitative implications for the ANN forecasting model, this sub-section therefore centers upon nominal and real Chinese GDP data measurement, including the construction of selected GDP components. The examination is accompanied by a critical reflection of the institutional scope for data compilation in China, with the NBS starring in the title role.

V.1.1 Past and ongoing falsification of Chinese economic data

Time and again, Chinese history has repeatedly seen certain events of potential data falsification on a national scope. For example, between 1959 and 1962, Chinese officials were said to intentionally overstate figures of agricultural production in times of China's "Great Leap Forward"; in the aftermath of the Tiananmen massacre of 1989, double-digit growth levels appeared to be implausible to some scholars given that the economy simultaneously recorded high levels of inflation and urban unemployment. Likewise, in more recent history, further inconsistencies were pointed out during the Asian Financial crisis when China reported 7.8% GDP growth in 1998 – only a minor annual decrease of 1%, whereas the regional context and more specific indicators of economic activity (such as energy consumption and airline travel) indicated towards a more dramatic decline.[391] By the same token, researchers have casted serious doubts on China's "newly normalized"[392] but still high single-digit growth rates throughout and after the global financial crisis in 2009, thereby refueling misgivings about Chinese economic data credibility.[393]

Although these isolated episodes of exaggerated growth statistics purport to an ever-existing and uniform modus operandi of data falsification in China, it is necessary to undertake a chronological differentiation: On the whole, up until the 1980s, the challenge of obtaining reliable statistical data in emerging markets have been largely cited for countries in Eastern Europe and Russia, but far less so for China.[394] Both sinologists and economists were hence

[389] Holz, Carsten A. (2014), p. 322.
[390] Koch-Weser, Iacob N. (2013), p. 4.
[391] Koch-Weser, Iacob N. (2013), p. 21.
[392] The term "new normal" refers to China's economic slowdown nowadays compared to double-digit annual growth rates since China's reform and opening-up policies in the late 1970s.
See: Naughton, Barry (2018), p. 7.
[393] Koch-Weser, Iacob N. (2013), p. 21.
[394] Holz, Carsten A. (2014), p. 310.

almost unanimously inclined to issue a clean bill of health for Chinese official statistics, stating that they are predominantly "honest"[395] and lay an "accurate"[396] foundation for sound and conclusive quantitative investigation.[397] However, with an increasing impact of structural reforms implemented since China's opening-up policies in the late 1970s and early 1980s, the quality of Chinese official economic data deteriorated significantly. Besides certain methodological divergences in GDP computation[398], triggered by newly introduced statistical methods that have taken greater account of the (partial) shift from material production towards a more value-based concept of measuring economic activity[399], evidence suggests that statistical inconsistencies are most pervasively detected at the local administrative level.[400] Indeed, what can be observed is that whilst the sum of gross regional GDP is typically expected to equal the national total in more advanced economies[401], economic growth figures reported by Chinese local governments have invariably, and notably over the past decade, surpassed those of the central government.[402] For instance, by 2004, gross regional product was 19.3% larger than (pre-economic census) GDP[403], with the highest incongruity in the service sector.

The issuance of deliberately falsified economic data reports serves as an important lever in obscuring potentially adverse provincial development figures, the latter of which are an essential determinant of the respective cadre's personal performance evaluation. The problem associated with data manipulation at a provincial level is that it inevitably causes **unpredictable directional effects on final aggregate statistics**.[404] This sort of institutional void at the lowest level of the Chinese data pyramid exemplifies the deeply striated legacy of (local) political interference in China's statistical work. It has also given rise to the widespread domestic slogan "jiabao fukuafeng" ("wind of falsification and embellishment"), which is used whenever such instances of data manipulation in China occur yet again.[405]

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395 Chow, G. C. (1986), p. 193.
396 Rawski, T.G. (1976), p. 440.
397 Holz, Carsten A. (2014), p. 310.
398 Rosen, Daniel et al. (2015). p. 34.
399 Holz, Carsten A. (2014), p. 310.
400 Koch-Weser, Iacob N. (2013), p. 22.
401 Rosen, Daniel et al. (2015). p. 57.
402 Holz, Carsten A. (2014), p. 310.
403 Later revisions of this data after the 2004 and 2008 Economic Census reduced the incongruities somewhat, but only temporarily.
See: Holz, Carsten A. (2014), pp. 313 f.
404 Rosen, Daniel et al. (2015). p. 64.
405 Holz, Carsten A. (2014), p. 311.

V.1.2 Institutional dimension of Chinese statistical data compilation

Seen and evaluated from an institutional perspective, statistical manipulation on the part of governmental authorities is chiefly facilitated by the evident weakness of the leading institution in the area of statistical data compilation in China, the NBS.[406] In effect, China's annual and quarterly GDP figures are officially gathered under the auspices of the NBS[407], a bureau directly under the administrative leadership of the State Council, or by affiliated institutions with approval of the NBS. The legal foundation for this is provided by the 1983 Statistics Law and its revision in 2009, which set out the regulatory framework for organizing, directing, and coordinating statistics work throughout the country to the NBS and affiliated institutions by gathering data either through surveys, censuses, or direct reporting.[408]

In statistical practice, one of the key problems in the present institutional setting lies in the fact that the greater part of data collection takes part outside the NBS. First, whilst the NBS may have unlimited authority to access its own survey data, it has little power over data compilation by local-level statistical bureaus, especially in the primary and tertiary sector. In its current version, the Statistic Law unmistakably sets forth that local statistical agencies are subject only to local governments in administrative affairs, entitling them, inter alia, to take control over personnel appointments and hence manipulate data in favor of its own needs.[409] Second, even though the NBS may conceptualize the design of the five-year general economic census[410], a national undertaking which was firstly established in 2004 to draw level with other major (advanced) economies in terms of comprehensive economic performance measurement, its implementation presupposes additional data from other central government departments[411], which weakens the authority of the NBS further.[412] Lastly, the systematic and persistent scope of data compilation inconsistencies is mirrored in the NBS' outdated system of direct reporting in which a pre-determined revenue threshold specifies whether an enterprise is eligible for direct reporting to the NBS or not. Given that the number of eligible enterprises, both state-owned and private, has increased proportionally with China's overall

406 Rosen, Daniel et al. (2015). p. 66.
407 Liu, Fang et al. (2016), p. 217.
408 Holz, Carsten A. (2014), p. 321.
409 Koch-Weser, Iacob N. (2013), p. 22.
410 Rosen, Daniel et al. (2015). p. 15.
411 Holz, Carsten A. (2014), p. 321.
412 When an economic census detects previously uncounted economic activities, nominal GDP figures are usually retrospectively revised up or down in the respective census year. In China, the most significant revision occurred in 2004 when the NBS revised up nominal GDP by 16.8% mainly due to underreported activities in the service sector.
See: Rosen, Daniel et al. (2015). p. 24.

economic growth, the NBS has been struggling with insufficient data processing capacities. In an attempt to enhance in-house operational efficiency, the designated revenue threshold for direct reporting was thus announced to rise continually, starting in 1998 when the number of directly-reporting enterprises was reduced from 460,000 to 165,000. After all, the failure of this measure rendered visible by 2009 when again 434,000 enterprises[413] were reporting to the NBS.[414]

All three reasons cited above constitute a plausible rationale for the conceptual difficulties of compiling accurate and comprehensive GDP data in China's highly decentralized statistical work.[415] Besides, there is yet another challenge for the NBS which, again, takes recourse to the Statistics Law, and – more generally speaking – a missing principle of checks and balances in China's political system.

In the current Statistics Law regulations, there is by no means an express provision conferring a *de jure* status of institutional independence and neutrality on the NBS. Instead, the Law sets forth that the "fundamental task of statistics work" is to carry out statistical examination towards the implementation of the national economic and social development plan (NPC, 1996, Art. 2; revised Statistics Law in NPC, 2009, Art. 2). As for the institutional role of the NBS, a "work regulation" from November 1995 stipulates that the NBS is to enforce "important decisions and instructions of the Chinese Communist Party Central Committee and the State Council".[416] These regulations are reinforced by statements of highly decorated NBS representatives, such as those by Zhang Sai, head of the NBS between 1984 and 1997, who expounded his understanding of the NBS' role as follows: "the government statistics organization primarily serves the needs of macroeconomic decision-making of Party and government leaders at each administrative level, and is responsible to the Party and government leaders at each administrative level"[417]. Following this notion, rather than acting as an assertive institutional setting of efficient and transparent data compilation, the NBS is instrumentalized as a transmission belt for the state's industrial policies and the forces leading to the actual composition of China's GDP remain the tacit knowledge of only a few selected insiders.[418] This

413 Koch-Weser, Iacob N. (2013), p. 9.
414 Meanwhile, since 2012, the NBS has been transitioning to an online national direct-reporting system that is meant to de-bureaucratize paper-based data collection. In most places, this has contributed to an alleviation of operational reporting efficiency.
See: Rosen, Daniel et al. (2015). p. 64.
415 Holz, Carsten A. (2014), p. 310, 321.
416 Holz, Carsten A. (2014), pp. 321 f.
417 Holz, Carsten A. (2014), p. 311, 322.
418 Holz, Carsten A. (2014), p. 322.

means that the *de facto* operationalization of political interference at the national level is accomplished through data access for selected representatives at the powerful[419] NDRC prior to publication of the statistics. At the local level, political interference implies that sensitive GDP data presupposes prior supervision and definitive approval by a local government official before it can be reported further up the hierarchy.[420]

V.1.3 GDP data measurement and publication

The aspect of political interference in Chinese data statistics is assumed to be continued in the methodologies applied to measuring national GDP. In principal, the measurement of GDP can be attained either through the production, income, or expenditure approach (see Figure V-1). All three approaches are theoretically expected to generate equivalent values, although slightly diverging results are not uncommon in statistical practice.[421]

	Expenditure approach	Income approach	Production approach
Definition	– Final use of the produced output as the sum of final consumption, gross capital formation, and exports less imports → **demand-oriented**	– Sum of the factor incomes generated to the economy → **income-oriented**	– Difference between value of output less the value of goods and services used in producing these outputs → **supply-oriented**
Components	– Final **household consumption** on goods and services – **Investment** of **private enterprises** on capital goods – **Government spending** on goods and services – **Net exports**	– Wages, salaries, and other **compensation payable to employees** – **Taxes** on products and production **payable to the government** – **Operating surplus** for producers/businesses – **Rent** from land property	– **Net output** from **primary, secondary, and tertiary sectors** of economic activity
Application	– Predominant approach in **advanced economies** – **Published in China** at only **irregular intervals**	– **NBS**: For **industrial activities** since 2004 – NBS in primary sector (minor part)	– **Local bureaucracies** in **primary sector** and possibly secondary sector – **NBS in primary sector** (for final GDP purpose)

Sources: Own illustration, based on Rosen, Daniel et al. (2015), pp. 30 ff. and Vu Quang Viet (2009), pp. 4 ff.

Figure V-1: Overview of GDP computation methods (simplified depiction)

The expenditure-based measure represents the most pervasively utilized GDP computation approach in advanced economies. By adding up consumption, gross capital formation, and net

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[419] Rosen, Daniel et al. (2015). p. 215.
[420] Holz, Carsten A. (2014), p. 322.
[421] Liu, Fang et al. (2016), p. 217 ; Vu Quang Viet (2009), p. 4.

exports, it is considered superior than its alternatives, because it accounts for the output of an economy that is actually demanded by domestic and foreign societies, including citizens, businesses, and governments.[422] It may therefore seem surprising that annual expenditure GDP in China has only been published at irregular intervals; quarterly expenditure GDP and inflation-adjusted real GDP growth have not been reported at all.[423] Instead, GDP computations in China refer to a heterogeneous mixture of the production and income approach as primary measure of annual and quarterly GDP.[424]

The income approach, as the term already suggests, measures GDP as the sum of all types of factor incomes generated in the production process.[425] On the other hand, the production approach adds up the net output of all three economic sectors (primary, secondary, and tertiary).[426] The production approach constitutes a relic of the pre-reform socialist economy's material production system[427], spotlighting what the economy supplies rather than what it actually consumes[428]. By implication, in comparison to the other two approaches of GDP computation, the production approach attaches more weight to the final gross output, which, in turn, serves as the methodological prerequisite for exaggerated growth figures reported by local cadres.[429] For this very reason, whereas the NBS began to convert its industrial GDP computations from the production to the income approach following the first nationwide Economic Census in 2004, there is still some indication that local statistical bureaucracies tend to abide fairly strictly by the production-based measure of GDP computation as yet.[430] Moving up the data pyramid, this non-coherent approach of GDP measurement across various reporting units in China largely reveals why inconsistent and contradictory aggregate growth figures are likely to occur in official Chinese publications.[431]

Following on from this, the lack of faith that is exhibited in the neglect of the expenditure-based approach to GDP computation in China is perhaps most evidently exemplified in the measurement of its main components, i.e. household consumption and fixed asset invest-

[422] Vu Quang Viet (2009), p. 20.
[423] Koch-Weser, Iacob N. (2013), p. 10.
[424] Holz, Carsten A. (2014), p. 313; Liu, Fang et al. (2016), p. 217.
[425] Vu Quang Viet (2009), p. 5.
[426] Koch-Weser, Iacob N. (2013), p. 10.
[427] Holz, Carsten A. (2014), p. 313.
[428] Koch-Weser, Iacob N. (2013), p. 10.
[429] Rosen, Daniel et al. (2015). p. 24.
[430] Rosen, Daniel et al. (2015), pp. 30 ff.
[431] Koch-Weser, Iacob N. (2013), pp. 4 f.

ment.[432] First, the measurement of **household consumption** in China[433] is predominantly based on retail sales data. This data is said to be overstated as well, given that it is already recorded when suppliers deliver their goods to retailers, rather when goods are actually distributed to final consumers. The conclusion is that large quantities of non-marketable goods may be stored in warehouses but still be statistically recorded as goods eventually consumed by end users. Equally remarkable is the fact that consumption figures, which have risen continuously after China's accession to the WTO, have not been accompanied by a proportionate increase in wages or decrease in household savings. This raises the question as to how Chinese consumers managed to finance their consumption if data were indeed reliable.[434] Moreover, the emphasis on retail sales means that some of the fastest-growing service markets are excluded from statistical consideration – which possibly entails a more pessimistic evaluation of economic recovery than official consumption figures actually reflect.[435] While this is an important argument that is frequently put forward by the NBS in an environment of high growth expectations raised by political decision-makers[436], the downside to this point is that market forecasters are confronted with yet another conceptual break in time series data.[437]

Second, as in the case of household consumption, the methodology used for measuring **fixed asset investment** raises similar inconsistencies. In China, rather than recording an investment when it results in the use of working capital, it is already covered in the statistics when funds are disbursed to their recipients. Provided that the Chinese government can determine the pace at which funds are released, this implies that it possesses de facto total control over domestic growth levels. Further, pursuant to Chinese Property Law, investors of infrastructure projects have a two-year leeway between land acquisition and development. Many investors fully exploit this timeframe by undertaking only small investments within the first two years of land ownership and declaring to the government that the land is "under construction"[438].

[432] Liu, Fang et al. (2016), p. 222.
[433] Household consumption data in China is retrieved from household surveys, such as the "China Household Finance Survey (CHFS)" published by the Southwestern University of Finance and Economics in Chengdu. See: Liu, Fang et al. (2016), p. 218.
[434] One may argue that rising household debt in China could be one fairly clear explanation. While this argument may be valid in general, it is to be said that Chinese household debt – even compared by the standards of advanced economies – is still to be found at very low levels (38% of GDP in 2017, up from 10% in 2006) and thus does not adequately explain the existing discrepancy between consumption and personal income/savings figures.
For household debt figures, see OECD (2018), p. 43.
[435] Koch-Weser, Iacob N. (2013), p. 11.
[436] Holz, Carsten A. (2014), p. 322.
[437] Rosen, Daniel et al. (2015), p. 40.
[438] Koch-Weser, Iacob N. (2013), p. 12.

Within this regulatory framework, it seems reasonable to assume that investments in infrastructure projects, a decisive sub-component of fixed asset investment, have presumably caused overstated fixed asset investment figures in recent years.[439]

Finally, irrespective of the three principal methodologies to GDP computation, the imponderables surrounding household consumption and fixed asset investment apply in much the same perplexing manner for **inflation**. As such, inflation is used to translate computations of nominal GDP to real GDP, thereby facilitating period-over-period comparisons. This process necessitates dividing the increase in nominal quantities into a real component and an inflation component by means of an appropriate GDP price deflator. In the U.S., for example, the overall GDP price deflator uses components based on the Consumer Price Index (CPI) and the Producer Price Index (PPI), which are estimated by the U.S. Bureaus of Labor Statistics and Economic Analysis.[440]

In China, to convert nominal into real GDP, the NBS follows a similar procedure by utilizing a combination of different indices, such as the **CPI, PPI**, and retail price index. The crucial difference is that the NBS is not very transparent as to the weights it uses to arrive at the deflator, nor does it even publish it in its GDP reports. In doing so, the intention of the government in the recent past was to disguise the then-present cyclicality in food prices – a practice being fiercely criticized by economists, but perceived less severe by consumers whose attention was diverted from food inflation to the more general (and moderate) CPI inflation rate.[441] To arrive at the CPI inflation rate, the NBS tracks price changes of a comparatively high amount of products in its CPI basket; pursuant to one account, it is referring to 262 products in China versus 211 in the U.S. As outlined in the case of household consumption, critics charge that this unusually high amount of products does still not sufficiently address the ever-increasing amount of services including the fast-growing information technology branch. Moreover, in an effort to create a (false) impression of price stability, price indices in China typically prefer state-regulated over market-oriented prices. The CPI for services, for example, emphasizes stable prices from the state-provided health, transport, and education sector,

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439 Koch-Weser, Iacob N. (2013), p. 12.

440 Feldstein, Martin (2017), p. 148.

441 Given some structural changes to food production in China, cyclicality in food prices have been reduced significantly in the present decade, narrowing the gap between food and general inflation. Even so, the structural break in time series data remains a challenge for forecasters.
See: Day, Iris (2017), p. 30.

rather than prices from the private service sector, which are inclined to exhibit higher volatility.[442]

V.2 Indicator selection process

The preceding section investigated the issue of Chinese economic data reliability from a broader literature perspective. This investigation appeared to be very important at this stage of research, because the success of the ANN forecasting model hinges to a large extent on the (undistorted) input patterns presented by the respective leading indicators.[443] For that reason, the goal of this section is to reconcile the key findings of the preceding literature research with the interviewees' statements as part of a multi-leveled indicator selection process.

As outlined in the expert interviews, the coverage of leading indicators must strike a balance between macroeconomic and microeconomic determinants providing a holistic depiction of historical, present, and future automotive development narratives. Hence, the author's task was to forge a monolithic typology of multiple leading indicators, which is likely to show superior predictive power, thereby pinpointing the most relevant signals of an emerging risk. To that effect, the interviewees' statements were processed based on five consecutive steps:

i) Visualization of all specified leading indicators:
Reproduces all indicators as specified in the expert interviews;

ii) Extraction of short-term indicators:
Focuses on indicators suitable for the short-term dimension of forecast;

iii) Prioritization in decision-making matrix:
Categorizes all indicators into four priorities and eliminates the least important one;

iv) Exclusion-criteria testing:
Examines sufficient time series data availability and consistency;

v) Post-selective consideration of key driving forces:
Verifies well-balanced indicator coverage of all relevant market drivers.

[442] Koch-Weser, Iacob N. (2013), p. 4, 13.
[443] Zhang, Peter G. (2004b), p. 4.

V.2.1 Visualization of all specified leading indicators

In an effort to summarize and structure the most essential interviewee' statements, all specified indicators were merged into a **mind map**[444]. The mind map method was chosen, because it enables a profound representation of ideas and statements that encircle a central theme, most particularly in selecting leading indicators. Moreover, mind maps feature a coherent way to condense wealth of information and decompose the underlying complexity in a graphically appealing manner.

As research progressed, the author's endeavor of selecting an appropriate mix of leading indicators revolved around three pivotal questions.

i) Which indicator was considered important?

ii) Who considered it important?

iii) Why was it considered important?

These questions went on to help the author to ascertain the relevance of all specified indicators by contextualizing and referencing the main aspects of the matter.

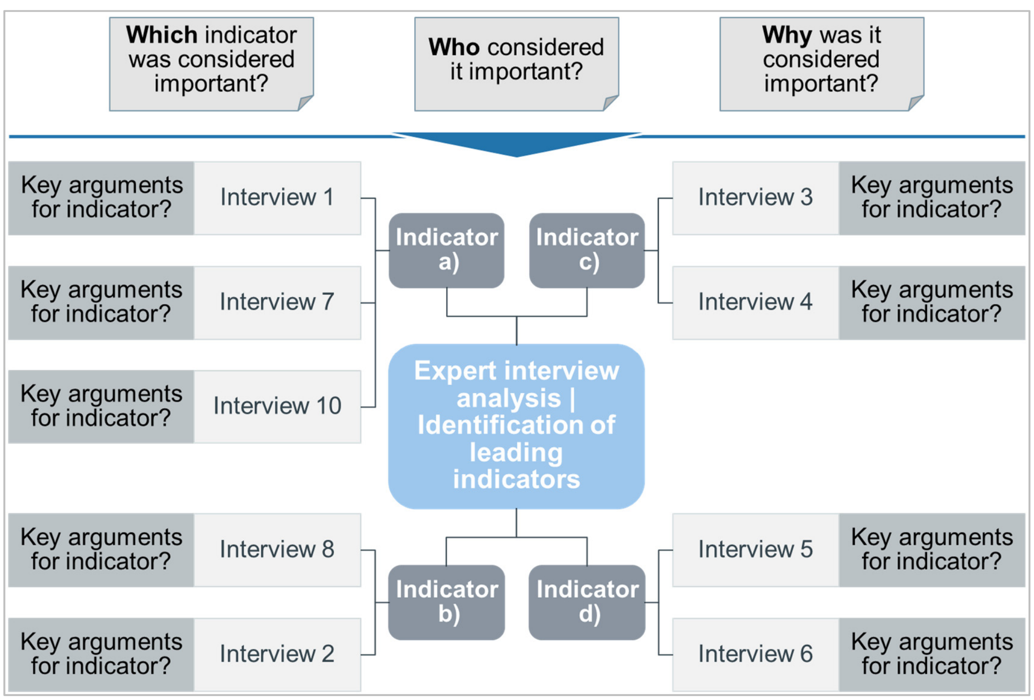

Figure V-2: Exemplary illustration of mind map structure for interview analysis[445]

[444] Crowe, Michael; Sheppard, Lorraine (2012), pp. 1494 ff.
[445] For purposes of presentation, the entire mind map is only submitted in the Appendix of this thesis.

V.2.2 Extraction of short-term indicators

Forecasting tasks are often classified into short-term, medium-term, and long-term dimensions. These different dimensions are not necessarily represented in clear-cut distinction. However, as specified in section III.1, the prevailing view in literature assumes that short-term forecasts are chiefly concerned with forecasting horizons of (less than) three months, whereas medium-term forecasts stretch from one to two years while long-term forecasts go even beyond that. Most of the experts who have been deeply engaged in forecasting implicitly confirmed that this theoretical guideline for different forecasting horizons has been widely applied in the practice of automotive sales forecasting in China.

Irrespective of the experts' statements, which provided a good account of China's projected mid to long-term automotive development, the author's research interest was placed on the more challenging **short-term dimension of forecasting.** In addressing this matter, the author followed the advice given by the expert in Interviews 8, which was to classify all specified indicators into short-term and mid to long-term forecasting horizons. In line with the remarks of the expert in Interview 10, all indicators need to exhibit a certain degree of change within the envisioned forecasting period. Thus, the author eliminated all indicators, where the short-term impact was not explicitly nailed down in at least one of the expert interviews.

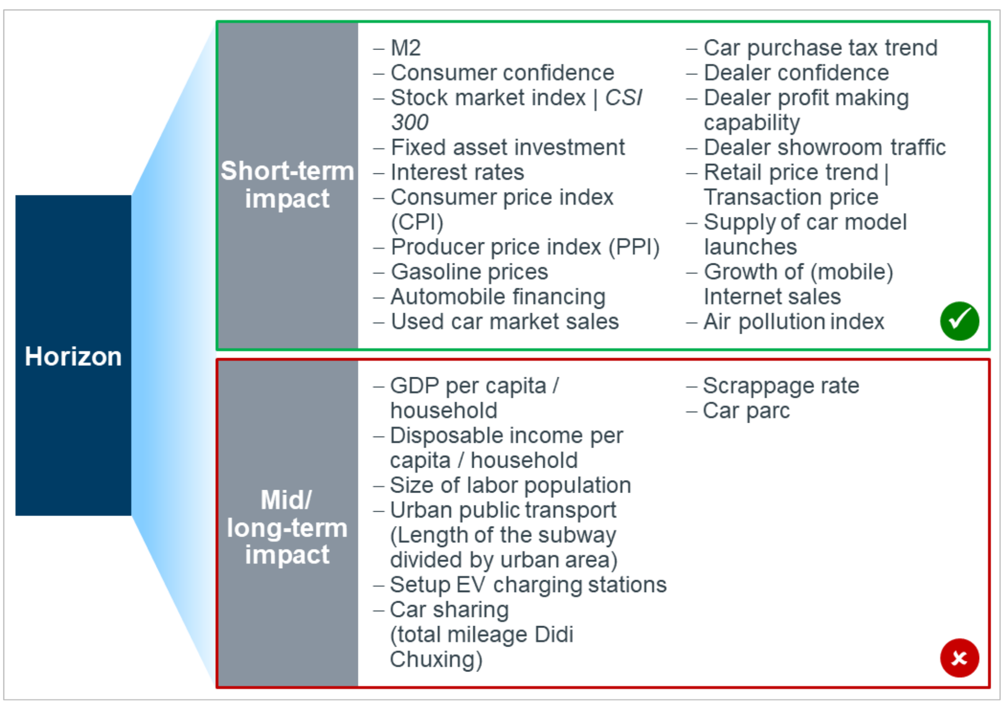

Figure V-3: Extraction of pre-selected indicators with assumed short-term relevance

The contradicting statements of the experts in Interviews 6 and 9 with respect to the alleged short-term pertinence of **car parc** remained an exception from the latter exclusion criterion. The expert in Interview 6 may have been the first to indicate the short-term total market relevance of car parc development. However, in contextual comparison with the statements of the expert in Interview 9, who preferred to categorize this indicator in the long-term and regional dimension, the argument of the expert in Interview 6 was rebutted to a substantial extent. In reference to these controversial vantage points, the author himself firmly reckons with a sustainable continuation of automotive growth in the short and medium-term future due to the overall low degree of passenger vehicle saturation in China. Therefore, he subsumed car parc development as a long-term indicator, consequently discarding it from further investigation in his short-term forecasting model development considerations. It follows that the pre-defined set of leading indicators has been reduced by eight mid to long-term indicators to a total of eighteen short-term indicators, as documented in Figure V-3.

V.2.3 Prioritization in decision-making matrix

Thus far, all analytical efforts were placed on reproducing the interviewees' core statements concerning the selection of leading indicators suitable for short-term sales forecasting in the Chinese automotive industry. On the assumption that even the most sagacious practitioners are not expected to be omniscient, this type of data synthesis does however not suffice to evaluate the findings in a comprehensive manner. In qualitative research, what matters even more is a critical reflection on the interviewees' standpoints, thereby providing rich ground for augmenting the scientific perspective on the object of investigation.[446]

That said, the interviewees' statements were contested on two counts. First, the indicators are classified within a prioritized order of importance. Second, in the next sub-section, the indicators are more closely linked to the theoretical framework of this thesis, i.e. the conceptual conclusions of managing institutional void-related risks. The pivotal objective of this two-sided approach was to reduce the remaining set of leading indicators to the most promising ones in terms of predictive power.

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[446] Bryman, Alan et al. (2015), p. 601.

In analogy to managerial decision-making concepts, as for instance illustrated in data envelopment analysis among entrepreneurial decision-making units[447], an actionable framework to prioritize the suggested indicators according to scalable decision components was devised. In the particular use case, a **2x2 matrix for a quantitative-qualitative assessment** within a 4-staged unit with a descending order of priority was crafted (see Figure V-4). The vertical axis measures the *quantitative* dimension, i.e. number of experts considering the respective indicator to be leading automotive sales. The decision threshold on whether the variables were placed in the higher prioritized upper quadrant is set to "3" – meaning that (at least) three interviewed experts attributed high relevance to it. The horizontal axis gauges the *qualitative* dimension, i.e. assumed strength of connection with automotive sales in an equidistant relationship of importance[448]. The decision threshold on whether the variables were placed in the higher prioritized upper quadrant was dependent on the qualitative assessment of the interviewees' line of reasoning.

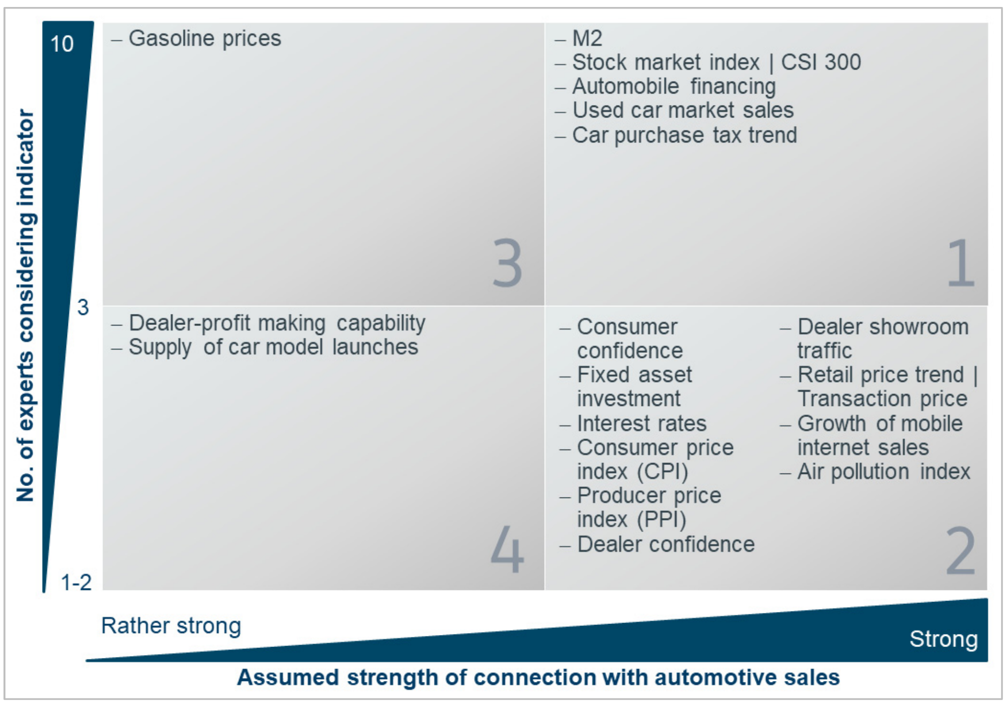

Figure V-4: Prioritized order of indicators in 2x2 decision-making matrix

447 Lu, Wen-Min; Hung, Shiu-Wan; Kweh, Qian Long et al. (2014), pp. 554 f.

448 At this stage of indicator analysis, a certain degree of importance pertinent to each of the respective indicators is determined. For this reason, unlike Likert-style scales, the decision-making matrix does not contain a middle point on the scale that allowed for a neutral evaluation.

From this point onward, the author has adopted a very reflective viewpoint on the interviewees' statements. The conceptual design of the decision-making matrix followed suit, because any indicator could be downgraded to the second-lowest priority, despite the suggested relevance of more than two interviewed experts. As a case in point, the importance of *gasoline prices* was explicitly highlighted by the experts in Interviews 2, 3, and 5, each of them referring to a relationship with the total cost of car ownership. In contrast, the expert in Interview 6 delivered palpable evidence that, within the last three years, no significant correlational effect with automotive demand could be detected, in all likelihood due to the comparatively low annual mileage of less than 10,000 kilometers per year. In this respect, the line of argumentation by the expert in Interview 6 has been more cogent as he refuted the assumed relationship on the basis of statistical findings. As a result, gasoline price was assigned a comparatively low third priority level, tantamount to dropping it out of further consideration.

Correspondingly, all indicators with the lowest priority level had to be ruled out, i.e. *dealer-profit making capability* and *supply of car model launches*. Concerning the first indicator, in abstinence of any statistical proof, the author has had serious doubts on whether there is a genuine lead-lag relationship with the output variable, because the profit-making capability rather tends to lag automotive sales. Besides, the capability to earn profits is contingent upon several factors, some of which are not truly representative enough to measure the overall health of the automotive industry (price policy, sense of entrepreneurship, region-specific competition levels etc.). With respect to the supply of car model launches, the expert in Interview 3 already denoted in the interview that this indicator proved to be successful at segment and city-based rather than at total market forecasting levels. As a result, this supply-side element was likewise discarded from further processing.

V.2.4 Exclusion-criteria testing

As for the remaining indicators, great importance was attached to comply with the fundamental requirements of business forecasting in an institutional void-related context. As outlined in section III.1, one key premise of data modelling is to acknowledge that information which is <u>reliable</u> in advanced economies, is not nearly as ubiquitous in emerging markets. In that sense, for the underlying case study of PV sales in China, a critical reflection of the interviewees' statements must also take into account previous findings on the opacity of key economic metrics in China. In fact, the prevalence of unreliable time series data complicates an already formidable task of devising an effective barometer that is capable of gauging the future clout of the Chinese economy and the closely associated well-being of its main industrial pillars. For that reason, all remaining specified indicators that are subject to potential inconsistencies had to be excluded from any sort of ANN forecasting model considerations. More specifically, previous findings on the credibility of Chinese economic indicators have unveiled that both *fixed asset investment* and *producer & consumer price indices* exhibit deficiencies in data measurement and presentation.[449] The same applies to an automotive industry-specific indicator, i.e. *used car market sales*, for which the expert in Interview 6 reported divergent trading volumes depending on the edition of the respective data publication source.

Beyond data reliability issues, non-available time series data would have thwarted the author's endeavor to construct a composite index of leading indicators in real-time format. Owed to the fact that ANNs generally presuppose larger sample sizes to adequately learn the functional relationship between empirically collected input and reference values, the corollary was that all selected indicators have had to be readily available on a monthly basis. It would then be best if they were since January of 2004, i.e. two years after the all-decisive but non-recurring impetus of automotive growth triggered by China's WTO entry.

To this end, the Shanghai *Stock Exchange Composite Index (SHCOMP)* was opted instead of *CSI 300*, given that no data was available for the latter indicator before May 2005.[450] In terms of their statistical significance, similar results were expected. That is because the historical time series data for SHCOMP and CSI 300 shows a strong correlation of 79% between 2005 and 2018[451], and very similar behavior in times of sudden and dramatic economic downturns, such as a 40% drop between June and September of 2015.[452] As for the interest rate, the focus was directed towards short-term interbank rates, which have proven to exhibit stronger ties with market-based supply and demand of money as opposed to officially-determined base lending and deposit rates.[453] Given that for the *Shanghai Interbank Offered Rate* (*SHIBOR)* data had not been available before October of 2006[454], the *China Interbank Offered Rate (CHIBOR)* data with a maturity of three months was used.[455] Similar to the aforementioned stock market indices, no significant statistical differences between SHIBOR and CHIBOR

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449 See for e.g. Koch-Weser, Iacob N. (2013), pp. 12 ff.
450 Wang, Shuai; Shang, Wie (2014) p. 872.
451 Supachart, Wannakomol (2019), p. 132, 136.
452 Trading Economics (n.a.).
453 Yi, Gang; Guo, Kai (2015), pp. 244 f.; Porter, Nathan; Xu, TengTeng (2016), pp. 148 f.
454 Zheng, Xiaolian; Chen Ben M. (2013), p. 55.
455 Wen, Jiandong (2015), p. 192.
455 Huang, Yiping; Wang, Xun; Wang Bijun et al. (2013), p. 74.

were expected. This is due to the fact that the movement of both time series data is highly consistent, evincing a correlation of up to 99% at short-term maturities.[456]

With regard to the remaining pre-selected indicators, non-availability of time series data was rooted in multiple causes. Paucity of data had an impact on the explanatory power of *automobile financing*, albeit five interviewees considered it a potent force affecting the future course of automotive sales. By the same token, *growth of mobile Internet sales* had to be eliminated, despite the convincing argument that individual mobility needs increasingly tend to be shaped and satisfied by burgeoning online services. Concerning the *air pollution index (API)* and its associated correlation with license plate restrictions in major Chinese cities (see Interviews 2 and 8), the use of a meteorological parameter called "*air quality index*" (*AQI)* appeared to be more straightforward. In contrast to the suggested API, statistical evidence revealed that AQI constitutes a more representative metric of air quality, mainly due to the inclusion of $PM_{2.5}$[457] in the calculation of the underlying index.[458] However, time series data for AQI has not been available before the Ministry of Environmental Protection released the official revisions to the Ambient Air Quality Standards in January 2013. Furthermore, as far as the *dealer showroom traffic*, *dealer confidence*, and *retail price/transaction price trend* are concerned, it may have been possible to accumulate sufficient data straight from Volkswagen's dealers in China. However, access to industry-wide data could not be obtained free of charge, as it is gleaned and exclusively licensed by an external agency specialized in this field of data distribution.

Henceforth, M2, SHCOMP, CHIBOR, consumer confidence (as NBS figure[459]), and *car purchase tax trend* qualified as indicators with superior predictive power for the underlying case study of PV sales in China (see Figure V-5). It followed that these indicators were supposed to form the actual input of leading indicators for the ANN forecasting model.

[456] Tao, Mengying, Xie Yuelan, Qu, Qiang et al. (2019), pp. 35 f.
[457] $PM_{2.5}$ refers to atmospheric particulate matter (PM) with a diameter of less than 2.5 micrometers in size.
[458] Zheng, Sheng; Cao C.X.; Singh, R.P. (2014), pp. 403 ff.; You, Mingqing (2014), pp. 4 ff.
[459] It turned out that the SIC version of consumer confidence is only available on a quarterly basis.

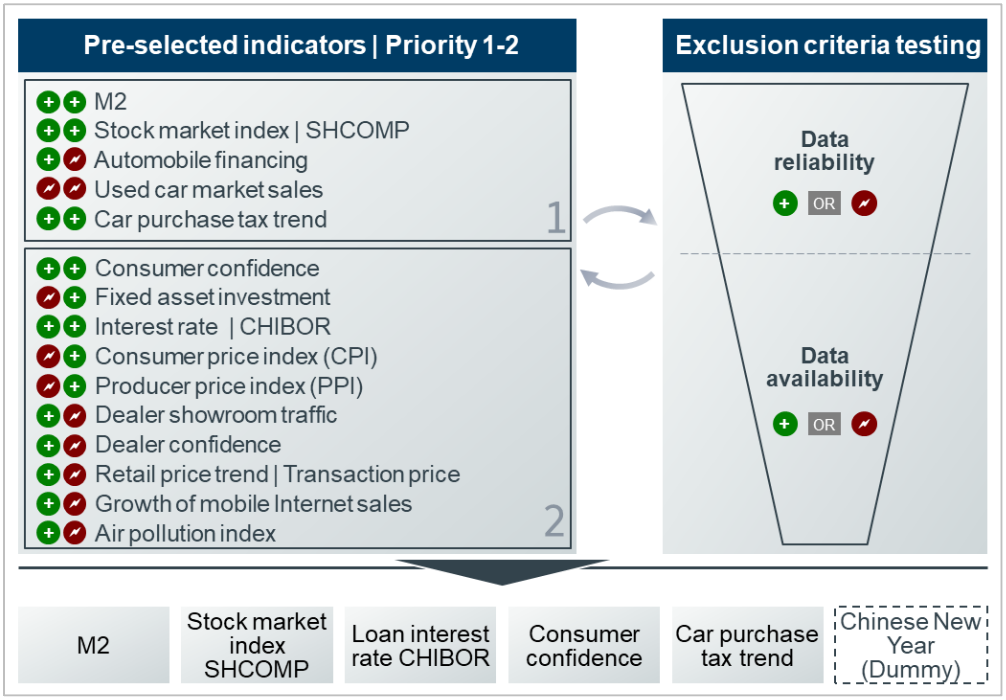

Figure V-5: Exclusion criteria testing of pre-selected indicators

V.2.5 Post-selective consideration of key driving forces

With the four incremental steps of interview reflection laid out above, a particularly strict yardstick was applied along the entire indicator selection process. This standard was deliberately set at a high level so as to exemplify the complexity that lies behind the illusions of simplicity in customizing forecasting processes to suit the institutional contexts of emerging markets.

Based on the hitherto pre-identified leading indicators, the last step of indicator selection was to verify a well-balanced consideration of all relevant market drivers. To this end, the quintessence of the interview material was that the conceptual pattern of short-term-oriented Chinese automotive forecasting has been inextricably linked to four constant driving forces. In addition to the already ascertained high magnitude and impact of **government-initiated policies**, the interviewees, and above all the SIC, convincingly set out two further clusters of short-term forecasting relevance, i.e. **purchase power** and **purchase willingness**, both of which constitute a formative element to capture the financial power and readiness of potential customers to purchase a new car. The last cluster, **segments/trends**, is the result of many interviewees' statements who have captured the effects of certain external ad hoc factors on specific automotive segments and the rising trend towards automobile financing methods.

What needs to be accentuated at this point is that a superior predictive indicator ought to reflect, in varying degrees, more aspects than it directly measures.[460] For example, CHIBOR is considered as a predisposing cause-effect antecedent of change in the money supply and automobile financing development. Moreover, it also serves as a seasoned monetary policy instrument to stir economic growth, thereby unfolding spillover effects to the automotive industry. These spillover effects, in turn, may unfold a significant impact on the peoples' willingness to purchase a big-ticket item within the short-term horizon to be forecasted.

As can be seen in Figure V-6, the final selection of leading indicators embraces all relevant dimensions, implying no need to re-consider the inclusion of previously eliminated indicators.

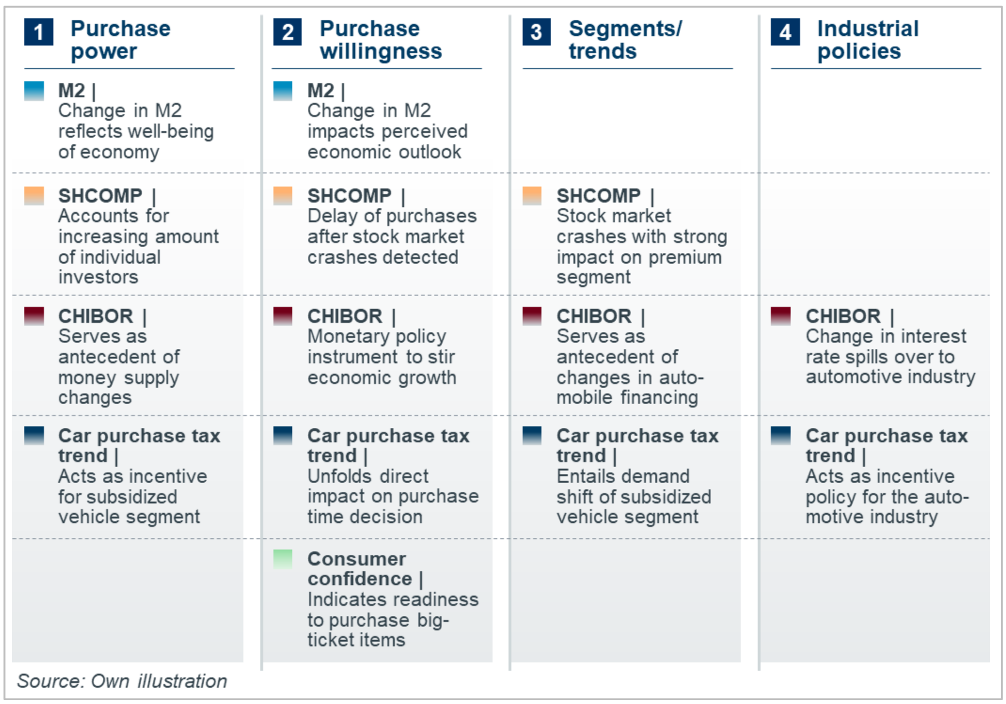

Figure V-6: Overview of selected indicators along four driving forces

[460] McGranahan, Donald (1972), p. 94.

VI Knowledge application: Artificial Neural Network development

The collection of qualitative data in the form of expert interviews and the subsequent analysis thereof has paved the way for an eclectic mix of leading indicators. In coherence with the underlying mixed method research approach[461], this chapter introduces a quantitative investigation to follow up qualitative findings by assembling the fragmented mosaics into a comprehensive ANN topology that is responsive to changing market conditions. For that purpose, this sub-section refers to the pre-processing of univariate time series data in a manner to assist the model in learning relevant relationships between input and output values. In the next sub-section, the experimental setup and final results of the multivariate ANN forecasting model are described.

VI.1 Pre-processing of univariate time series data

The idea of data pre-processing is to convert raw data into a format that is apt for application through a sequence of machine learning operations.[462] Related to the case study of PV sales in China, transforming time series data in a way that simplifies pattern recognition tasks became even more critical, because the availability of time series data constitutes a restrictive factor. Along these lines, one key question is how to deal with the presence of **data outliers**. In principal, there are two kinds of outliers that might occur in predictive analytics, namely invalid and valid outliers. Invalid outliers are often referred to as noise in the data as they are included in a sample through error. Valid outliers are correct values that are simply very different from the remaining set of data.[463] In machine learning, removing any sort of outliers may enhance generalization performance in general and the feature selection process in particular.[464] On the other hand, rejecting data merely on the grounds of unexpected behavior, pretending that outliers did not exist in the first place, appears to be too simplistic. It follows that however one deals with them, this should not be carried out without thoughtful consideration.[465] From the author's vantage point, removing outliers at this juncture of the data investigation would not have been in line with previous research findings on Chinese institutional voids on two counts. First, with respect to the invalid outliers, a significant effort was spent on exclud-

461 Bryman, Alan et al. (2015), p. 646.
462 Li, Hongxing; Chen, C.L. Philip; Huang, Han-Pang (2000), pp. 255 ff.
463 Kelleher, John D.; D`Arcy, Aoife; Namee, Brian Mac (2015), p. 69.
464 Mashrgy, Mohamed Al (2011), p. 127.
465 Hair, Joseph F.; Celsi, Mary W.; Money, Arthur H. et al. (2015), pp. 315 ff.

ing all indicators, the time series data of which gave rise to distortions in terms of data collection or reporting. Secondly, with respect to the valid outliers, a strong correlation between domestic state intervention in the form of car purchase tax policy reductions and PV sales has already been reported by most of the interviewees. These statements did not necessarily hint at further hidden correlations beyond the most obvious cause-and-effect relationships. However, they provided rich grounds for the assumption that disproportionate observations in the dataset may possibly have, figuratively speaking, an important story to tell. To account for these potentially weak or more subtle correlations, it seemed advisable to **proceed with the original data records**, including all valid data outliers.[466]

As the research progressed, yet another, if not the most important aspect of data preprocessing had to be resolved, namely how to determine the **lead time** between the PV sales indicator and its respective predictors. As such, the lead time is defined as "(…) the number of time intervals ahead that a forecast is made from a given forecast origin"[467]. In fact, while previous steps of indicator analysis have centered upon the principal question as to whether the specified indicators contain any predictive power whatsoever, little attention has been placed on the timing of their corresponding relationship.

Correlation studies are among the most seasoned instruments in measuring the extent of lead-lag relationships between input and target variables.[468] In conceptual terms, the correlation coefficient indicates the extent of linear dependencies between two variables.[469] Thus, it can be used to measure the portion of change in a target variable that is explained by a change in one of its explanatory metrics.[470] Traditional correlation measures, however, deal merely with cross-sectional relationships between variables, thereby ignoring their respective temporal attributes. By contrast, the **cross-correlation** method is instrumental in detecting the time lag at which changes between two sets of time series data occur.[471] This method makes use of both cross-sectional and time series components of dependence. It In more statistical terms, cross-correlation expresses the relationship between two time series w_{1t} and w_{2t}, which is described

[466] The only discernable exception to this line of reasoning was provided by the Interviewee 10, who suggested to remove all potential outliers emanating from the 2011 Japan earthquake and tsunami. However, the author's inspection of PV sales in 2011 revealed that this outside-in effect figured negligibly, not legitimizing any sort of data interference.
[467] McLeod, Gordon (1983), p. 18.
[468] Van Drongelen, Wim (2010), p. 9.
[469] Wooldridge, Jeffrey M. (2015), p. 758.
[470] Webster, Allen (2013), p. 49.
[471] McLeod, Gordon (1983), p. 14; Warner, Rebbecca M. (1998), p. 148.

in part by the cross-correlation coefficient $r_{12}(k)$ measuring the correlation between w_{1t} and w_{2t+k}. The plot of $r_{12}(k)$ against the lag k for $k=0,1,2\dots$ is called a "cross-correlation function" (CCF).[472] The use of CCF extends to various fields of temporal sequence theory, many of them belonging to pertinent ANN forecasting domains, such as the prediction of business cycle movements[473], the development of leading economic indexes[474], and financial[475] and stock market[476] applications.

The application of the CCF method for the purpose of determining the lead time requires the time series under investigation to exhibit a property called **stationarity**.[477] A stationary time series features a state of statistical equilibrium, i.e. its statistical characteristics do not evolve with time and a certain notion of replicability is recreated.[478] Intuitively, this implies we assume that the mean and variance of time series to be inspected are constant over time and that the overall structure of the series depends only upon the relative position in time for the two observations. It is acknowledged that significant correlations between stationary time series are a reliable indicator of dependence given the fact that they fall into the category of inferential statistics.[479] Hence, the main objective of data pre-processing for the subsequent ANN forecasting model was set to producing statistical equilibrium in each time series. This was effectuated by three consecutive steps:

i) Eliminate the trend by non-seasonal differencing;
ii) Remove the regular component of seasonality by seasonal adjustment;
iii) Stabilize the variance by Z-score normalization.

With respect to **non-seasonal differencing**, the value of each series in the previous month is subtracted from the current month, leading to a situation in which the differencing operator is equated as $\nabla Z_t = Z_t - Z_{t-1}$. The operator ∇ is used to transfer a non-stationary time series Z_t, which is characterized by random jumps in its level, into a stationary series w_t.[480] Particular weight is attached to the auto-correlation test, which serves as an important indication for the actual presence of stationarity. Stated differently, the auto-correlation test for stationarity

472 McLeod, Gordon (1983), p. 14.
473 Backus, David K.; Kehoe, Patrick J.; Kydland, Finn E. (1992), pp. 749 ff.; Comin, Diego; Gertler, Mark (2006), pp. 530 ff.
474 Layton, Allan P. (1991), pp. 212 ff.
475 Gallegati, Marco (2014), pp. 125 ff.; Kumar, Anoop S. (2017), pp. 55 ff.
476 Pan, Heping; Tilakaratne, Chandima; Yearwood, John (2005), pp. 48 ff.
477 Christensen, Ronald (2001), p. 154.
478 McLeod, Gordon (1983), p. 19.
479 Kendall, Maurice G.; Ord, J. Keith (1990), p. 51.
480 McLeod, Gordon (1983), p. 21.

gauges the magnitude to which a value of the series above or below the mean at time *t* tends to be followed by a value of the series above or below the mean *k* time units later. The plot of the auto-correlation coefficient r_k against *k* for $k=1,2\ldots$ is called "auto-correlation function" (ACF).[481] If a series is stationary, there is a rapid decay of r_k to zero[482], whereas if the series is non-stationary, the auto-correlation diminishes gradually over time.[483] In conjunction with ACF, the partial correlation function (PACF) describes the difference between the autocorrelation coefficient s_k at lag *k* and its extrapolated estimates from lower order correlations.[484] By implication, when working at *k* lags, PACF adjusts for confounding auto-correlations in the intermediate lags, leaving only the auto-correlation between the current and k^{th} observation.[485]

Statistical equilibrium in time series data is not necessarily produced by removing the underlying trend through non-seasonal differencing. Time series data may still have to be **seasonally adjusted** to remove components with regular patterns of intra-year variations. To this end, this study refers to a seasonal decomposition procedure, known as "**ratio-to-moving-average method**". This method is an implementation of the "Census Method I" that decomposes a series into three distinct components, namely seasonal, trend/cycle, and error.[486] For the majority of economic applications, a multiplicative model is deployed in which the size of seasonal oscillations increases with the level of the series while the magnitude of seasonality does not vary with the time series level in additive models.[487] With this kind of time series decomposition, the aim was to seasonally adjust already differenced values by expressing them as percentages of moving averages.[488]

Given the heterogeneous scale of measurement for the selected indicators, normalization techniques were applied as instruments of variance-stabilizing transformation. As opposed to non-normalized approaches, normalizing input values can facilitate faster and more accurate convergence of numerical optimization methods such as the gradient descent.[489] Among the two most pervasively used normalization techniques, i.e. min-max and Z-score normalization,

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[481] McLeod, Gordon (1983), p. 11.
[482] Moore, Basil J. (2006), p. 98.
[483] Yaffee, Robert A.; Mc Gee, Monnie (2000), p. 6.
[484] McLeod, Gordon (1983), p. 22.
[485] Yaffee, Robert A. et al. (2000), p. 122.
[486] For further literature on the history and methodology of Census seasonal adjustment methods, refer to Shiskin, Julius; Young, Allan H.; Musgrave, John C. (1965) et al.
[487] Ghysels, Eric; Osborn, Denise R. (2001), p. 94.
[488] Sharma, J.K. (2007), p. 571.
[489] Han, Jiawei; Kamber, Micheline; Pei, Jian (2012), p. 113 ff.

Z-score normalization was utilized because of its attenuation effects on the otherwise presumably overarching "story" of outliers.[490]

In addressing all three issues for the underlying case study of PV sales in China, a systematic scheme of data pre-processing was executed for each relevant time series of input variables.

VI.1.1 Output indicator: Passenger vehicle sales (PV sales)

The time series data for PV sales in China provides an exemplary account of the high statistical requirements that time series have to meet in correlation studies in order to attain the necessary state of statistical equilibrium.

Figure VI-1 shows the upward trend of PV sales time series data, which was retrieved from the expert in Interviewee 8. The sequence of data exhibits regular peaks and troughs in the same distance to each other, indicating the presence of seasonality.

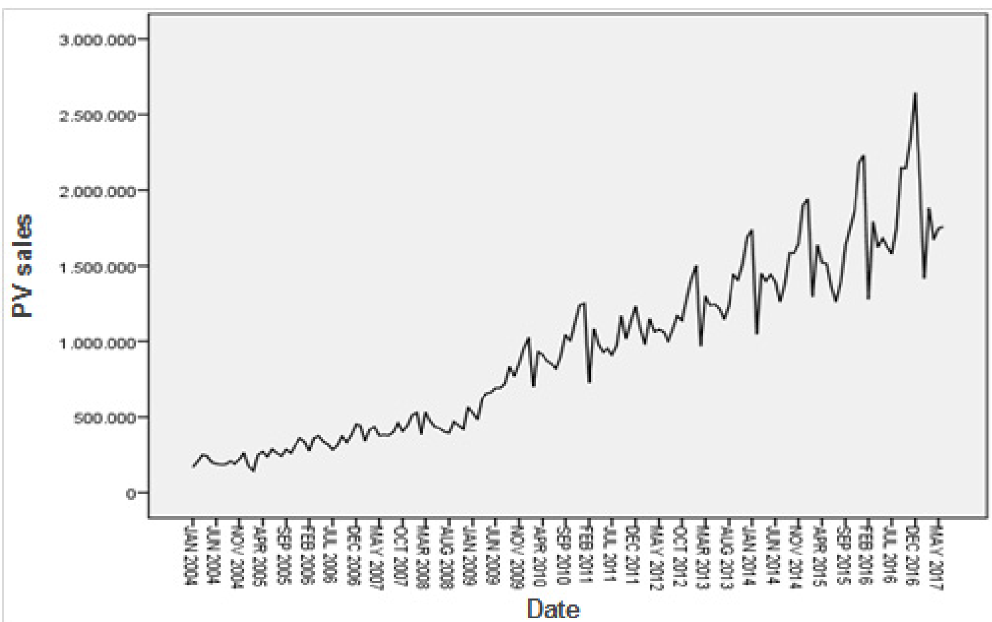

Figure VI-1: Plot of PV sales from January 2004 to June 2017

Once the underlying trend was eliminated through non-seasonal first-order differencing (see Annex 8), ACF was applied to investigate more closely the magnitude of periodicity in PV sales data. The plot of the auto-correlation coefficient in Figure VI-2 and the corresponding

[490] Priddy, Kevin L. et al. (2005), pp. 15 f.

PACF in Annex 9 demonstrate a recurring cycle with a fixed period at lag 12, which can be explained by one particular seasonal factor that is specific to China, namely the dating of the Chinese New Year.

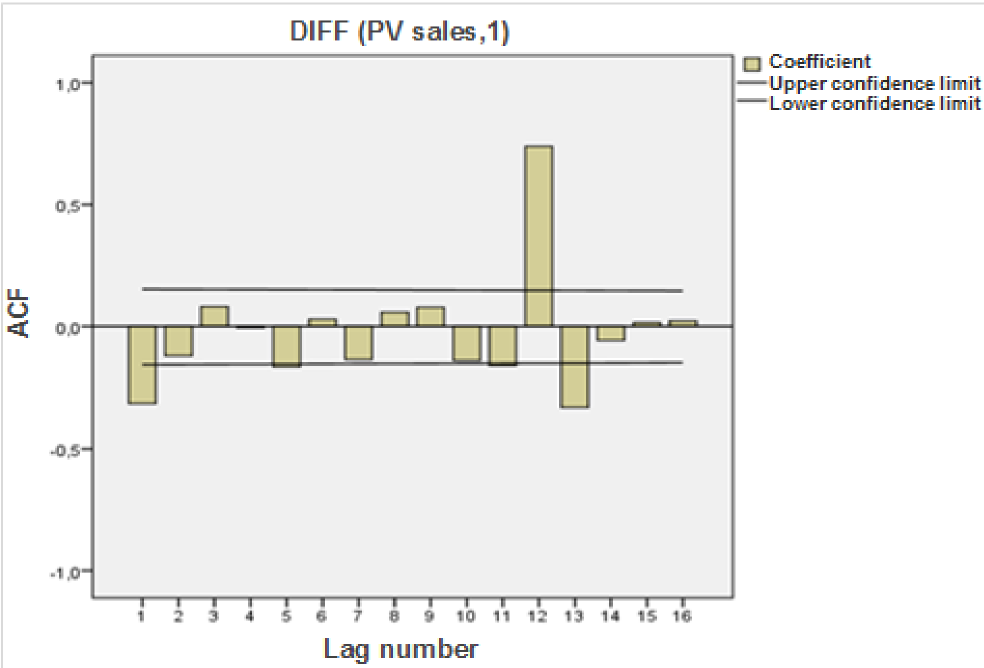

Figure VI-2: ACF of first-order differenced PV sales

In line with the experts' statements in Interviews 8 and 10, Chinese New Year unfolds a great impact on PV sales. Prior to the beginning of the holiday, retail sales figures are likely to strengthen, often reaching an annual peak while the growth momentum usually subsides during and immediately after the holiday.[491] The timing of Chinese New Year occurs sometimes in January and sometimes in February, which means that it has a differential quantitative impact, depending on the number of days of the holiday that fall in each month.[492]

To eliminate the ensuing periodic component from the data, experiments were conducted with additive and multiplicative model types as well as different moving-average weights. It turned out that the multiplicative model type with the endpoints of each moving-average span weighted by 0.5 successfully eliminated the series' auto-correlations.

[491] Mak, Wendy (2009), p. 47.
[492] Roberts, Ivan (2015), p. 8.

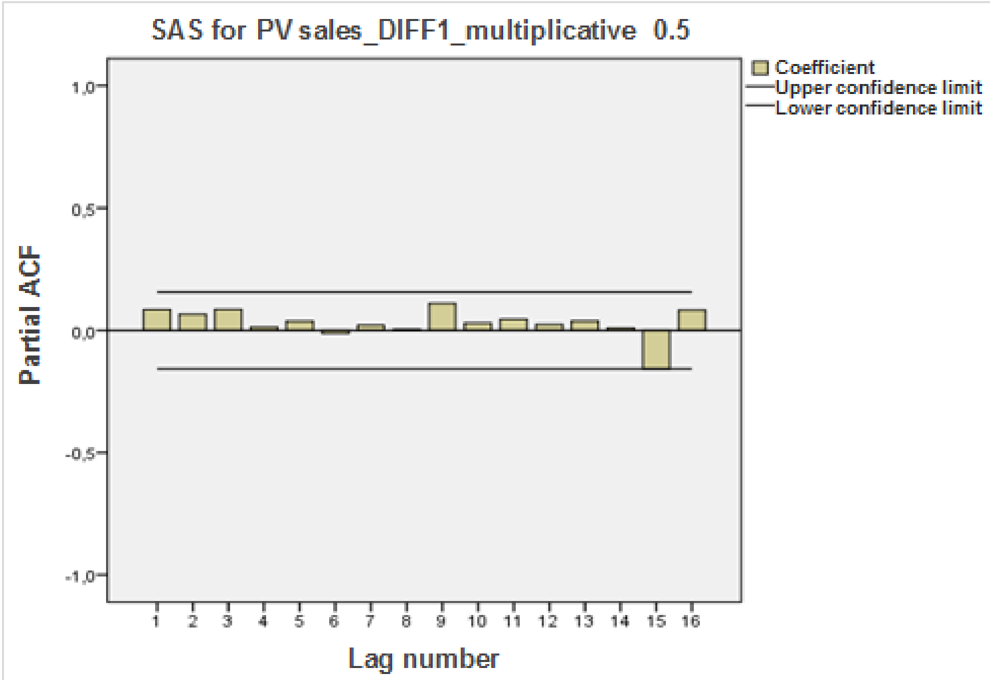

Figure VI-3: PACF of seasonally-adjusted PV sales

In addition to the visual inspection at each individually lagged auto-correlation, the Box-Ljung statistic in Annex 10 verifies whether the residuals in a time series resemble white noise. The null hypothesis of this test assumes linear independence, which, in the case of PV sales, is *not* rejected. This is due to $p > 0.05$ for all observations. It follows that there is a 95% probability that all residuals in PV sales time series are independently distributed[493] and thus ready for the ensuing cross-correlation analyses with the leading indicators of PV sales.

VI.1.2 Leading indicator: China Interbank Offered Rate (CHIBOR)

For reasons of comparability, time series data for all economic indicators was pre-processed in an equivalent manner to PV sales. The data basis for each of the indicators was retrieved from an online platform called "Trading Economics"[494].

The cyclical nature of CHIBOR time series, for which a monthly average was calculated from daily trading values, is reflected by ups and downs of data points which, on the whole, denote

[493] Warner, Rebbecca M. (1998), p. 38.
[494] Founded in 2008, Trading Economics is an often-quoted source in economic literature. It has specialized in the provision of economic indicators based on official sources for 196 countries. Examples of citation include Barkley Rosser John Jr.; Rosser, Marina V. (2018), p. 406 f.; Wright, S. (2013), p. 80.

a non-linear trend. In contrast to PV sales, no regular peaks or valleys are recognizable, which does not however preclude the presence of seasonal components.

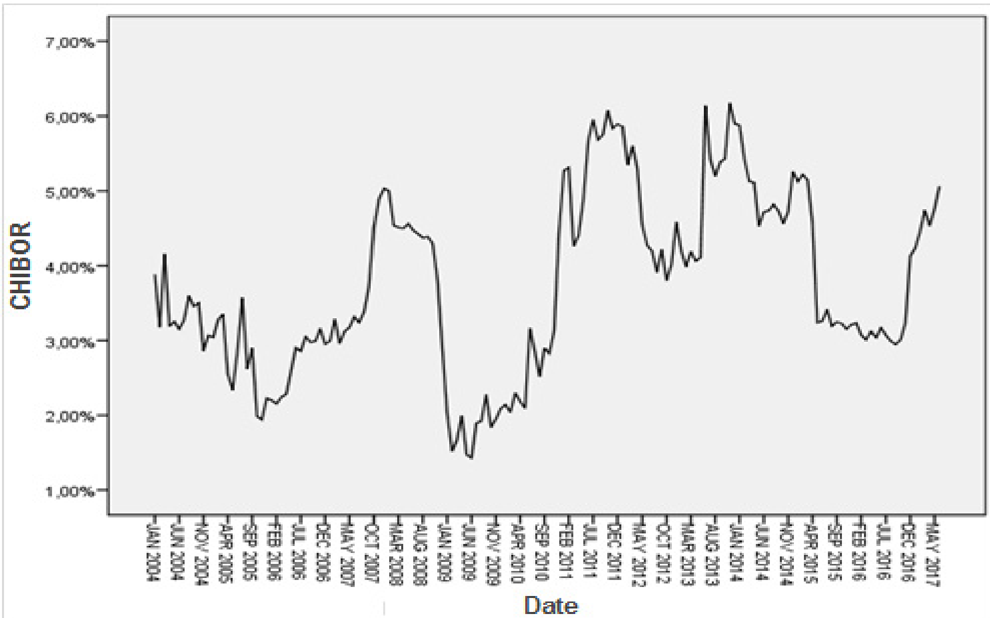

Figure VI-4: Plot of CHIBOR from January 2004 to June 2017

Once the underlying trend was eliminated through non-seasonal first-order differencing (see Annex 11), ACF was applied to examine whether a regular cycle with a fixed period can be detected. The plot of the auto-correlation coefficient in Figure VI-5 and the corresponding PACF in Annex 12 may not necessarily point at periodicities in CHIBOR time series data. Still, the coefficients at lag 6 and 8 are tangent to their respective confidence limit, prompting further efforts to carry out seasonal decomposition.

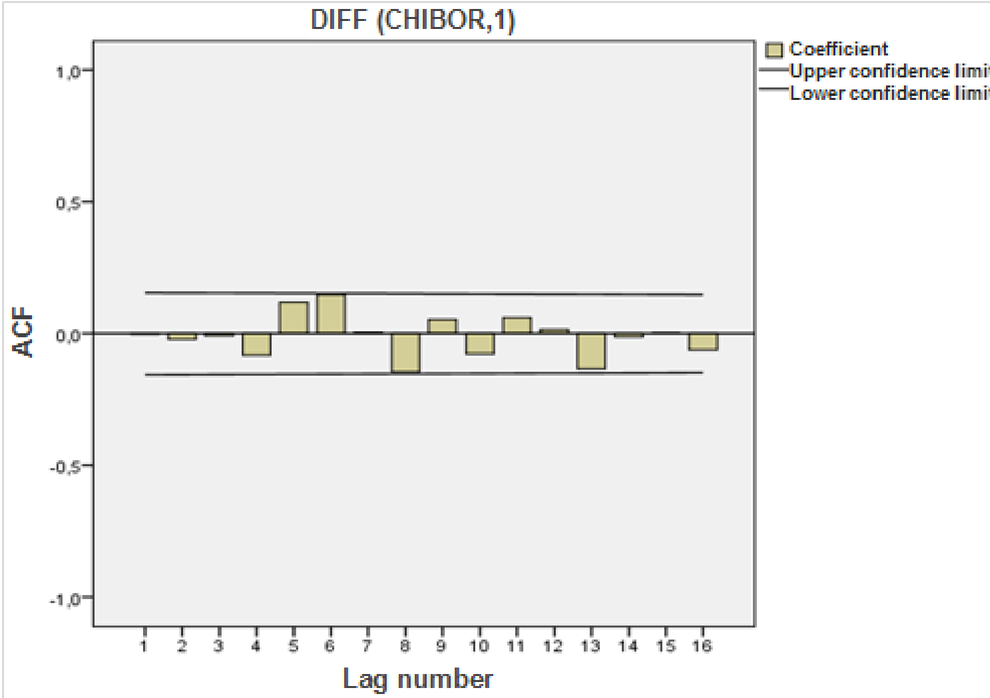

Figure VI-5: ACF of first-order differenced CHIBOR

Although a sizeable adjustment effect was not to be reasonably expected, a multiplicative model type with the endpoints of each moving-average span weighted by 0.5 considerably increased the probability that all residuals in the time series are independently distributed, as depicted in Figure VI-6 and Annex 13.

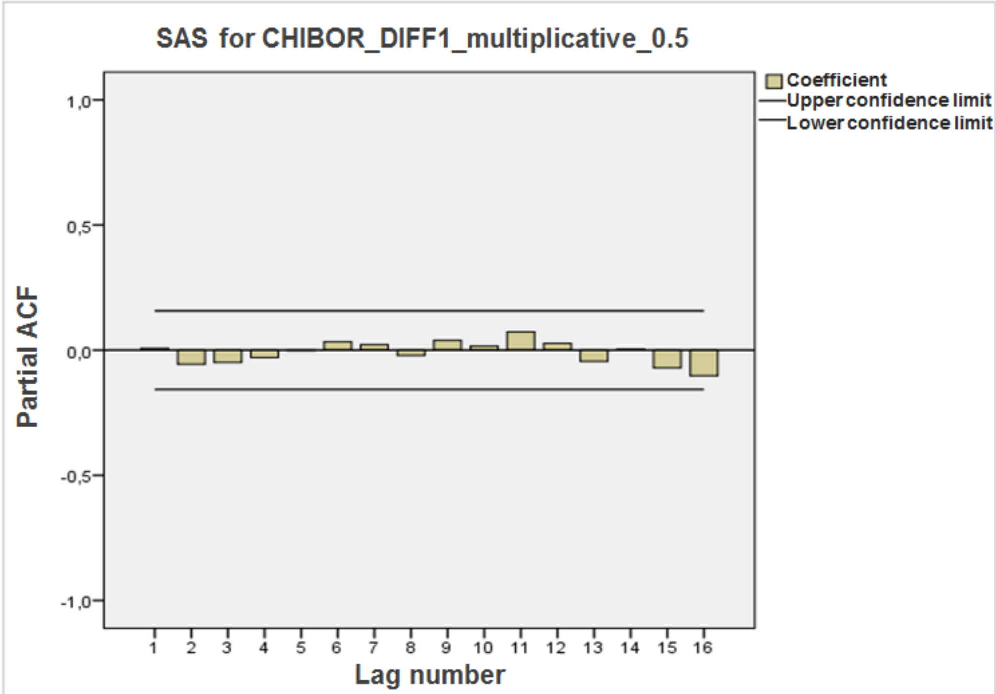

Figure VI-6: PACF of seasonally-adjusted CHIBOR

After both trend- and seasonally-adjusted time series under investigation were normalized by Z-score normalization, the framework was set to ascertain the respective lead-lag relationship between them. As can be seen in Figure VI-7, the cross-correlation coefficient exceeds the upper bound tolerance at lag 12 with r= 0.224, implying that CHIBOR leads PV sales by twelve months.

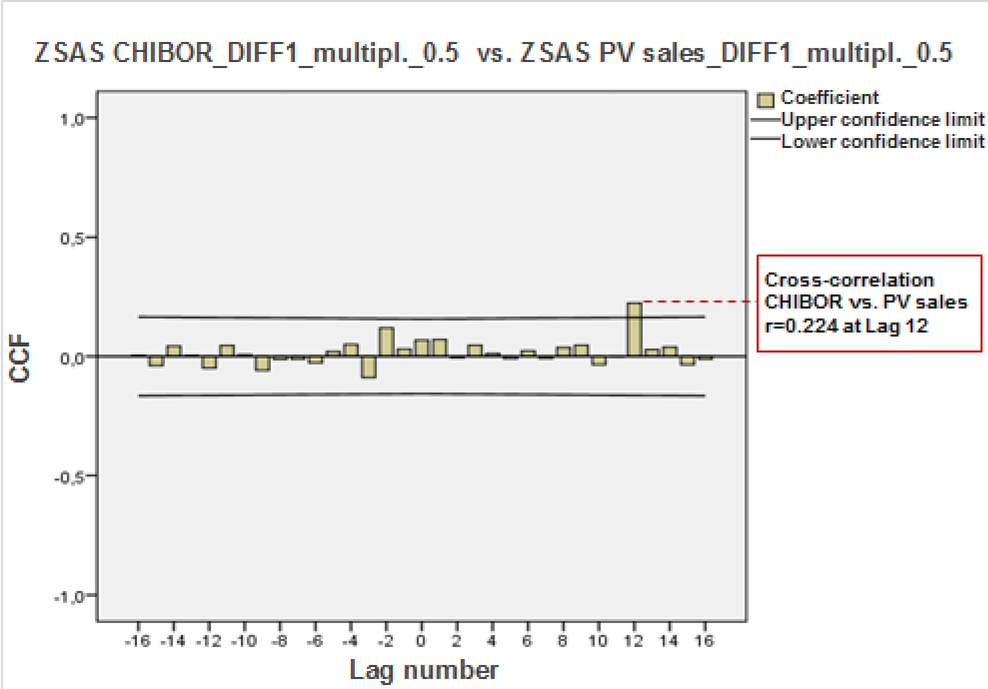

Figure VI-7: CCF of entirely processed CHIBOR vs. PV sales

VI.1.3 Leading indicator: Money supply (M2)

As discussed earlier, one of the key findings that emerged from the expert interviews was that M2 demonstrated an impressively strong relationship with PV sales.

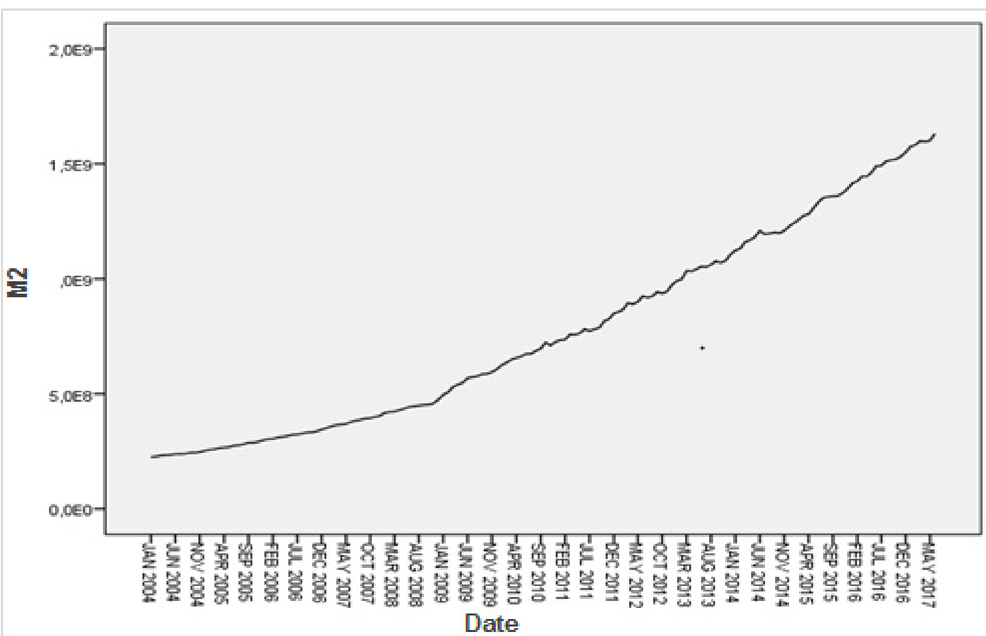

Figure VI-8: Plot of M2 from January 2004 to June 2017

To explore deeper nuances in the relationship between PV sales and M2, the change in the level of M2 resulting from the underlying trend was stabilized by first-order differencing. We can see that the purpose of trend removal may have succeeded, yet at the same time, a series of regular peaks and troughs becomes visible.

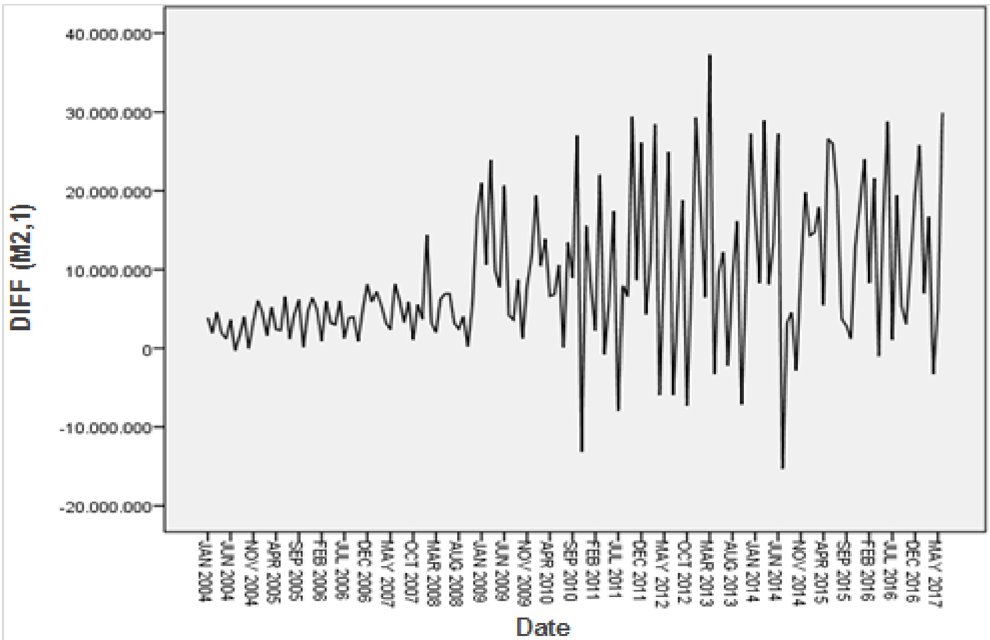

Figure VI-9: Non-seasonal first-order differencing of M2

This finding made per visual inspection is affirmed by the ACF for first-order differenced M2 data and corresponding PACF (see Annex 14), which display a discernible periodicity in quarterly intervals.

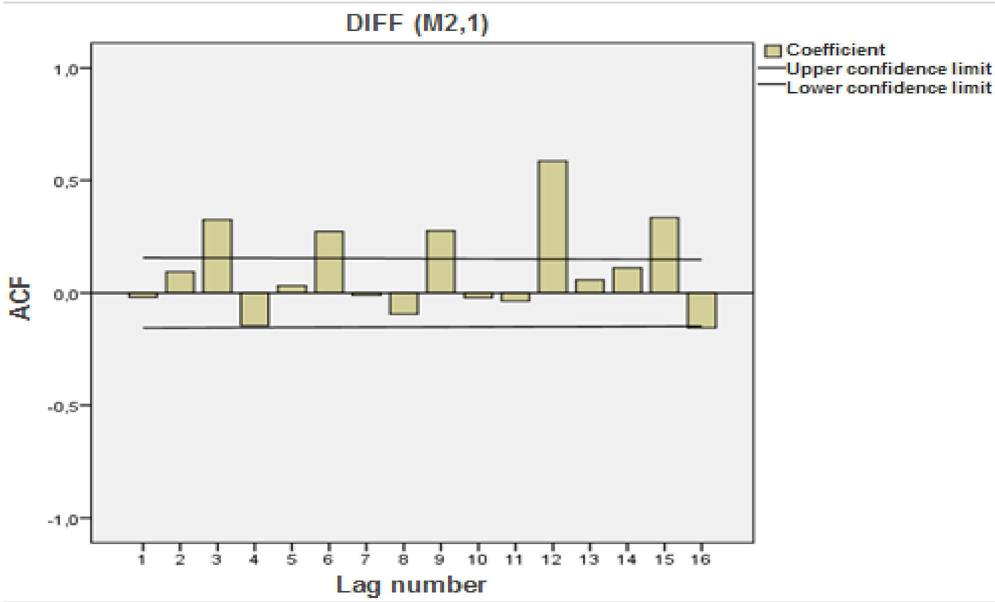

Figure VI-10: ACF of first-order differenced M2

As documented in Figure VI-11 and Annex 15, a multiplicative model type of seasonal adjustment with the endpoints of each moving-average span weighted by 0.5 ruled out any sort of significant auto-correlation, contributing to a high probability of residual independence.

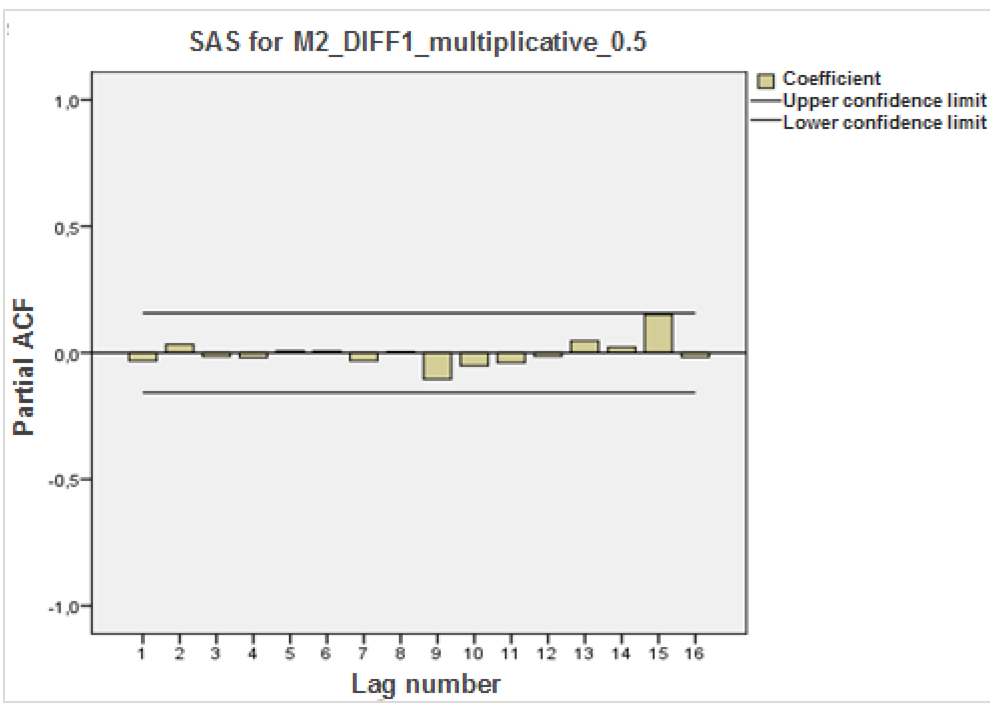

Figure VI-11: PACF of seasonally-adjusted M2

However, Figure VI-12 shows that the cross-correlational computation between Z-Score normalized M2 and PV sales does not display a significant lead-lag relationship between both time series.

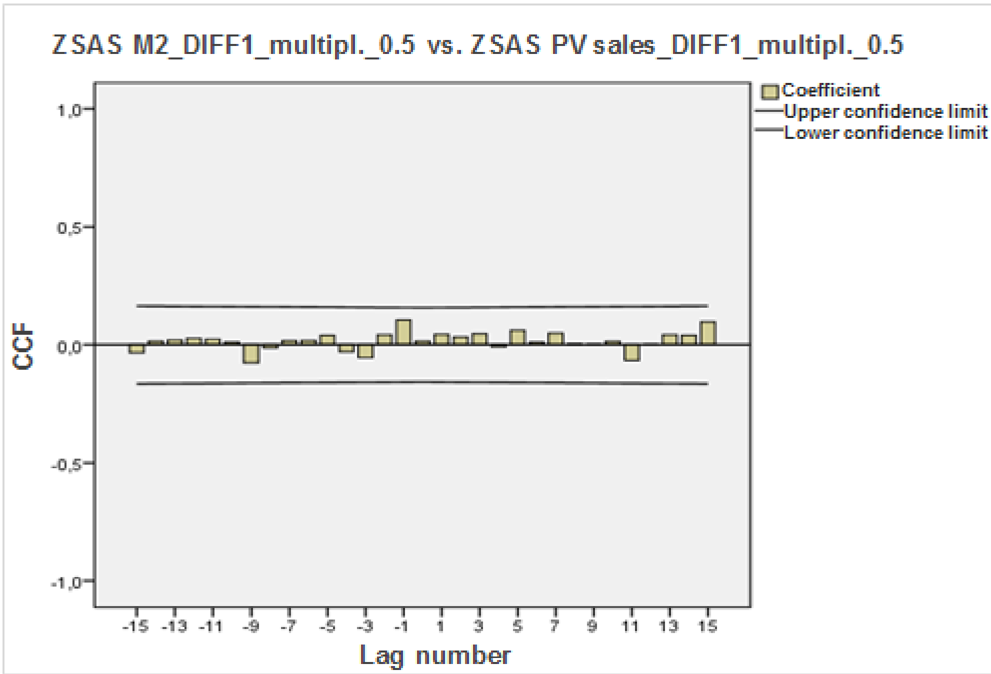

Figure VI-12: CCF of entirely processed M2 vs. PV sales

At first glance, this conclusion seems to be counter-intuitive given that the statements of four well-established experts in Interviews 3, 8, 9, and 10, would then be proven wrong. Pertaining to this finding, the author followed up the interview with the expert from Interview 9 to gain an understanding of the reason for this circumstance. It turned out that at least Volkswagen's market analysts have been more likely to prefer year-over-year (YoY) data for M2, most especially for the sake of alleviating prevailing seasonality variations.

The author reviewed pertinent literature that has discussed a similar matter of forecasting with mixed-frequency data in economic applications. It was found that a dilemma that forecasters often encounter is, that in the wake of computer technology innovations, many leading financial indicators are sampled at a very high frequency, whereas most macroeconomic indicators are collected on a monthly or quarterly basis. To solve this issue, many analysts simply time-aggregate higher-frequency data in order to match with the sampling rate of lower-frequency data, thereby restoring a common denominator of observation.[495] With that in mind, one solution for the present case study of PV sales in China would have been creating a common denominator by unifying the observation periods to a YoY basis across *all* indicators. This, however, would have been in stark contrast to the overall intention to develop a superior model for monthly forecasting purposes. The YoY time series, per se, captures a more remote time span than does a month-over-month (MoM) time series (the latter of which expresses changes in level with respect to the preceding month). It follows that the use of YoY data may have eventually been accompanied by a certain loss of information due to *over*-year rather than *intra*-year changes in the market.[496] Therefore, with the intention of capturing the frequent zig zags of development in the Chinese automotive market, MoM data was used for all indicators except of M2. For M2, being fully aware of its repeatedly underlined importance, the author resumed data pre-processing with YoY observation samples.

In the further course of data pre-processing, it should be noted that all pre-processing steps for M2 YoY data were precisely the same as for M2 MoM data (see Annex 16-20). It is also important to emphasize that M2 YoY data actually displays significantly less seasonal variation over M2 MoM data, as documented in Figure VI-13.

[495] For further literature on forecasting issues with mixed-frequency data, refer to Andreou, Elena; Ghysels Eric; Kourtellos, Andros (2011); Armesto, Michelle T. (2010).
[496] Sun, Rongrong (2015), p. 284; Carnot, Nicolas; Koen, Vincent; Tissot, Bruno (2011), p. 40.

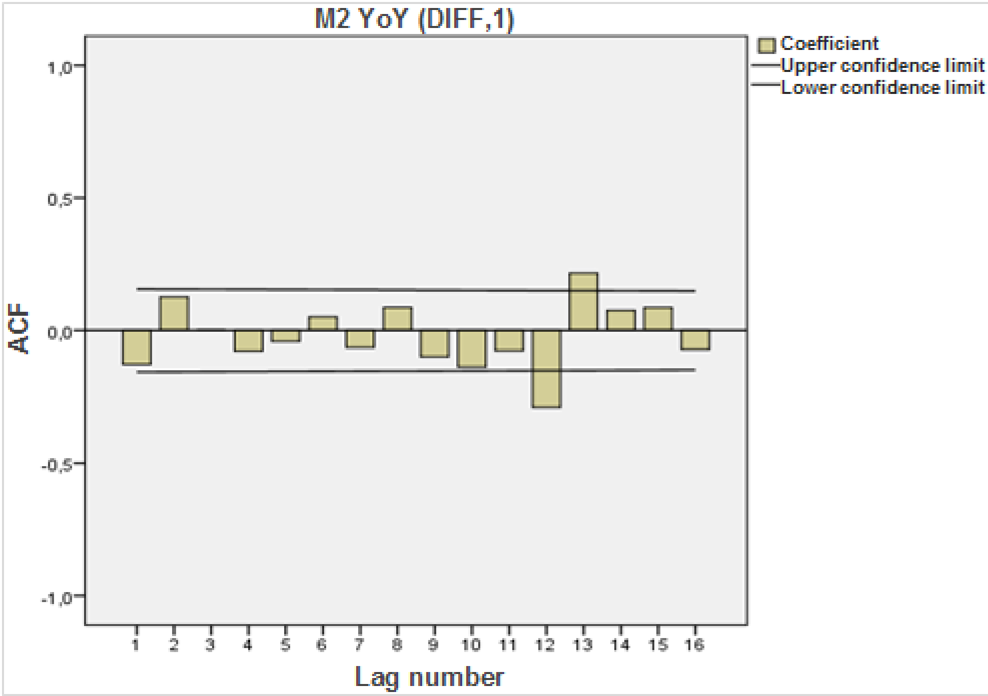

Figure VI-13: ACF of first-order differenced M2 YoY

As a final step in determining the lead-lag relationship between entirely pre-processed PV sales and M2 YoY data, Figure VI-14 exposes two significant correlations at lag 1 (r= 0.184) and, to a slightly lower extent, at lag 6 (r= -0.179).

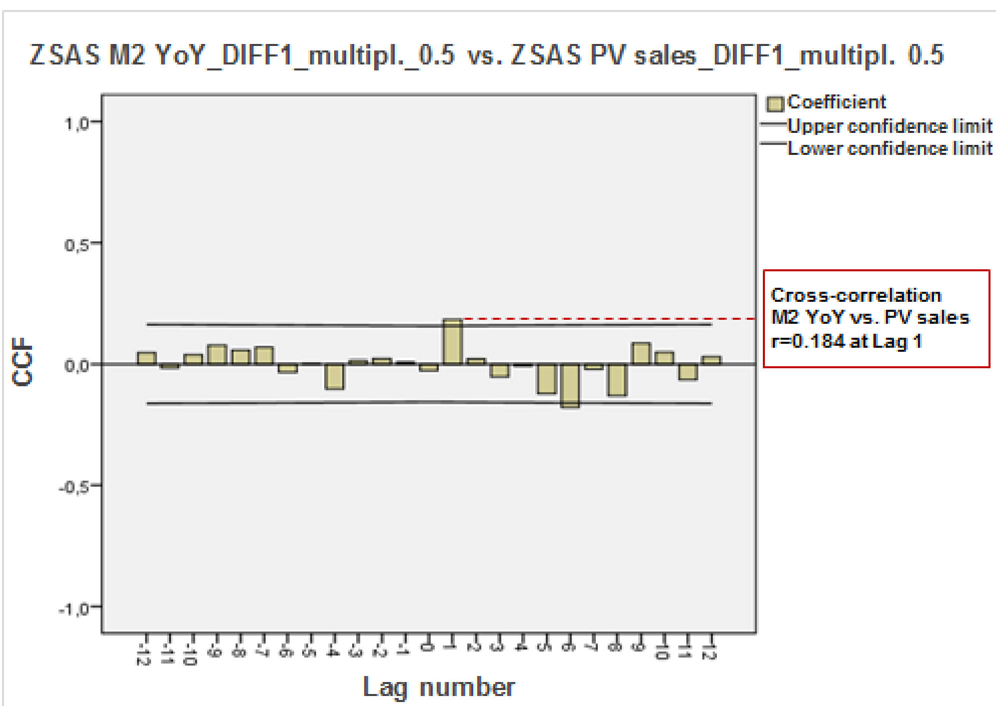

Figure VI-14: CCF of entirely processed M2 YoY vs. PV sales

In light of the previous remarks on mixed input periodicities, the role of M2 YoY time series data ought not to be overestimated in a model that was to be designed for monthly forecasting applications. That said, the author only proceeded with the higher correlated finding at lag 1, assuming that M2 leads PV sales by just one month.

VI.1.4 Plausibility check of lead time for CHIBOR and M2 YoY

To validate and justify previous results pertaining to the lead-lag relationship between CHIBOR and PV sales, as well as that between M2 YoY and PV sales, a potential relationship between CHIBOR and M2 YoY was also explored.

The expert in Interview 10 indicated that interest rates have been acting as a monetary policy instrument to stimulate the Chinese economy with loan-financed investment, suggesting a direct relationship between both determinants. Indeed, from a quantitative viewpoint, Figure VI-15 delivers tangible evidence of such a relationship in market reality, as the correlation coefficient exceeds the upper and lower confidence level at lag -1 (r= -0.221) and lag 11 (r= 0.269) respectively.

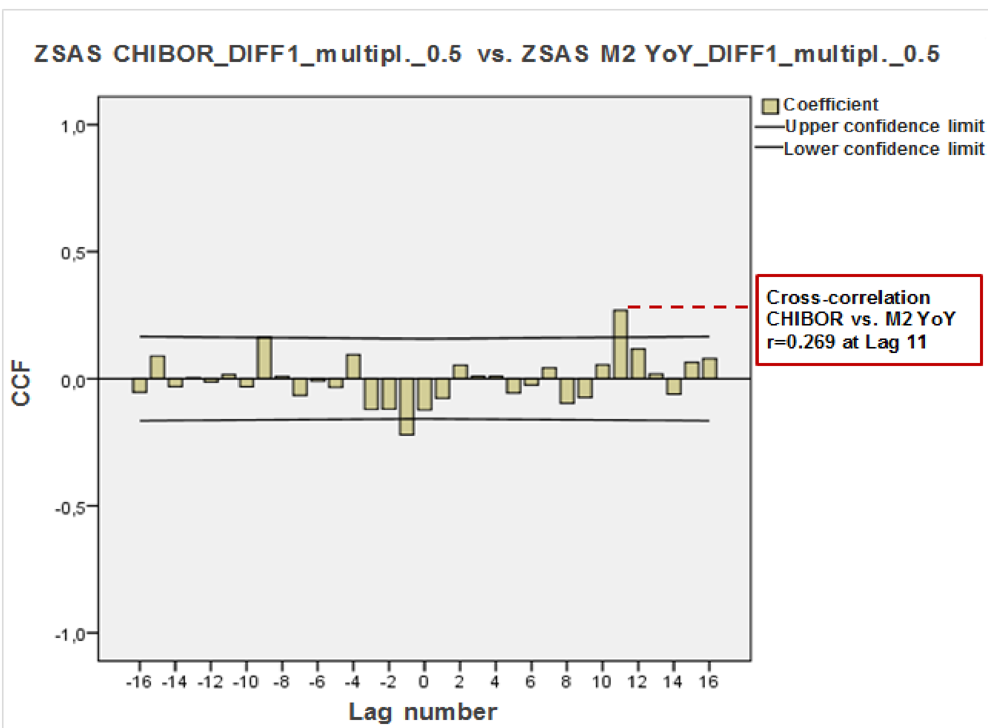

Figure VI-15: CCF of entirely processed CHIBOR vs. M2 YoY

The latter finding at lag 11 seems particularly striking, because it buttresses pre-established hypotheses on the interdependency of all indicators that have been investigated up to this point. More specifically, in examining the bivariate correlations between PV sales, CHIBOR, and M2 YoY, a sequence of cumulative order could be inferred. In this triangular relationship, a change in CHIBOR at lag 12 may set the first domino in motion, followed by a chain reaction resulting in a change of M2 11 lags later, and ultimately effecting PV sales at lag 0.[497]

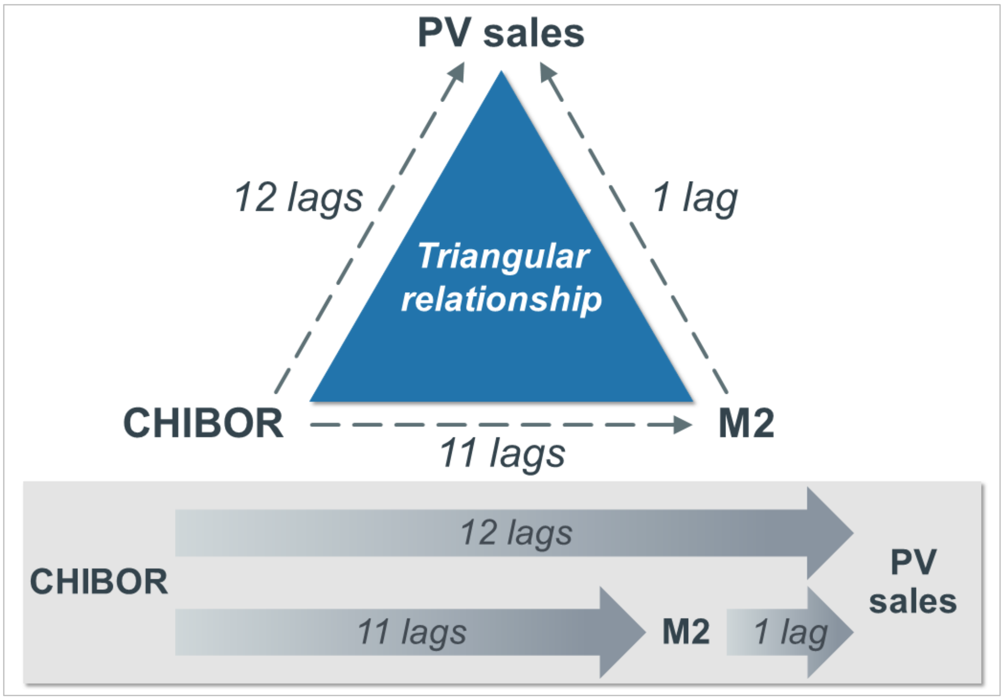

Figure VI-16: Comparison of cross-correlations for PV sales – CHIBOR – M2 YoY

VI.1.5 Leading indicator: Consumer confidence (ConConf)

As determined in the expert interviews, the use of consumer confidence constitutes an important yardstick in gauging potential customers' purchase willingness. The plot of its development from 2004 to 2017 shows a trend with an irregular course of direction, see Figure VI-17.

[497] Also worth mentioning is that the author saw no grounds for carrying out a multi-collinearity analysis. That is because ANNs, as outlined in section III.3.1, demonstrate a greater flexibility in combining the effects of predictor variables than do regression models.

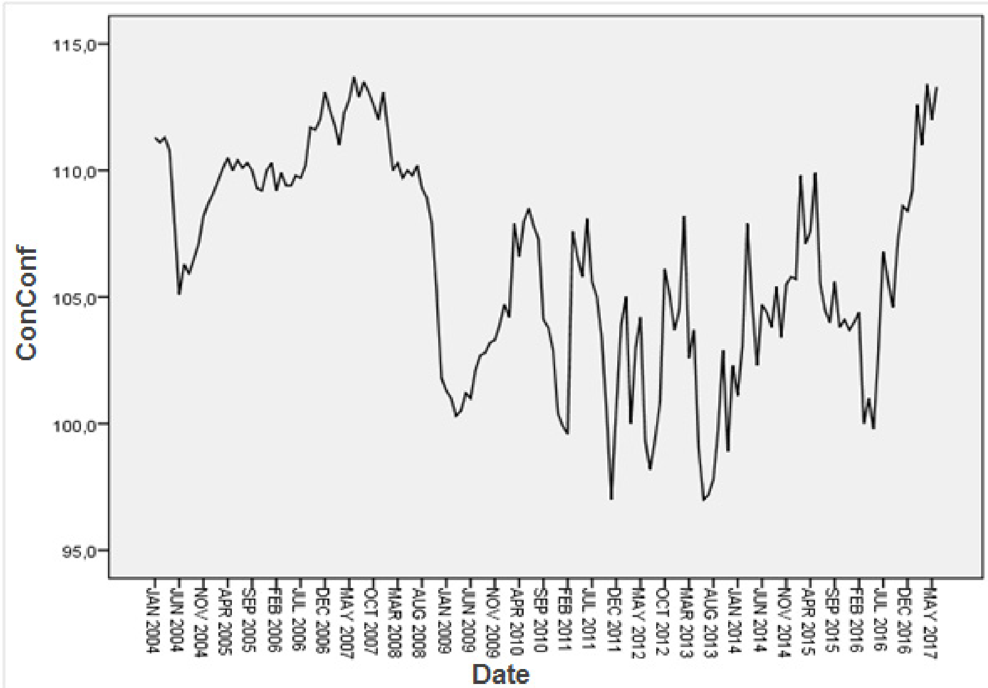

Figure VI-17: Plot of ConConf from January 2004 to June 2017

To investigate conceivable seasonal components in the time series data, the underlying trend had to be removed through first-order differencing (Figure VI-18).

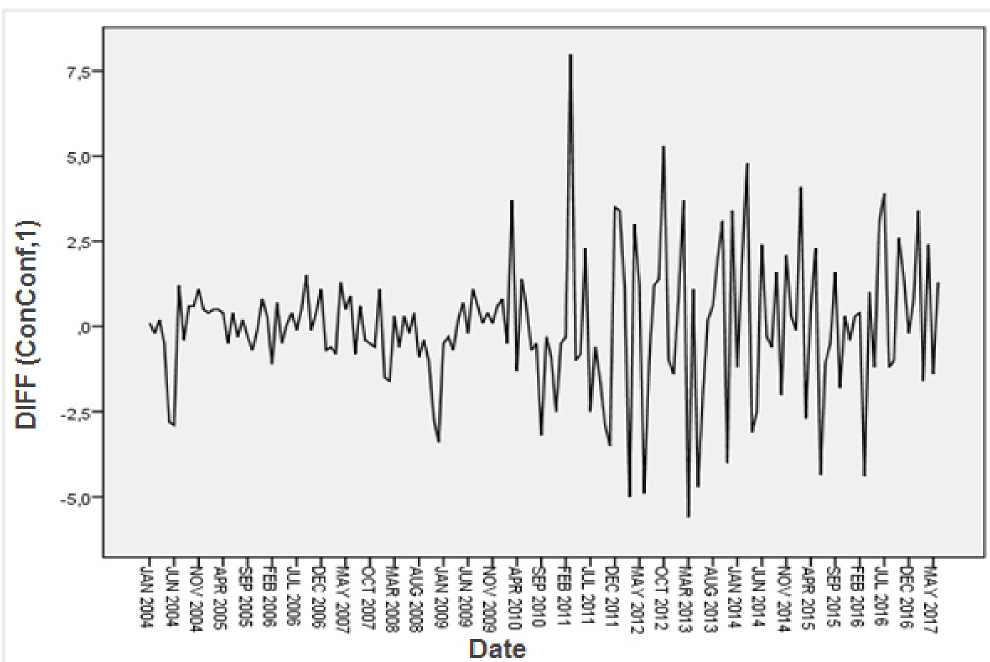

Figure VI-18: Non-seasonal first-order differencing of ConConf

Given that the series now varies around a constant mean, regular peaks and valleys are recognizable, synonymous to a possible presence of seasonal variation. Figure VI-19 and Annex 21 concur with the findings of the initial visual inspection by displaying significant autocorrelations within and beyond the intra-year observation horizon.

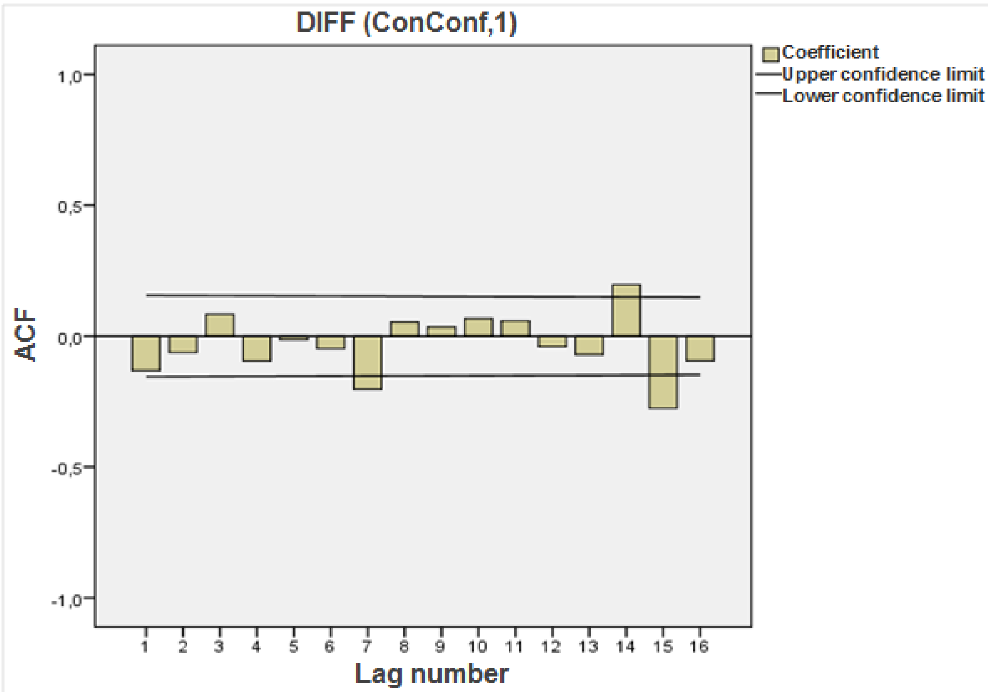

Figure VI-19: ACF of first-order differenced ConConf

As a next step, all potential seasonal patterns from the data records were eliminated by computing moving averages with all points weighted equally (Figure VI-20), leading to a high probability of independent residual distribution (see Annex 22).

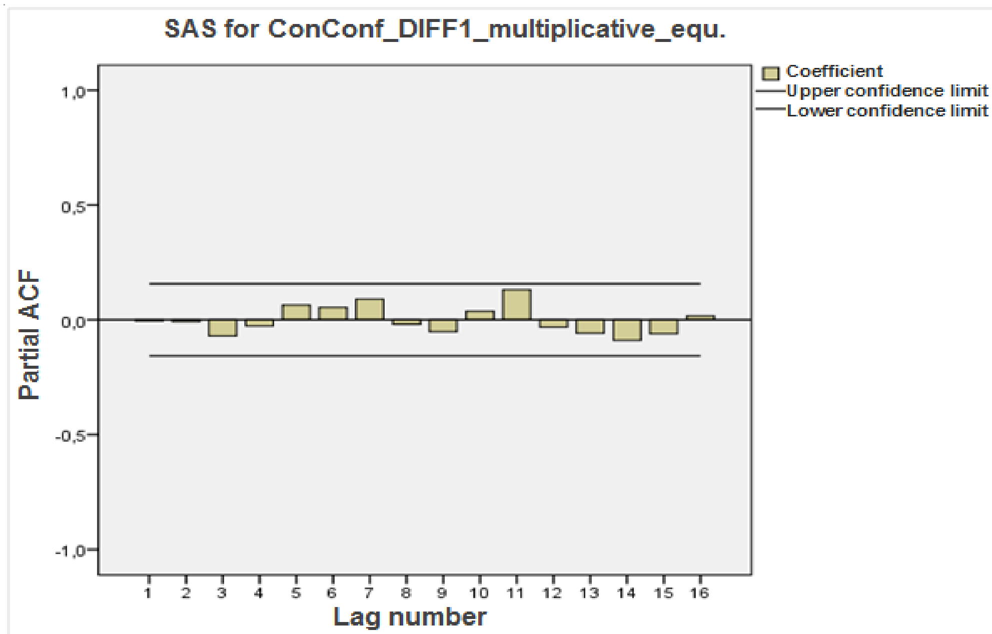

Figure VI-20: PACF of seasonally-adjusted ConConf

For the most part, the final results of the cross-correlational analysis demonstrate no relationship whatsoever, except for lag 8, which shows a weak, but (due to a relatively large sample size) statistically significant negative correlation with r = -0.178. It is therefore assumed that consumer confidence leads PV sales by eight months.

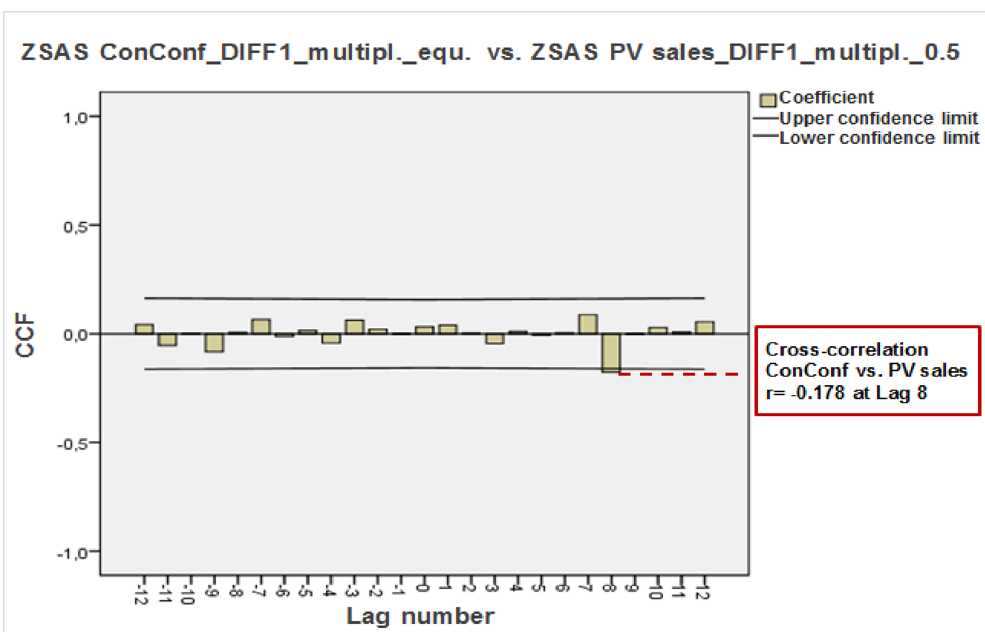

Figure VI-21: CCF of entirely processed ConConf vs. PV sales

VI.1.6 Leading indicator: Shanghai Stock Exchange Composite Index (SHCOMP)

Lastly, in expectation of a highly volatile dataset, a statistical equilibrium for stock market-related time series data was produced. As outlined before, SHCOMP data was opted instead of CSI 300, because the latter index was only launched in May 2005. To avoid analyzing a snapshot of stock market realities by merely referring to the month's closing value, the average market value at the end of each month was computed.

The plot of SHCOMP time series data from 2004 to 2017 exhibits a very dynamic developmental course with two particularly striking amplitudes in September of 2007 and May of 2015 respectively.

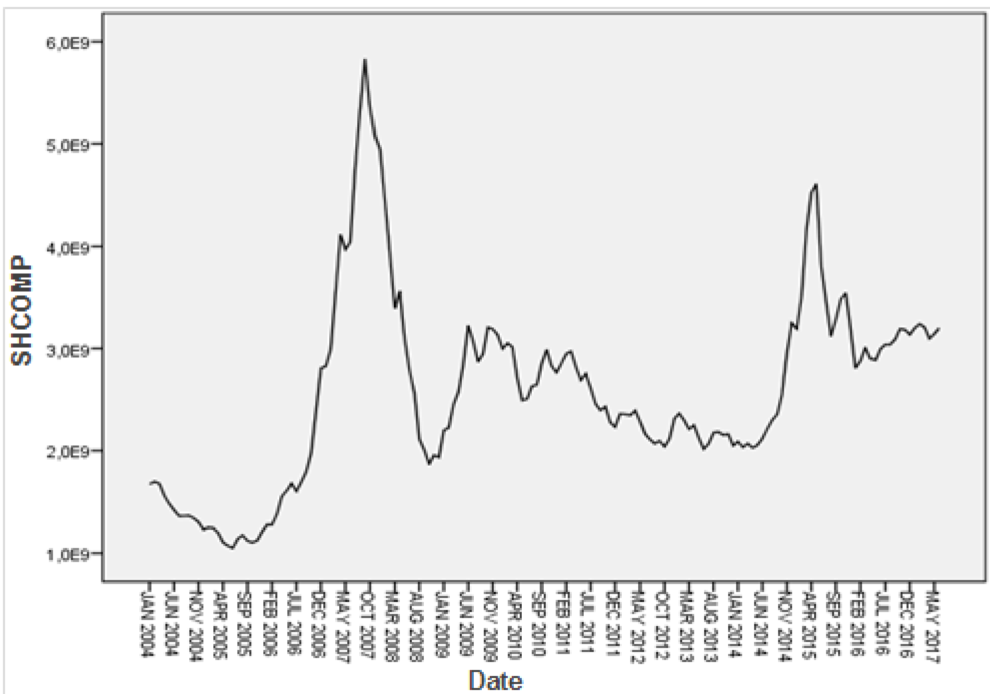

Figure VI-22: Plot of SHCOMP from January 2004 to June 2017

The two peaks seen here can be traced back to two stock market bubbles that eventually burst for different reasons. In the initial nine months of 2007, excess liquidity caused by "hot money" portfolio inflow and a foreign trade plus were the key driving forces in an unprecedented boom of Chinese stock markets.[498] This was in addition to high profit growth rates of listed enterprises and the residents' demand for hedging assets, which was due in part to low interest rates. At that time, China's export-oriented growth model was highly correlated with interna-

[498] Liang, Priscilla; Ouyang, Alice; Willet, Thomas D. (2009), p. 296.

tional economic cycles, rendering the country susceptible to changes in the global economy. Those changes occurred with the breakout of the global financial crisis in August 2007, causing the Chinese stock market to see an equally unprecedented plunge.[499]

The most recent collapse in 2015 has been ascribed to financial sector reforms, which enterprises and private investors obviously misjudged as another government-administered financial "medication"[500]. In taking this stance, massive amounts of heavily leveraged stock market investments followed, casting mounting concerns on the extent of external financing in the market. As a consequence, regulators investigated and adjusted the magnitude of external funding[501], triggering the most precipitous decline in stock market value since 2007.

With respect to the matter of time series data pre-processing, the ACF (Figure VI-23) and PACF (Annex 24) of SHCOMP data showed significant correlations at several lags, especially at lag 1 once the trend had been removed (see Annex 23).

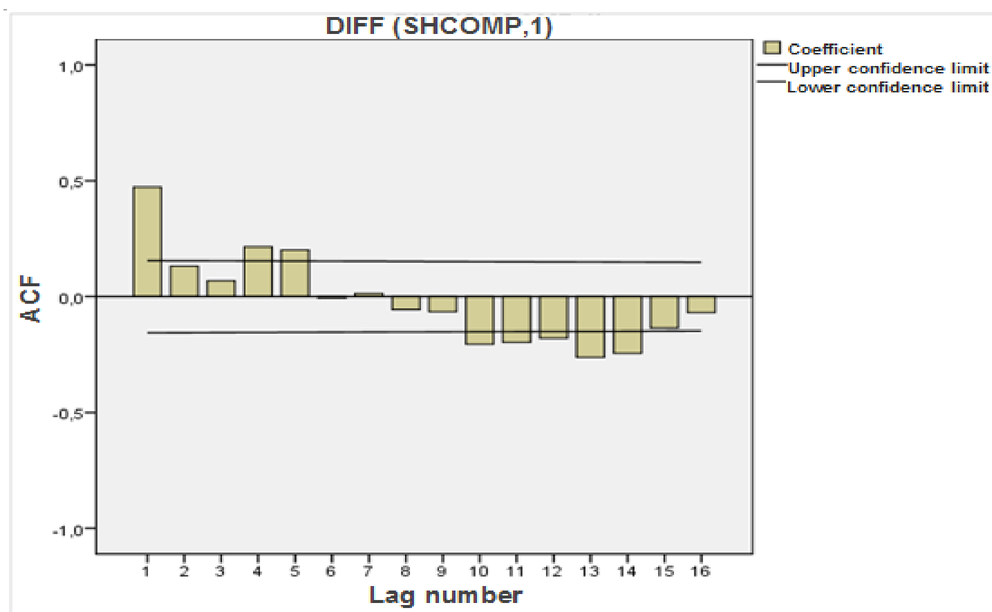

Figure VI-23: ACF of first-order differenced SHCOMP

499 Li, Ziran (2015), p. 97; Liang, Priscilla; Ouyang, Alice; Willet, Thomas D. (2009), p. 296.
500 Fischer, Doris (2015), p. 18.
501 Interview with Yan Hong (Shanghai Advanced Institute of Finance) conducted by Beifuss, Annika (2015), p. 24.

The seasonal decomposition of time series data, in which all points were weighted equally (Figure VI-24), and the corresponding Box-Ljung statistic (Annex 25) left certain doubts at lag 3 as to whether all residuals are independently distributed.

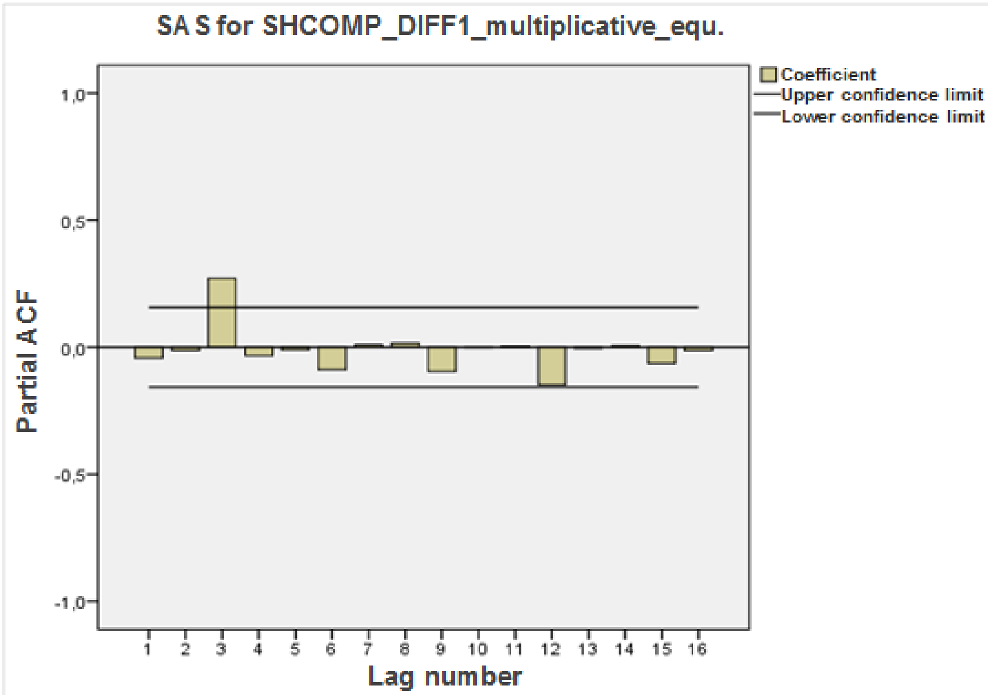

Figure VI-24: PACF of seasonally-adjusted SHCOMP

Given this pattern of residual serial correlation, the Augmented Dickey-Fuller (ADF) test is a suitable instrument for detecting potential seasonality-related non-stationarities. The presumption of this unit root test is that the errors are independent of one another, i.e. they are distributed as white noise and are homogenous. The null hypothesis states that a unit root is present, implying non-stationarity of the time series.[502] As for SHCOMP, as well as in terms of all other time series under investigation, the null hypothesis is however rejected with p= < 0.05 (see Annex 26), indicating a state of statistical equilibrium.

However, the plot of SHCOMP and PV sales (with stationary time series data) shows no significant cross-correlations, as displayed in Figure VI-25.

502 Yaffee, Robert A. et al. (2000), pp. 85 f.

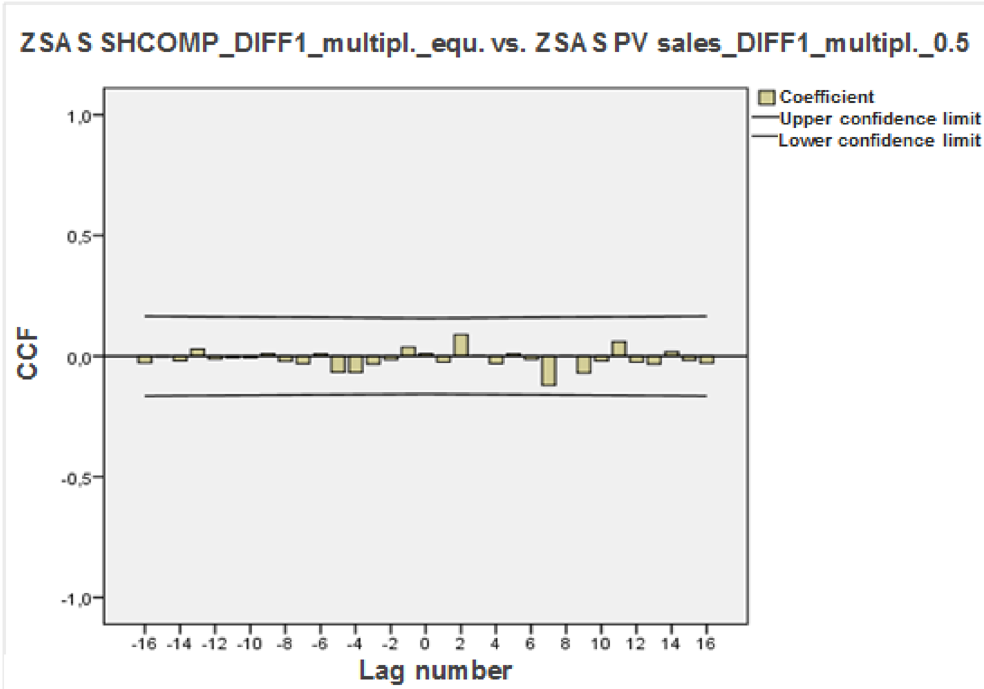

Figure VI-25: CCF of pre-processed SHCOMP vs. PV sales

In light of the experts' statements in Interviews 2, 5, 9, and 10, all of them connoting a relationship between both metrics only in times of sudden and dramatic economic downturns, this finding was not unexpected. Indeed, it would have been surprising if a significant correlation had been observed over the entire time span. Nonetheless, in view of the fact that four interviewees considered stock market performance to be an indispensable ingredient of a comprehensive short-term PV sales forecasting model in China, the author decided to depart from this template of univariate data pre-processing by introducing a new perspective on SHCOMP data. In a quest to capture the most meaningful characteristics, he extracted two distinct but chronologically cumulative sections from the SHCOMP time series of data, one reflecting the gestation of a stock market crash and the other one focusing on the recovery from the same. More specifically, substantiated by the background explanations concerning both stock market bubbles in 2007 and 2015 stated above, the following two sections were selected to be representative for stock market performance in times of "sudden and dramatic economic downturns":

i) February – November 2007, i.e. the deflation of the first stock market bubble;

ii) June 2015 – February 2016, i.e. the aftermath of the second stock market bubble, including the financial "medication" administered by the government to restore economic health.

Both time series sections served as a foundation for estimating the degree as to which the SHCOMP extract is correlated with PV sales. A salient finding with r= 0.598 could be determined at lag 1, which was then to be assumed over the entire SHCOMP time series span.

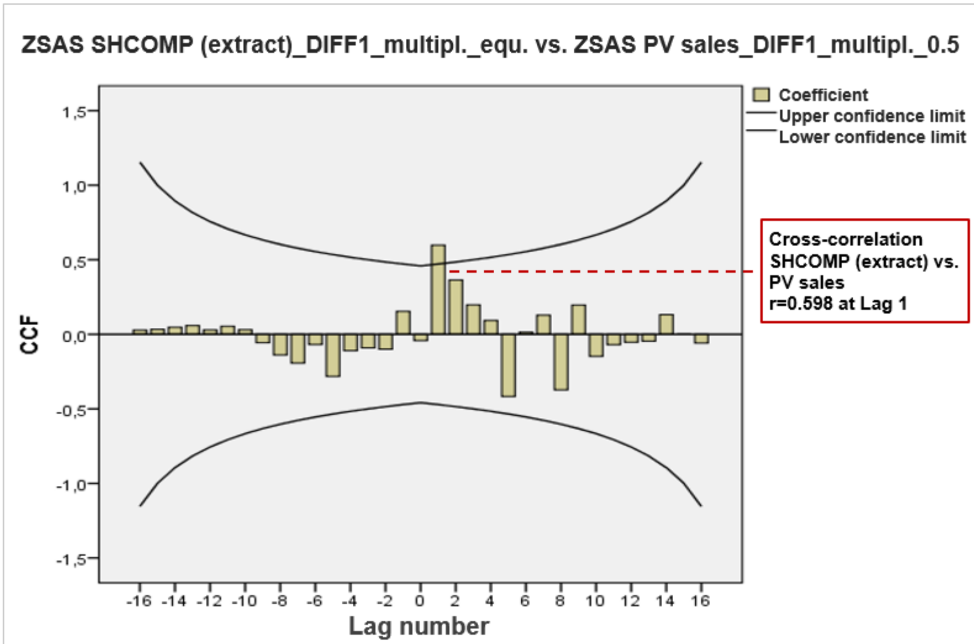

Figure VI-26: CCF of entirely processed SHCOMP (extract) vs. PV sales

VI.1.7 Coinciding indicators: Chinese New Year and car purchase tax

At this stage of ANN forecasting model development, the lead-lag relationship between all leading indicators and PV sales yielded a fairly complete picture. In addition to the four leading indicators, the interviews had revealed two further coinciding "special events", which also proved to wield a considerable influence on short-term automotive forecasting in China, i.e. Chinese New Year and car purchase tax trend.

As exemplified in the pre-processing stage of PV sales, the magnitude of the *Chinese New Year effect* is reflected in numerous economic indicators. Previous studies have indeed demonstrated that the signals of key Chinese economic metrics, such as retail sales, M2, and credit supply, are often seriously distorted by the presence of the week-long public holiday.[503] Another difficulty is that the seasonal impact of the Chinese New Year varies from year to year, because it sometimes takes place in January and sometimes in February according to the

[503] Roberts, Ivan (2015), pp. 2, 19 f.

Western calendar.[504] To account for this differential quantitative impact, two options to purge the data of the Chinese New Year effects were contemplated. First, as proposed (and executed) by the expert of Interview 10, the idea was to average the values of January and February, much as is common practice, for instance, in fixed asset investment releases by the NBS.[505] This way, on the assumption that no spillover effects into March are triggered by holidays extending into mid-February, the distortions around the Chinese New Year may indeed be dampened to a certain extent. However, this option occurs not only at the cost of lessening some valuable dynamic variation from the time series[506], but also with a certain loss of timely information because a read of the momentum in time series cannot be obtained until the February data is publicized. Therefore, the incorporation of a **dummy variable**, the second option to purge the data of the Chinese New Year effects, suggested a more consistent way of monthly forecasting. By construction, the coefficient of the dummy variable for a particular condition measures the differential effect of being in that condition, coded by a value of 1, and is compared with some baseline state in which all the dummies equal a value of 0.[507] The advantage of this approach is that it is well-suited to correspond with the different dates of the Chinese New Year (either in January or February), predicating upon the majority of public holidays that fall in each month.[508] For example, the number of public holidays during the Chinese New Year in February of 2014 exceeds the number of holidays in the preceding month, which is expressed by a value of 1 on the very right-hand side of Figure VI-27 below. For all other months in that year, including January, the value is set to 0. It should be noted that this approach may generate less predictive accuracy in the output variable (PV sales), given that the distortions around the Chinese New Year are not dampened, as was the case in the first option.

[504] Roberts, Ivan (2015), p. 8; Mak, Wendy (2009), p. 47.
[505] Roberts, Ivan (2015), p. 17.
[506] Roberts, Ivan (2015), pp. 23 f.
[507] Ord, Keith et al. (2013), p. 273.
[508] Roberts, Ivan (2015), p. 8.

Historical Chinese New Year Public Holiday Dates			
Year	**Date of first day**	**Public holidays**	**Month with dummy coded as 1**
2005	9 February	9 - 15 February	February
2006	29 January	29 January - 4 February	February
2007	18 February	18 - 24 February	February
2008	7 February	6 - 12 February	February
2009	26 January	25 - 31 January	January
2010	14 February	13 - 19 February	February
2011	3 February	2 - 8 February	February
2012	23 January	22 - 28 January	January
2013	10 February	9 - 15 February	February
2014	31 January	31 January - 6 February	February
2015	19 February	18 - 24 February	February
2016	8 February	7 - 13 February	February
2017	28 January	27 January - 2 February	January

Source: Own illustration, based on Roberts, Ivan et al. (2015), p. 16.

Figure VI-27: Dummy variable coding for the Chinese New Year effect

Likewise, as for the *car purchase tax*, dummy variable coding would have been a conceivable method for gauging the differential impact of tax cuts in comparison to all other months without tax reductions in place. Yet at the same time, utilizing this approach would have blanked out the varying degrees of tax rates, which appear to follow a systematic scheme of implementation.[509] This kind of inducible pattern gave rise to the use of **continuously-valued variables** in favor of binary-coded data. It is crucial to recall that the challenge here is to obtain an early date of knowledge about a changing trend of car purchase tax policies.

In conclusion, the complete set of indicators to be used in the subsequent forecasting exercise can be encapsulated as follows:

509 On both occasions, the car purchase tax was halved to 5% at first and then increased to 7.5% respectively.

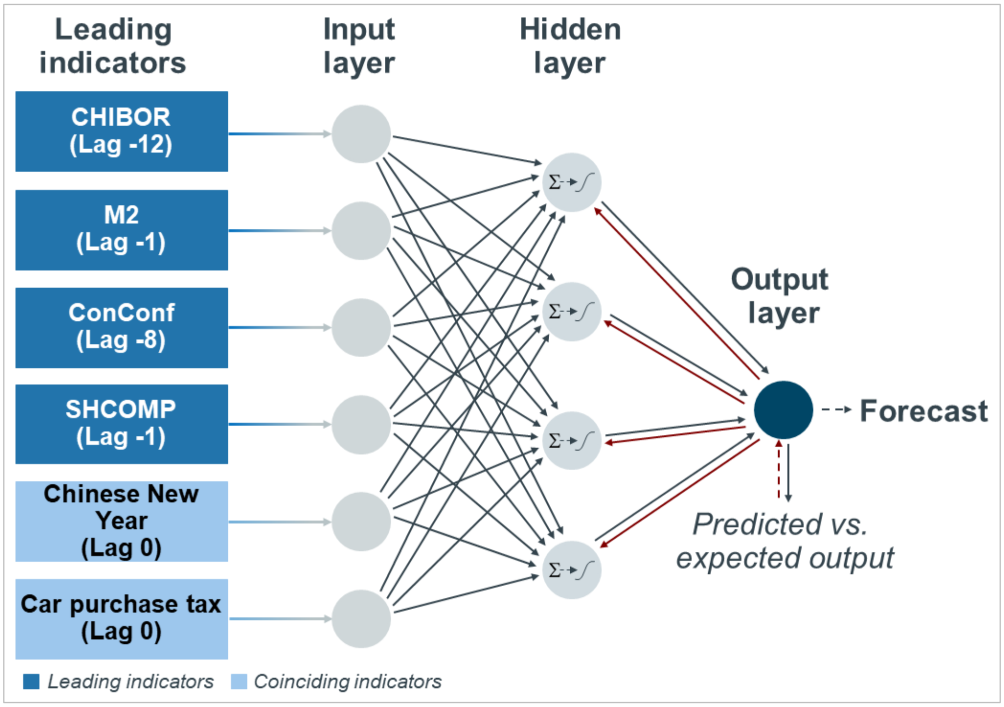

Figure VI-28: Overview of time-shifted input variables for multivariate forecast

VI.2 Configuration of the Neural Network for the case study experiments

Once all relevant input variables for monthly sales forecasts in the Chinese automotive market had been identified and pre-processed, the prerequisite groundwork for a successful ANN forecasting model was established.

As a next step, the intention was to capture the structure of relationship between all six input variables and the output variable PV sales. To be effective in performing this task, an experimental approach for various ANN training settings was conducted to reduce the all-important forecasting error to the lowest possible degree.

VI.2.1 Import of univariate time series data into the Neural Network model

With respect to the four leading indicators, the first step of ANN model configuration was to ascertain the optimal form of time series import that ought to deliver superior predictive performance.

As outlined before, traditional time series analysis necessitates a state of statistical equilibrium so as to draw statistically reliable conclusions with respect to the lead-lag relationship of input variables. In the present case study, first-order differencing and seasonal adjustments were carried out to comply with the assumption that all statistical properties under investigation do not evolve with time. However, the process of inducing time series into a state of statistical equilibrium entails a certain distortion of data signals, which may otherwise help unveil precisely the type of empirical regularities that provide clues on hidden mechanisms beyond the surface of evident data relationships.[510] In a context of systematic structural change in emerging markets, postulating this kind of idealized behavior[511] can be termed an inevitable weakness of traditional approaches to time series forecasting as it may lead to a misrepresentation of actual market realities .[512]

On the other hand, ANNs, as non-parametric models, do not necessarily presuppose any sort of data transformation. By contrast, they have the inherent advantage of representing non-constant and evolving processes, regardless of a time series' non-stationary characteristics, thereby preventing signal distortion and the associated loss of valuable information.[513] Seen in this light, it would be advisable to frame an experimental setup that aims to inquire about both stationary and non-stationary forms of time series data.[514] Stationary data is considered the entirely transformed dataset, which was also used in the preceding cross-correlational analyses, whereas in non-stationary data only the variance was stabilized by Z-score normalization. The ultimate decision as to which of the two forms of time series data would eventually be selected was contingent on their actual forecasting performance.

VI.2.2 Data partitioning

As outlined in section III.3.4, available time series data can be part of any one of the training, testing, or validation stages. There is no incontrovertible guideline on how available time series data should be portioned in an ANN model. However, ranging in size between 70-90%, the largest proportion of data is typically allocated to the training and testing stage given that the learning of patterns in the data constitutes by far the most essential aspect of ANN model building. Based on the premise that the best ANN forecasting model is selected at the minimum validation error[515], there is also broad consensus that a sufficient sample size must be

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510 Juselius, Katarina (2009), p. 350.
511 Milton, John; Ohira, Toru (2014), p. 333.
512 Durbin, James; Koopmann, Siem Jan (2012), p. 70.
513 Kennedy, Peter (2003), p. 326.
514 This methodological approach has been widely used in various time series forecasting tasks. See for e.g. Selviah, David R.; Shawash, Janti (2009), p. 222 ff.; Qi, Min; Zhang Peter G. (2008), pp. 809 ff.; Kuvulmaz, Janset; et al. (2005), pp. 504 f.
515 Ord, Keith et al. (2013), p. 333.

available for validating the trained model, preferably consisting of the most recent contiguous observations.[516] In time series forecasting, the data records for out-of-sample forecasting typically lie in forecasting horizons of several quarters or one to two years at the maximum.[517]

In the present case study of PV sales in China, the whole sample encompassed monthly data from January of 2005[518] to June of 2017, a total of 150 observations. On the basis of this data, twelve observations, from January to December of 2014, were set aside for out-of-sample validation. For the remaining set of data, 115 observations were randomly allocated to the training set, another 23 observations to the testing stage.[519] Different from the principal recommendations of data partitioning, the most recent observations between 2015 and 2017 were incorporated into the training stage. This was mainly because the latest stock market crash in 2015 and associated car purchase tax reductions were explicitly documented as supposedly essential patterns of the Chinese automotive development narrative in the majority of the expert interviews. In the training stage, these patterns were assumed to be particularly essential for the ANN to "study" the behavior of time series data in times of drastic supply and demand changes.

VI.2.3 Neural Network hyper-parameters

Similar to data partitioning, there are no strict procedures or rules for crafting an ANN forecasting model. In fact, successful modelling encompasses a great deal of trial and error, given that ANNs contain a wide array of configuration choices. Essentially, the configuration process can be divided into two intertwining planks, i.e. the selection of a suitable ANN topology and corresponding training parameter settings.

In summarizing from section III.3.3, the topology of ANNs is primarily reflected by the number of neurons in each layer and the type of activation function in the hidden layer(s). While the number of input and output neurons is congruent with the number of input and output variables, the de facto magnitude of hidden layers and their respective neurons is limited only by

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[516] Maciel, Leandro S. et al. (2010), pp. 10 f.; Kaastra, Iebeling. et al. (1996), p. 223.
[517] McNelis, Paul D. (2005), p. 95.
[518] At this stage of model development, the lead-lag relationship between all input and output variables had to be considered. Owed to the lead-lag relationship between PV sales and its predictor with the largest lead time (CHIBOR), the observation period was hence to be reduced by twelve months. It followed that, for instance, PV sales data for January 2005 was to be contrasted with CHIBOR data for January 2004.
[519] Kaastra, Iebeling. et al., p. 223.

computational constraints.[520] According to the topology principle, the hidden layer(s) equip the ANN with the ability to generalize on unseen time series data.[521]

A **three-layered ANN topology** with a **hyperbolic activation function** in the hidden layer was used in the underlying case study of PV sales in China. The decision in favor of a three-layered ANN was met because it has proven to be successful in related economic applications of a comparable scope[522]. Concerning the activation function, and the question as to whether to use the hyperbolic or logistic sigmoid function, several empirical studies have delivered evidence that the hyperbolic activation function provides a quicker level of convergence for non-linear forecasting applications.[523] The decisive reason for this finding may be that a hyperbolic activation function produces symmetry around the origin, because its values lie in a different range (-1; 1) than that of the logistic sigmoid function (0; 1). Ultimately, this different value range is what contributes to a more stable behavior[524], even in regions where observations denote deviations from average behavior.[525]

With respect to the amount of hidden neurons, an increase of neurons proportionally enlarges not only computation time, but also the risk of poor out-of-sample forecasting results due to a potentially over-fitted model than that required to capture the dynamics of time series data.[526] To nonetheless determine the optimum number of hidden neurons, several rules of thumb were deployed that have, based on a multitude of experimental case study references, evolved in the practice of forecasting:

i) Sqrt (the number of inputs x number of output neurons) or 75% of the number of input neurons;[527]
ii) (Number of inputs + number of outputs)/2;[528]
iii) For a small number of inputs, approximately twice as many hidden neurons as there are input neurons.[529]

520 Thawornwong, Suraphan et al. (2004), p. 60.
521 Ord, Keith et al. (2013), p. 333.
522 Zhang, Dabin et al. (2010), pp. 256 ff.; Qi, Min (2001), p. 386; Khalafallah, Ahmed (2008), pp. 326 f.; Tkacz, Greg et al. (1999), p. 9.
523 Yu, Lean (2007), p. 116.
524 Anders, Ulrich; Korn, Olaf (1999), p. 310, 322.
525 Kaastra, Iebeling. et al. (1996), p.227.
526 Kaastra, Iebeling. et al. (1996), p. 225; Brooks, Chris (2014), p. 274; Qi, Min (2001), p. 386.
527 Kaastra, Iebeling. et al. (1996), p. 225.
528 Kruse, Rudolf et al. (2016), p. 79.
529 Priddy, Kevin L. et al. (2005), p. 43.

Considering the binary representation of the Chinese New Year and an additional bias unit within the ANN forecasting model, the total amount of inputs accounted for eight neurons. In application of the referenced guidelines, the resulting bandwidth to be configured equated to a range between three to sixteen hidden neurons.

Closely connected to the buildup of an appropriate topology, the second pillar of ANN configuration chiefly concerns itself with the following training parameter settings:

i) Selection between different types of gradient descent algorithm;

ii) Initialization and fine-tuning of learning rates;

iii) Determination of stopping criteria for training process.

The backpropagation algorithm seeks to locate the global minimum of an error function and utilizes the method of **gradient descent** to adjust the weights by moving down the steepest slope of the error surface. Different gradient descent algorithms indicate how to adjust the current set of weights so that the predicted values converge to the known correct output values. In this setup for ANN modelling, both types, i.e. **batch/mini-batch and online gradient descent**, were tested with an equitable allocation of time resources.

Prior to the actual start of ANN training, another basic point to consider at the outset was to formulate a dovetailed strategy of learning rate initialization and adjustment that is designed to facilitate faster convergence to the optimum global solution. However, finding the global minimum is not necessarily guaranteed, because the error surface may include numerous local minima of the error function in which the algorithm can become "stuck".[530] This problem often occurs when learning rates are too small, because more learning steps are required to achieve a (global) minimum of the error function.[531] On the other hand, if weights are modified on a broader scale, there is a greater likelihood of falling into oscillatory traps of backpropagation. The resulting upshot is that any sort of learning algorithm must carefully balance the speedup of convergence it attempts to obtain with the risk of divergence involved.[532] For the present case study, the learning strategy consisted in starting with randomly chosen weights and their subsequent step-by-step fine-tuning until the desired function was computed.[533] In the case of online and mini-batch gradient descent, an additional weight decay term

[530] Kaastra, Iebeling. et al. (1996), p. 229.
[531] Kruse, Rudolf et al. (2016), p. 70.
[532] Rojas, Raul (2013), p. 190.
[533] Kruse, Rudolf et al. (2016), p. 23.

was introduced to help adjust ANN complexity by incrementally reducing weight magnitudes to a lower boundary of 0.001 after ten epochs.[534] The random weights were uniformly distributed, contingent on an initialization heuristic where the interval center (α_0) and interval offset (α) specified the interval [$\alpha_0 - \alpha, \alpha_0 + \alpha$].[535] In conjunction with the default setting in SPSS, the interval center was defined as 0 and interval offset was set to 0.5. Moreover, common research practice was applied by using a wide range of representative initial learning rates from 0.05 to 0.7, starting with the highest learning rate and decreasing it by 0.05 steps as training proceeded.[536] At the same time, various momentum rates between 0.1 and 0.95 were simultaneously tested to either accelerate training in regions of parameter space in which the error function was fairly flat or prevent large oscillations in which the error function occurred to be rather steep.[537]

With respect to the decision as to at which juncture in the process training should be discontinued, two criteria appeared to be of paramount significance:

First, a number of maximum steps without a decrease in error within a bandwidth of one to four steps was tested. The author deliberately deviated from the one-step default setting in SPSS, because this criterion constituted the principal reason for the discontinuation of training. Second, in lieu of setting a fixed value, the maximum number of epochs ranged between a scale of 500 and 1000.[538] The rationale behind this decision was that batch gradient descent requires more training cycles, because weight adjustments are performed only *at the end* of each epoch, whereas online and mini-batch training conduct weight adjustments in *intra-epochal* iterations.[539]

VI.2.4 Description of model outputs

Once an appropriate setup of ANN topology and training parameter settings had been forged, a series of experiments within an overall scope of about 20,000 model updates was per-

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534 Reed, Russell; Marks, Robert J. II (1999), p. 63; Ruß, Georg; Kruse, Rudolf; Schneider, Martin, et al. (2008), p. 114.
535 Rojas, Raul (2013), p. 197; Shoemaker, Patrick A.; Carlin, Michael J.; Shimabukuro, Randy L. (1991), p. 234; Sodhi, Sartaj S.; Chandra, Pravin (2013), pp. 22 ff.
536 Yu, Lean (2007), p. 112 ff.; Maciel, Leandro S. et al. (2010), p. 12; Wilson, Randall D.; Martinez, Tony R. (2001), pp. 117 f.
537 Yu, Lean (2007), p. 112 ff.; Kruse, Rudolf et al. (2016), p. 73.
538 Yu, Lean (2007), p. 112; Ermis, Murat; Sahingoz, Ozgur K.; Ulengin, Fusun (2004), p. 845.
539 Wilson, Randall D.; Martinez, Tony R. (2003), p. 1431.

formed. These updates were initialized as soon as one of the pre-determined thresholds of relevant stopping criteria materialized in actual effect.

An initial preliminary finding of ANN training was that forecasting accuracy for non-stationary time series data was clearly superior to models that were predicated on stationary data records. With this in mind, after about 2,500 re-initializations for both datasets, training was interrupted to conduct an additional assessment of the models' generalization ability on several pre-selected testing sets. For each of the comparative assessments, those models based on non-stationary data evinced a considerably lower validation error – equivalent to a higher expected forecasting performance. Viewed from this perspective, the resulting implication was that further experiments concentrated upon non-stationary data records to minimize the forecasting error for both estimation and hold-out sample to the lowest possible extent.

The best-performing ANN forecasting model was identified after 15,000 model updates. It comprises **ten hidden neurons**, which are interconnected by means of synaptic weights to the downstream input layer and upstream output layer respectively.

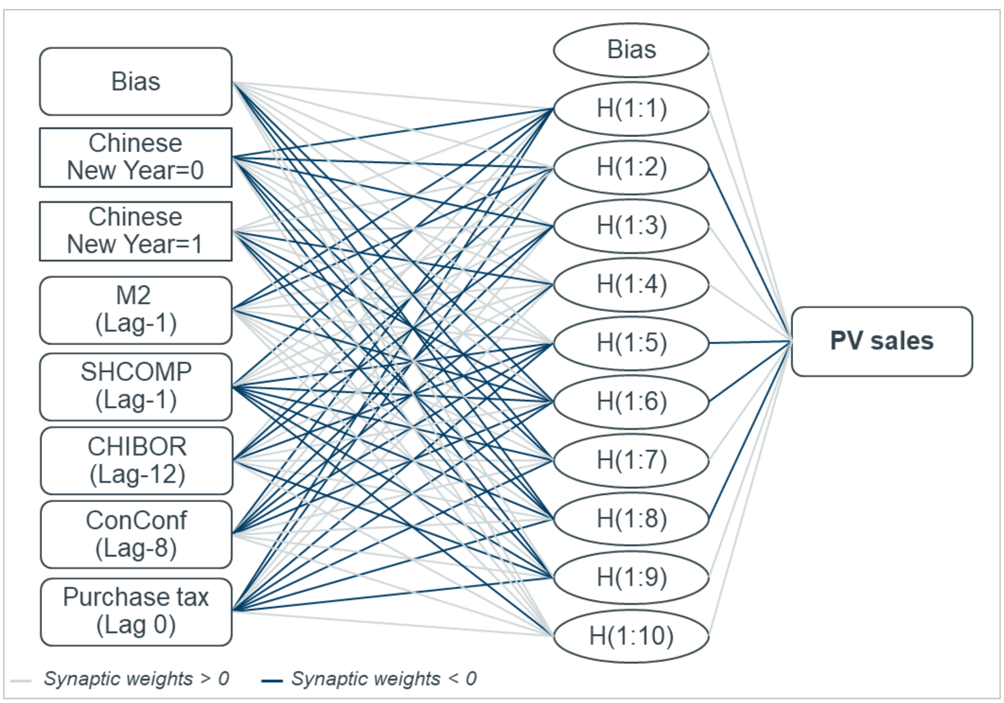


Figure VI-29: Topology of the selected Artificial Neural Network model

In Figure VI-29, the binary representation of the Chinese New Year is visualized by rectangular units whereas all other metrically scaled input and output neurons are depicted through rounded rectangular units. The most distinguishable commonality between all connections to and from the hidden layer lies in the direction of linkage, which is expressed by either a blue line for synaptic weights smaller than zero or a grey line for synaptic weights greater than zero.

The error sum of squares[540] represents the first commonly used statistic to evaluate forecasting accuracy by converting the topological design into an in-sample goodness-of-fit metric.[541] By definition, the error sum of squares reflects the remaining degree of non-predictable random variation after the contributions of all specified sources of variation have been ascertained.[542] The general principle of application is that the smaller the value of this metric, the smaller is the average squared difference between the fitted and observed values.[543]

For the case study of PV sales in China, the **error sum of squares** amounts to a fairly low degree of 3.351 or **5.9% relative error** during the **training stage** and 0.837 or **7.4% relative error** during the **testing stage.** This result was achieved after four seconds of training and one consecutive step without decreasing the error in the test sample (see Figure VI-30).

Summary of data processing

		N	Percent
In-sample data	Training	115	83.3%
	Test	23	16.7%
Valid		138	100.0%
Excluded		0	
Total		138	

Summary of model accuracy

Training	Error sum of squares	3.351
	Relative error	**0.059**
	Stopping criteria applied	1 consecutive step without reducing the error[a]
	Training time	0:00:00.04
Test	Error sum of squares	0.837
	Relative error	**0.074**
Dependent variable: Passenger vehicle sales		
a. Error calculations based on test sample		

Figure VI-30: Summary of data processing and in-sample model accuracy

540 In variance analysis, the error sum of squares is also called sum of squares error (SSE) or residual sum of squares error (RSS).
See: Upton, Graham; Cook, Ian (2014), p. 10.

541 Yaffee, Robert A. et al. (2000), p. 16.

542 Upton, Graham et al. (2014), p. 10.

543 Ord, Keith et al. (2013), p. 218.

A scatterplot depicting the linear relationship between predicted and actual PV sales provides more valuable insights as to how accurate the predicted in-sample values correspond to market reality. The clearly strong linear development path between the pair of variables concurs with **Pearson's coefficient of *correlation* (r = 0.969)**, which was applied to translate visual inspection into quantitative terms.[544] Squaring this value into a **coefficient of *determination* (r^2 = 0.939)** expresses that almost 94% of the variation in actual PV sales is accounted for by predicted PV sales.[545]

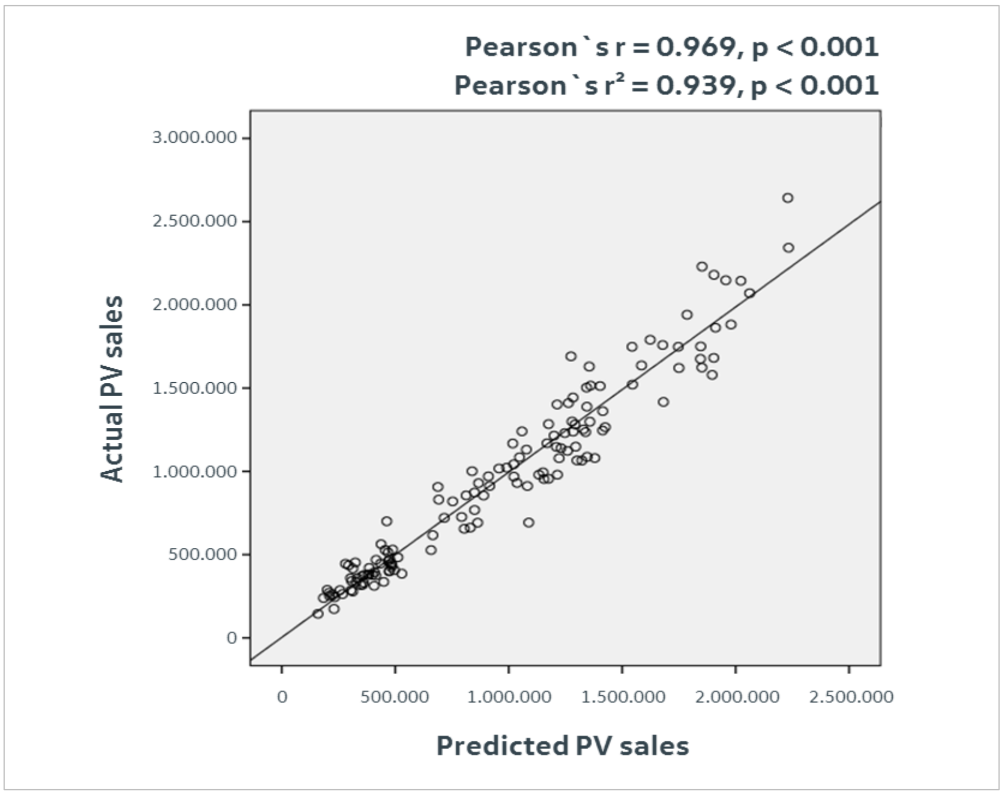


Figure VI-31: Scatterplot of relationship between predicted and actual PV sales

On the basis of both metrics, clear-cut indications were given stating that the trained ANN model encapsulates all necessary conditions for stable short-term forecasts. However, the final decision whether the eventually selected model could effectively bring about superior predictive performance in future business applications was decisively contingent on its output in the cross-validating out-of-sample review. For this reason, the model's forecasts for the validation set in 2014 were initially contrasted with the actual observations from the remaining set of

544 Bryman, Alan et al. (2015), p. 352 f.
545 Wilcox, Rand R. (2009), pp. 172 ff.

data (see Figure VI-32 and Annex 27). The author referred to the mean absolute percentage error (MAPE), which is defined as the average of the unsigned percentage error. Unlike a numerical size of the error, the MAPE has the inherent advantage of being dimensionless, turning it into a more customary yardstick for reporting forecasting performance in business practice.[546] This metric facilitated an ease of comparison between different model outputs and was (therefore) also utilized as main referential anchoring point for assessing the performance of the interviewees' divergent forecasting model approaches.

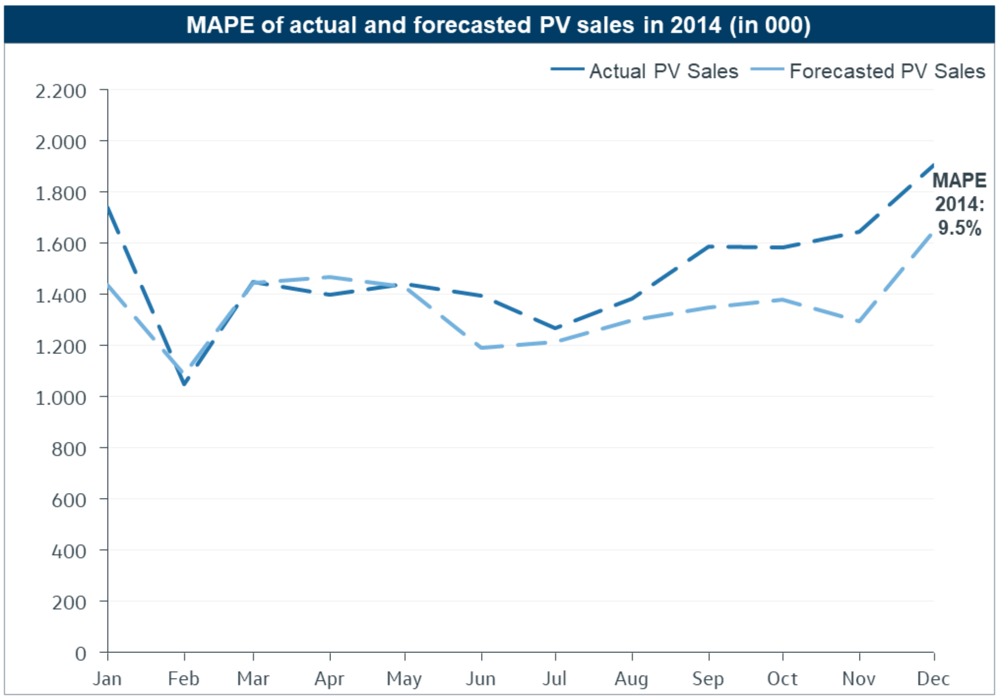


Figure VI-32: MAPE of actual and forecasted PV sales in validation set (2014)

A fairly accurate approximation of actual market development was obtained by applying this yardstick to the entire validation set of observations between January and December of 2014 (MAPE: 9.5%). Particularly outstanding model outputs were achieved between February and May (MAPE: 2.3%). Moreover, Figure VI-32 evidences that the market's ups and downs were almost entirely forecasted correctly, suggesting that the model is well able to truly map the market's inherent dynamics. Yet at the same time, in the second half of 2014, forecasts tend to become more pessimistic than actual PV sales figures, thereby slightly affecting the results accomplished to that point.

546 Kennedy, Peter (2003), p. 361.

VI.2.5 Discussion of model outputs

The upshot of ANN training and application is that the model has, in all likelihood, learned and generalized certain patterns that are relevant for producing stable monthly sales forecasts in the Chinese automotive market. The cross-validating out-of-sample review, the most crucial milestone in ANN development, confirmed previous indications of high-accuracy forecasts during the training stage by falling below the all-decisive MAPE threshold of 10%. This ambitious threshold constitutes the only comparative benchmark[547] that was formulated in the expert interviews for assessing the quantitative capability of dealing with month-over-month automotive market fluctuations in China. It was defined by the consulting enterprise A (see Interview 6) in 2010/11 and predicated upon a much more demanding and resource-intensive process of market predictions, including an elaborate bottom-up approach of forecasting across all 31 provinces in China. Beyond that, the ANN forecasting model performance is all the more remarkable in that it was achieved despite the dynamic variation originating from the inclusion of all data outliers and the timely differential impact of the Chinese New Year, each constraining generalization performance in general and the feature selection process in particular.

When comparing the MAPE for out-of-sample forecasts from the validation set with its equivalent for in-sample forecasts from the training set (see Figure VI-33), we can see that the error resulting from the former sample exhibits a somewhat lower output error (MAPE: 9.5% vs. 12.0%).

[547] An out-of-sample MAPE of 12.4% was achieved in a recent study on Chinese monthly automotive sales forecasting (reference year 2016), based on a vector error correction model. Yet, this result could only be achieved using monthly sales of Chery Automobile (coincident indicator). The optimum result without this indicator was found to be at almost 20% MAPE.
See: Gao, Junjie et al. (2018), p. 3, 9.

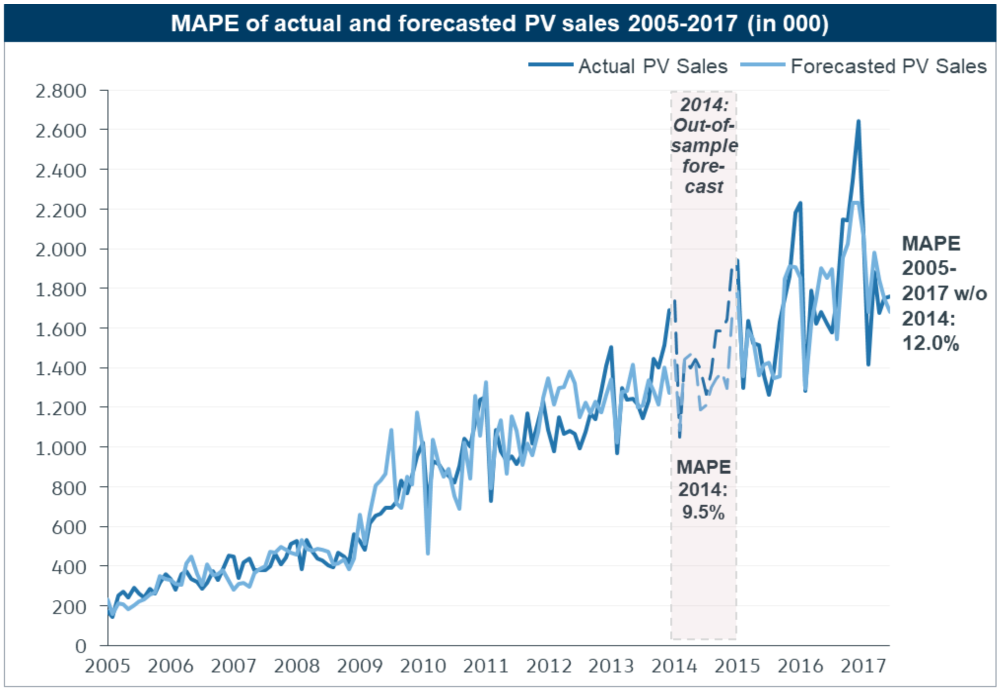


Figure VI-33: Comparison of MAPE for in-sample and out-of-sample forecasts

At first glance, this finding seems implausible. The one-year hold-out sample did not play any role whatsoever in estimating the ANN model's synaptic weights.[548] A more accurate forecast of exactly this yet unseen data in comparison with the forecasts of data that had already been used by the ANN during the training stage would appear to be counter-intuitive.

However, the underlying data sample delineates a representation of heterogeneous and extreme input conditions. Conditions of this sort reflect the endemic structural change in both the economy as well as the automotive industry. They have the potential to occasionally distort the basic structure of time series data, entailing notably higher forecasting errors in these months which, in turn, unfold an adverse impact on the overall outcome. As a case in point, during the gestation and after the breakout of the stock market crises in 2007 and 2015, the ANN forecasting model failed to anticipate correctly the market's direction of development between March and April of 2007 (MAPE: 28.6%) as well as in July and September of 2015 (MAPE: 14.7%).

548 McNelis, Paul D. (2005), p. 95.

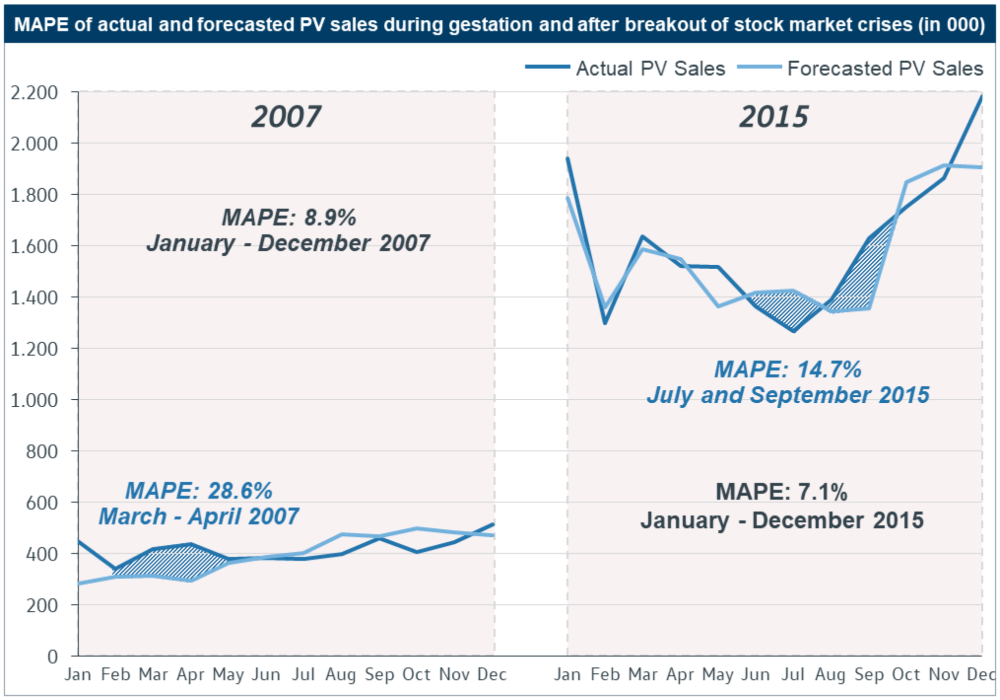


Figure VI-34: Occasional discrepancies between actual and forecasted PV sales

With fewer opportunities to relativize such erroneous forecast trajectories at hand, these occasionally occurring discrepancies exemplify the persisting contingencies that short-term forecasters face with monthly reporting intervals. On the other hand, evaluating the quality of forecasts in light of the entire two-year span suggests that the model does indeed generate excellent results (MAPE: 8.9% in 2007 and 7.1% in 2015) – notably taking into account, at that time, the overall turbulent economic environment and resultant impact on the underlying time series data.

In this context, the question arises as to how the "fragmented mosaics" were assembled into a comprehensive ANN topology that is responsive to suchlike ever-changing market conditions. As outlined in section III.3.1, the extraction and interpretation of knowledge from trained ANNs is often subject to criticism. That is because the process of parameter estimation between all connections to and from the hidden layer is non-transparent and the generated knowledge of this process is encoded in a mysterious[549] "black box" of synaptic weights. As a result, the presentation of linkage strengths in Figure VI-35 provides only little account into the actual composition of the model; one can only surmise from the relatively high real-valued numbers that M2 is assigned greater weight than all other input variables.

[549] Kruse, Rudolf et al. (2016), p. 89.

		H (1:1)	H (1:2)	H (1:3)	H (1:4)	H (1:5)	H (1:6)	H (1:7)	H (1:8)	H (1:9)	H (1:10)	PV sales
Input layer	Bias	.561	.366	.155	.007	.361	-.554	-1.460	-.419	.113	.437	
	[Chinese New Year=0]	-.019	-.565	-.325	.176	.414	-.917	-2.198	-.691	-.641	.244	
	[Chinese New Year=1]	.426	.767	.233	-.742	.520	-.005	.337	-.296	-.152	.216	
	M2 (Lag-1)	-.236	-2.180	.202	.180	.135	-.181	2.216	.834	.858	.233	
	SHCOMP (Lag -1)	-.788	.011	1.046	1.118	-.193	-.721	-.440	-.741	-.621	-.221	
	CHIBOR (Lag -12)	.909	-.104	-2.139	-.507	-.227	.297	.742	.261	-.612	.134	
	ConConf (Lag -8)	-.097	.069	-.843	-.100	-.030	-.701	1.125	1.038	1.070	.211	
	Purchase tax (Lag 0)	-.973	-1.212	1.039	.731	-.669	-1.125	-2.002	-.699	-1.035	.329	
Hidden layer	Bias											.268
	H(1:1)											1.097
	H(1:2)											-.805
	H(1:3)											.396
	H(1:4)											.577
	H(1:5)											-.936
	H(1:6)											-.384
	H(1:7)											1.003
	H(1:8)											-.593
	H(1:9)											.624
	H(1:10)											.244

Figure VI-35: Parameter estimates for synaptic weights between different layers

To nonetheless gain deeper insights into the functional relationship between PV sales and its leading indicators, a sensitivity analysis was executed, one that aimed at measuring the sensitivity of the ANN model's output to changes in its input parameters.[550] The sensitivities of model output are partial derivatives that are summed up with respect to the input parameters; the resulting sum is divided by the number of iterations to render the result independent of size of the training data set.[551] To determine the relative importance of predictors, the absolute importance values are divided by the largest importance values and expressed as percentages.[552] The implementation of this analysis to the ANN forecasting model confirms the interviewees' accounts on the essential role of money supply for short-term automotive sales forecasting, because M2 is ranked highest on the sensitivity scale of all input variables employed (see Figure VI-36).

550 Yeung, Daniel S.; Cloete, Ian; Wing, W.Y. Ng (2010), p. 20.
551 Kruse, Rudolf et al. (2016), p. 89.
552 Alabi, M.A.; Issa, S.; Afolayan, R.B. (2013), p. 25.

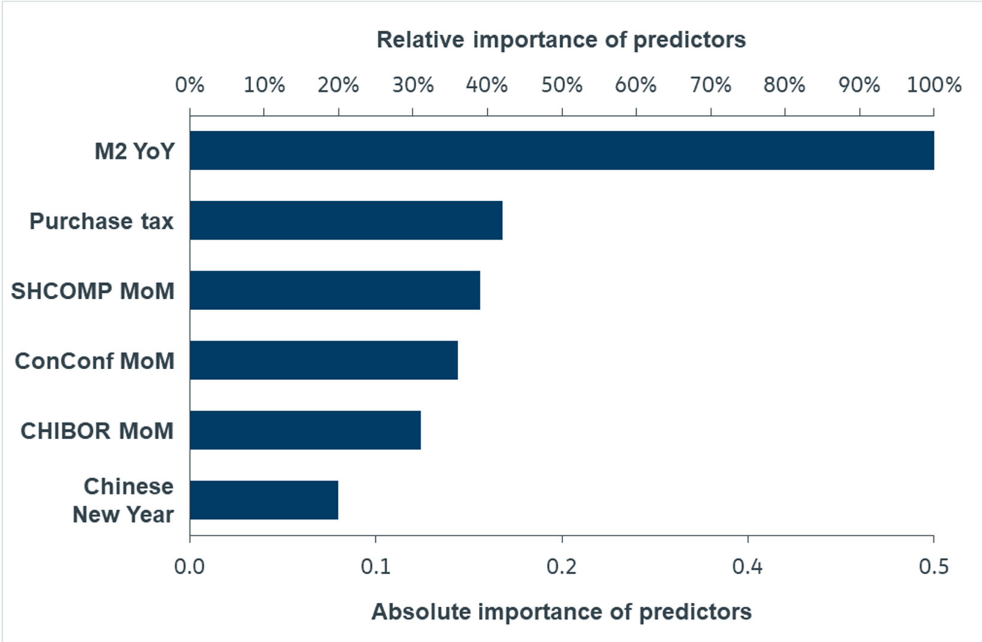


Figure VI-36: Determining indicator performance from a sensitivity analysis

At the other end of the sensitivity scale, it becomes conspicuously evident that the Chinese New Year is relegated to a subordinate role in model construction. This is truly a noteworthy finding, because the ANN forecasting model has nevertheless adequately factored the annually recurring pattern of cyclical fluctuation emanating from the Chinese New Year effect, as Figures VI-32 and VI-33 document. The most logical conclusion for this outcome is that all other predictors are likely to possess even greater predictive capabilities – an assumption that needs to be substantiated by exercising the supreme discipline of forecasting, i.e. the evaluation of forecasting performance in times of government-initiated policies.

To investigate whether the ANN forecasting model can navigate through these asymmetric market conditions, the forecasting performance was examined by means of the car purchase tax-related indicator, ranked second highest in modelling importance, over the period in which the state abated the levy on purchases of vehicles with 1.6-liter engines or smaller.

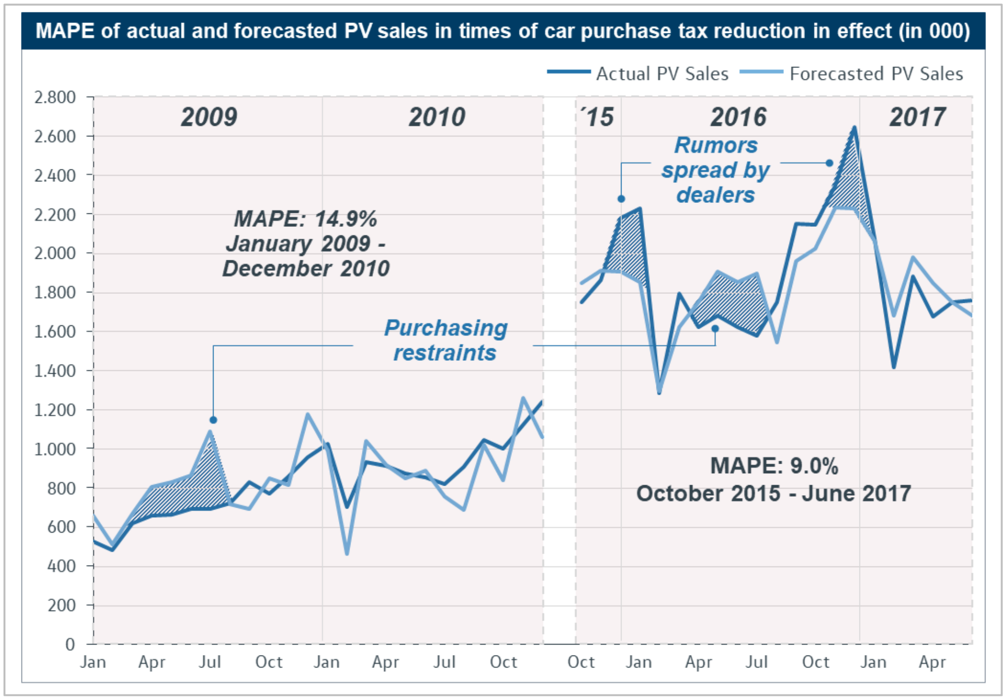


Figure VI-37: Model performance in times of car purchase tax incentives

As Figure VI-37 demonstrates, featuring an overall MAPE of 14.9% between January of 2009 and December of 2010 and an even lower MAPE of 9.0% between October of 2015 and June of 2017, the model evinces quite decent performance revolving around the 12% mark, which was achieved throughout the in-sample forecasting horizon between 2005 and 2017. That is to say, the ANN forecasting model delivers palpable evidence that it has detected certain patterns enabling it to produce robust forecasting performance, even in times of artificially-generated customer demand. Yet at the same time, and this is probably to be understood as an invariable limitation of ANN capabilities to date, the model has not managed to recognize the so-called "frontloading effect" that was explicitly described by the experts in Interview 6 and Interview 10: In the wake of rumors spread by automotive dealers, many customers were misled by alleged government announcements on imminent policy termination dates. These rumors induced customers to engage in panic-based purchases, which triggered a significant sales momentum at the turn of the year in both 2015 and 2016. By the same token, shortly after cutting the car purchase tax rate in half to 5% in 2009 and 2016 respectively, the market saw an atypical stagnation in customer demand between April and July, which could not be anticipated by the ANN forecasting model.

VII Conclusions and suggestions for future research

In essence, sources of risk for MNEs in emerging markets are reflected in two key facets. Above all else, a country's macro context provides an anchor for evaluating whether the local economy is truly emerging in terms of sustainable growth rates or simply experiencing a short-lived episode of economic upswing. In this regard, MNEs are well-advised to pinpoint symptomatic indications of macro risk emanating from the emerging market's inevitable exposure to volatility and transition. In Latin America, these indications may include reinforcing tendencies towards long-lasting current account deficits and a high degree of dollarization.

At a micro level of risk management in emerging markets, MNEs have to acknowledge their inherent vulnerability to institutional voids. In response to these voids, MNEs are required to depart from conventional strategies they have (successfully) deployed in advanced economies and embark on more actionable strategies that take an adequate account of an emerging market's distinct peculiarities. These strategies allow MNEs to economize on transaction costs, thereby achieving a sustained competitive advantage over domestic and international rivals.

This thesis aligns both sources of risk into a unified risk management strategy on behalf of MNEs in emerging markets. A key element of this strategy is to adapt in-house forecasting processes in a manner that anticipates changing market development tendencies and, based on that, adjusts entrepreneurial planning premises prior to competition. For the present case study, a more viable framework for PV sales forecasting in China is suggested, one that aims at reconfiguring a MNE's resources and dynamic capabilities to respond to the two main dimensions of institutional voids in emerging markets, i.e. regulatory insecurity and unreliable market information. This framework consists of the following three phases:

i) **Acquisition phase** – When knowledge resources are acquired from Chinese domestic enterprises to obtain a markedly nuanced picture of automotive development in China;

ii) **Assimilation phase** – When the tacit dimension of acquired knowledge resources is assimilated as part of a multi-leveled indicator selection process to adjust for unreliable and/or not sufficiently available macro and microeconomic time series data;

iii) **Application phase** – Where the assimilated knowledge resources are eventually applied in an ANN forecasting model so as to address the frequency of structural change that predominantly results from the ad hoc initiation of government policies in China.

The implementation of this so-called “triple-A” framework to the present case study of PV sales in China is encouraging: With an overall MAPE of 12.0% for the in-sample forecasting period between 2005 and 2017 and an even lower MAPE of 9.5% for the all-decisive out-of-sample period in 2014, the ANN forecasting model effectuates superior monthly forecasting performance in comparison with models featuring comparable resource-consuming efforts. It is even able to keep pace with a much more resource-intensive bottom-up approach of forecasting across all 31 provinces in China, the outcome of which is a 10% MAPE threshold that sets the benchmark for monthly out-of-sample PV sales forecasts in the Chinese automotive industry.

The gains achieved in the forecast accuracy/efficiency ratio seem to originate from the ability of ANNs to learn and generalize certain revolving patterns in rather complex data structures. As we look ahead, one may expect that even better forecasting results will be achieved over time, because ANN forecasting models tend to improve their ability to generalize with larger sample quantities employed. Moreover, it can be assumed that the success of ANN forecasting in a Chinese automotive market environment can be readily transferred to other emerging market case studies. That is because all emerging markets face similar challenges with respect to the nature of macro and microeconomic time series data, which, per se, is highly dynamic, partially unavailable, and/or statistically unsound.

On the downside for the proposed ANN forecasting model, the discrepancies between actual and forecasted PV sales at times of policy implementation and (supposed) termination lend credence to some of the interviewees’ statements. These statements have captured the *full* effect of government-initiated polices and how they still remain a distant goal of a purely quantitative approach to market forecasting. The limitations of quantitative forecasting became particularly visible at the turn of the year in both 2015 and 2016, when customers were misled by some “black sheep” dealers, who spread rumors about the imminent termination of tax incentives on purchases of small-engine vehicles with 1.6-liter engines. In light of this finding, additional attention is given to the fact that some elementary determinants are (still) non-quantifiable in nature and thus cannot be formalized in any unit of measurement. For that very reason, the output of quantitative forecasting models should be augmented by complementary resources. In the Chinese automotive industry, these resources should especially include qualitative judgements about the direction of intended policy change initiated by the Chinese government and the effects of – quantitatively judged – irrational customer behavior.

Likewise, one final point of note is that the proposed set of leading indicators for the ANN forecasting model does not lay claim to containing all information deemed imperative to build a model with the best achievable forecasting performance. Although the current evolvement of (quantitative) big data collection opportunities is certainly conducive to the long-term establishment of ANNs in business forecasting practice, the qualitative composition of indicators in ANN forecasting models still remains a critical issue (more so than the quantitative availability of data). To prevent the effect of conditioning on time series data, a situation in which a statistical model is predicated only on prior knowledge rather than on (changing) market realities, MNEs have to closely monitor structural evolvements in emerging markets at both macro and microeconomic levels. Based on the lessons learned in Argentina, future researchers in China should particularly monitor the country's vanishing current account surplus, as the growth of the Chinese economy is forecasted to become increasingly reliant on foreign capital. Besides, the focus of future ANN forecasting research in China should avoid using indicators that apply, for the most part, to the old economy. Although this thesis has achieved some quite remarkable forecasting results by referring to old economy indicators, this should not obscure the fact that automobile financing and used car market sales are only two of many more ground-breaking trends that have only just begun to trigger a sweeping impact on automotive development in China.

Annex

Annex 1: Advanced economies by subgroups[553]

1. Euro Area		
Austria	Greece	Netherlands
Belgium	Ireland	Portugal
Cyprus	Italy	Slovak Republic
Estonia	Latvia	Slovenia
Finland	Lithuania	Spain
France	Luxembourg	
Germany	Malta	
2. Major Advanced Economies		
Canada	Italy	United States
France	Japan	
Germany	United Kingdom	
3. Other Advanced Economies		
Australia	Korea	Singapore
Czech Republic	Macao SAR	Sweden
Denmark	New Zealand	Switzerland
Hong Kong SAR	Norway	Taiwan Province of China
Iceland	Puerto Rico	
Israel	San Marino	

Annex 2: Emerging market and developing economies by regional subgroups[554]

1. Emerging and Developing Asia		
Bangladesh	Malaysia	Philippines
Bhutan	Maldives	Samoa
Brunei Darussalam	Marshall Islands	Solomon Islands
Cambodia	Micronesia	Sri Lanka
China	Mongolia	Thailand
Fiji	Myanmar	Timor-Leste
India	Nauru	Tonga
Indonesia	Nepal	Tuvalu
Kiribati	Palau	Vanuatu
Lao P.D.R.	Papua New Guinea	Vietnam

553 International Monetary Fund (2018), p. 220.
554 International Monetary Fund (2018), pp. 244 ff.

2. Commonwealth of Independent States		
Russia	Georgia	Tajikistan
Armenia	Kazakhstan	Turkmenistan
Azerbaijan	Kyrgyz Republic	Ukraine
Belarus	Moldova	Uzbekistan
3. Emerging & Developing Europe		
Albania	Hungary	Poland
Bosnia & Herzegovina	Kosovo	Romania
Bulgaria	FYR Macedonia	Serbia
Croatia	Montenegro	Turkey
4. Middle East, North Africa, Afghanistan and Pakistan		
Afghanistan	Kuwait	Saudi Arabia
Algeria	Lebanon	Somalia
Bahrain	Libya	Sudan
Djibouti	Mauritania	Syria
Egypt	Morocco	Tunisia
Iran	Oman	United Arab Emirates
Iraq	Pakistan	Yemen
Jordan	Qatar	
5. Latin America and the Caribbean		
Antigua & Barbuda	Dominican Republic	Panama
Argentina	Ecuador	Paraguay
The Bahamas	El Salvador	Peru
Barbados	Grenada	St. Kitts & Nevis
Belize	Guatemala	St. Lucia
Bolivia	Guyana	St. Vincent and the Grenadines
Brazil	Haiti	
Chile	Honduras	Suriname
Colombia	Jamaica	Trinidad & Tobago
Costa Rica	Mexico	Uruguay
Dominica	Nicaragua	Venezuela

Annex 3: Overview of policies in the (Augmented) Washington Consensus[555]

Washington Consensus	Augmented Washington Consensus
1. Reduction of budget deficit to a non-inflationary level	11. Corporate governance
2. Redirection of public expenditure to areas such as education, infrastructure etc.	12. Anti-corruption
3. Tax reforms to lower marginal rates, broadening the tax base	13. Flexible labor markets
4. Transition to market-determined interest rates (financial liberalization)	14. Adherence to WTO discipline
5. Sufficiently competitive exchange rates which induce a rapid growth in non-traditional exports	15. Adherence to international financial codes and standards
6. External trade: removal of quantitative trade restrictions; tarif reductions	16. “Prudent” capital account opening
7. Abolition of barriers to foreign direct investment	17. Non-intermediate exchange rate regimes (completely fixed or completely flexible rates, corner solutions)
8. Privatization of state-owned enterprises	18. Independent central bank/inflation targeting
9. Deregulation for start-ups; general abolition of restraints on competition	19. Social safety nets
10. Better protection of property rights, particularly in the informal sector	20. Targeting poverty reduction (for e.g. heavily indebted poor countries initiative)

[555] Herr, Hansjörg et al. (2005), p. 84.

Annex 4: Interview guideline in English language

Interview guideline

Participants		Organization	Language | Translator
Mr. Jan Brzoska	x	Volkswagen AG	English
			Date | Time
			Location

	Agenda items	Duration
00	**Introduction** ▪ Mutual introduction of academic and professional background ▪ General remarks towards personal data protection	5 min.
01	**Methodology of total market forecast** ▪ Can you provide me with a short explanation of the total market forecast methodology you currently use? ▪ Brief presentation of Mr. Brzoska`s forecast methodology ▪ <u>In-depth question:</u> What are strengths and shortcomings of your methodology?	7-12 min.
02	**Selection of leading indicators** ▪ Which indicators do you use in your forecast? Why? ▪ Which of the *shown* indicators deserve special emphasis? Why? ▪ <u>In-depth question:</u> Looking ahead, are there any other indicators that might become relevant in the future? Which ones?	12 min.
03	**Data preparation for statistical analysis** ▪ Based on your specified indicators, is and will data be readily available on a monthly basis? ▪ Since which year is that data readily available? ▪ From which institution do you retrieve your data?	7-12 min.

	Agenda items	Duration
03	**Data preparation for statistical analysis (continued)** ▪ <u>In-depth questions:</u> ▪ Is and will that data also be available for Tier 1-5 segment levels? ▪ Do you think that the exclusion of data outliers is necessary for certain time periods? If so, for which time periods?	
04	**Data evaluation and processing** ▪ Do you follow a systematic process to review the validity of your market intelligence deliverables? ▪ <u>In-depth question:</u> From your standpoint, what will be the best achievable approximation (in %) of in-sample and out-of-sample data?	7-12 min.
00	**Final remarks** ▪ Would you recommend including any further issues in Mr. Brzoska's total market forecast approach? ▪ Outlook of next steps by Mr. Brzoska ▪ Check of contact details for further correspondence ▪ Expression of thanks and closure of meeting	7 min.

Annex 5: Interview guideline in Chinese language

面谈指导

参会者		公司 | 协会	会议语言
罗忠扬先生	x	大众汽车公司	中文

会议时间

地点

	会议内容	时长
00	介绍 ▪ 学术和专业背景的的互相介绍 ▪ 个人数据保护说明	5 分钟
01	汽车总市场预测方法 ▪ 您能否对您现在使用的汽车总市场预测方法进行一个简要的说明? ▪ 罗忠扬先生汽车总市场预测方法的简要介绍 ▪ <u>深入调查:</u> 现用方法的优点和缺点是什么?	7 至 12 分钟
02	指标选择 ▪ 在您的预测分析里使用哪一些指标?为什么? ▪ 哪些展示的指标应该受到重点关注?为什么? ▪ <u>深入调查:</u> 展望未来,是否有其他重要指标?有哪些?	12 分钟
03	为统计分析而做的数据准备 ▪ 您的特定指标是否在现在和未来都能按月度收集? ▪ 您的数据从哪所机构中得到? ▪ 数据可以从哪一年开始收集?	7 至 12 分钟

	会议内容	时长
03	**为统计分析而做的数据准备 (接上)** ▪ 深入调查: ▪ 有关这些指标，是否在现在和未来都可以收集到大部分 1-5 线城市的数据？ ▪ 从您的经验来看，需要排除某些时间段出现的数据异常值吗？如果是，是哪些时间段？	
04	**数据评估和处理** ▪ 请问您是否依照系统化流程去检验过市场调研成果的有效性？ ▪ 深入调查: 根据您的经验，样本内和样本外数据的最佳近似值是多少？ (百分比)	7-12 分钟
00	**结束语** ▪ 对于这次面谈和总市场预测方法，您有何建议或意见？ ▪ 罗忠扬先生的未来计划展望 ▪ 未来联系方式确认 ▪ 感谢语与会议结束	7 分钟

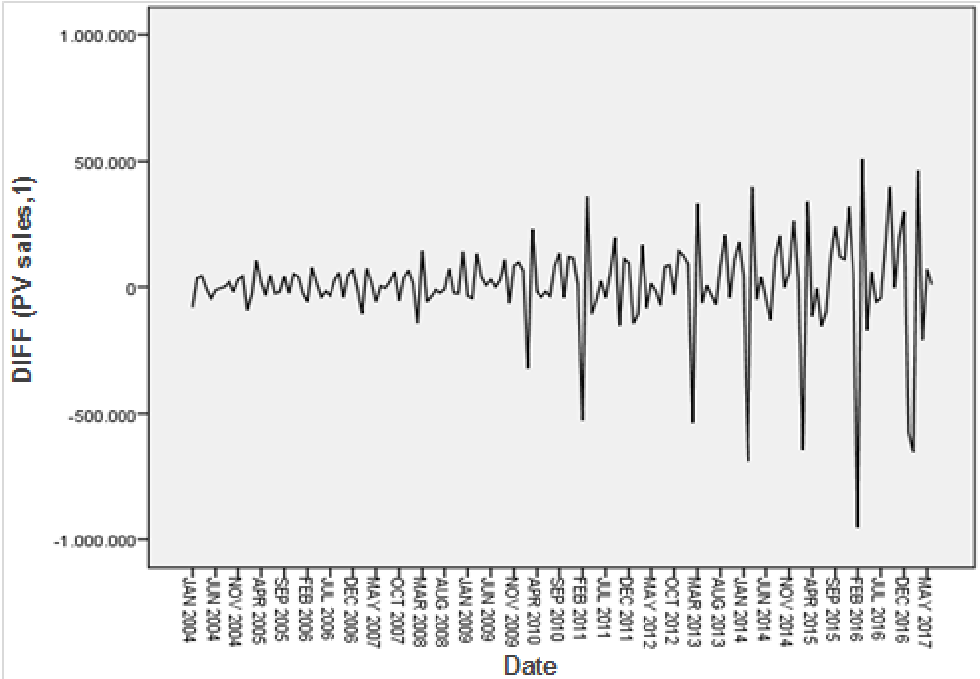
Annex 6: Pre-selected indicators in English language

Traditional economy	New economy	Automotive
GDP per capita	Sales of mobile telephony contracts	Showroom traffic (VW brand & industry)
M2	Railway passenger transport (as proxy for tourism activities)	Industry stock level
Disposable income per capita	Box office revenues (票房收入)	Gasoline price
Purchase Manager Index	Total sales revenue e-shopping	Total market MSRP (manufacturer's suggested retail price)
Consumer Price Index (CPI)	Air pollution index	Total length of roads
Consumer Confidence		Total mileage Didi (car sharing)
Industrial value added		Traffic congestion index
Industrial output		Tire production / consumption
Fixed asset investment		Financial indicators of representative Chinese automotive supplier
Real estate development		
FX exchange rate RMB / USD		
Producer Price Index (PPI)		
Gini coefficient		
Steel output		
Total population density		
CSI 300		
Freight volume of whole society (FVWS)		
Household debt		

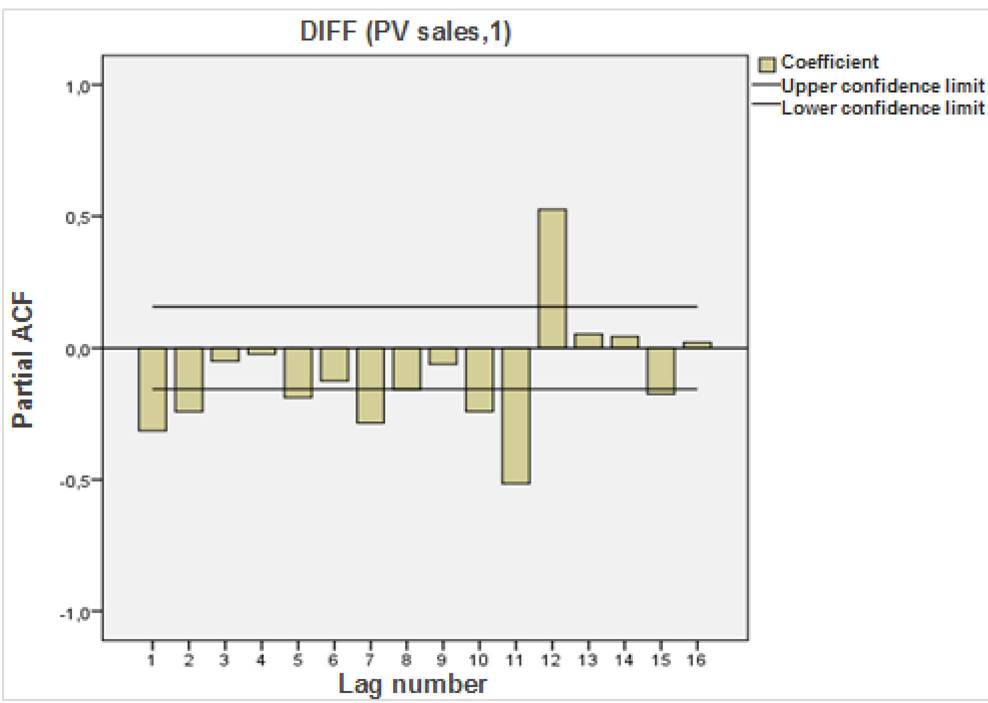
Annex 7: Pre-selected indicators in Chinese language

传统经济	新经济	汽车行业
人均国内生产总值	移动电话的合同销售	陈列室交通 (大众和汽车行业)
货币供应量之二	铁 路旅 客 运 输 (代表旅游活动)	汽车行业存货水平
人均可支配收入	票房收入	汽油价格
采购经理指数	网上购物的销售收入的份额	制造商建议零售价格
消费物价指数	空气污染指数	公路总里程
消费者信任		滴滴出行总里程 (汽车共享)
工业增加值		交通拥挤指数
工业产 量		轮胎生产或消费
固定资产投资		中国汽车供应商的财务指标
房地产开发		
美元对人民币汇率		
生产价格指数		
吉尼系数		
钢产量		
总人口密度		
沪深300指数		
整个社会的货运		
家庭债务		

Annex 8: Non-seasonal first-order differencing of PV sales



Annex 9: PACF of PV sales



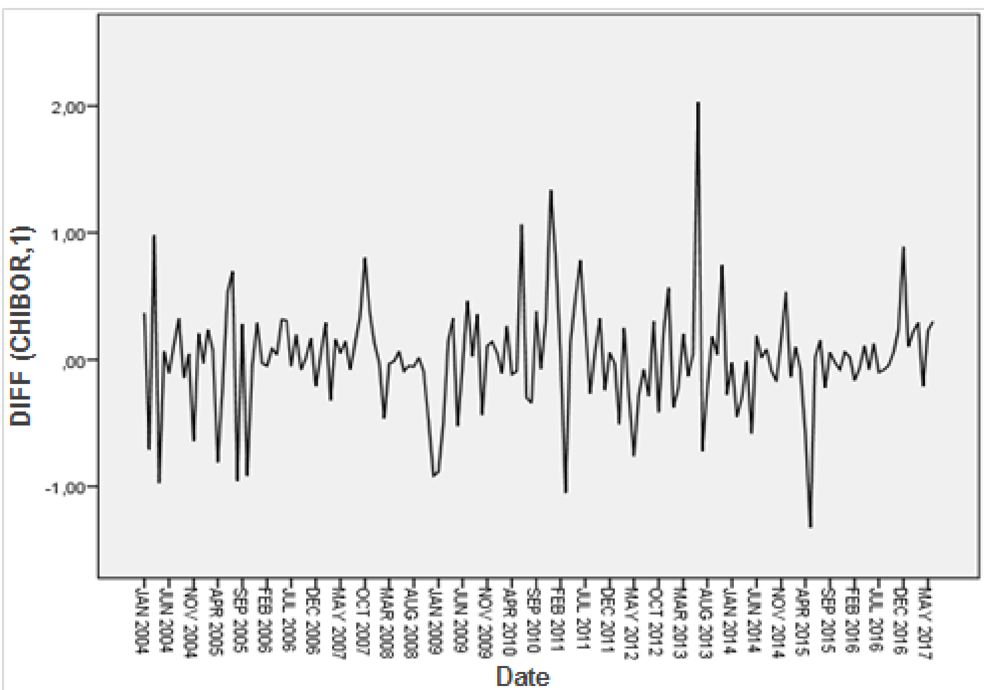
Annex 10: Box-Ljung statistic for seasonally-adjusted PV sales

Auto-correlation

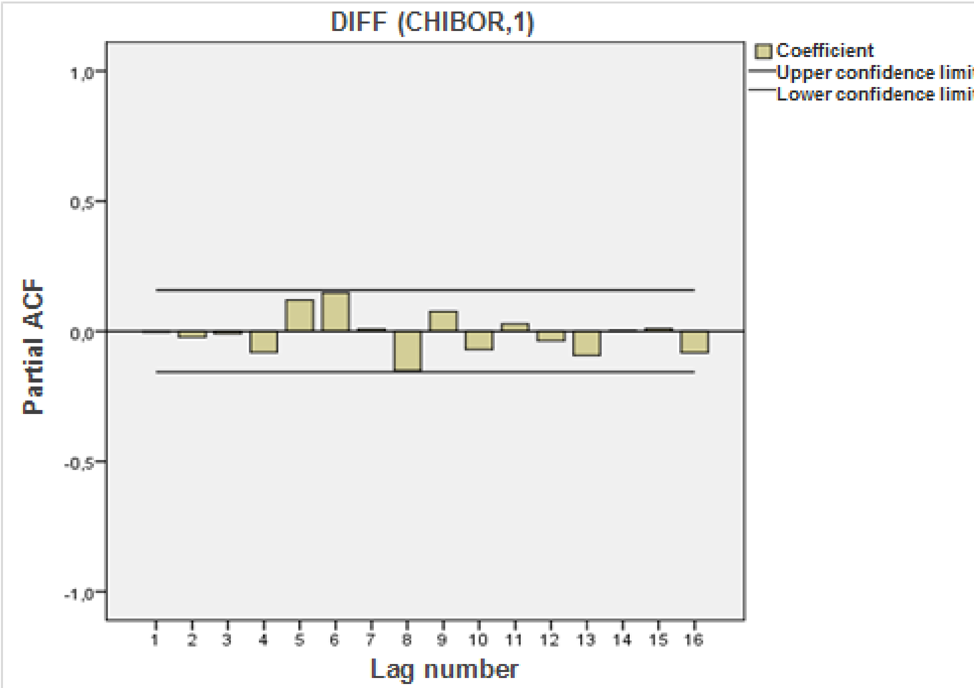
Time series: Seasonally adjusted DIFF (PV sales,1)

Lag	Auto-correlation	Standard error	Box-Ljung statistic Value	df	Sig.
1	,084	,078	1,168	1	,280
2	,072	,078	2,025	2	,363
3	,095	,077	3,539	3	,316
4	,031	,077	3,706	4	,447
5	,051	,077	4,141	5	,529
6	,005	,077	4,146	6	,657
7	,030	,076	4,303	7	,744
8	,016	,076	4,348	8	,824
9	,113	,076	6,564	9	,682
10	,051	,076	7,023	10	,723
11	,063	,075	7,717	11	,738
12	,057	,075	8,288	12	,762
13	,057	,075	8,875	13	,782
14	,039	,075	9,143	14	,822
15	-,135	,074	12,414	15	,647
16	,077	,074	13,502	16	,636

Annex 11: Non-seasonal first-order differencing of CHIBOR



Annex 12: PACF of CHIBOR



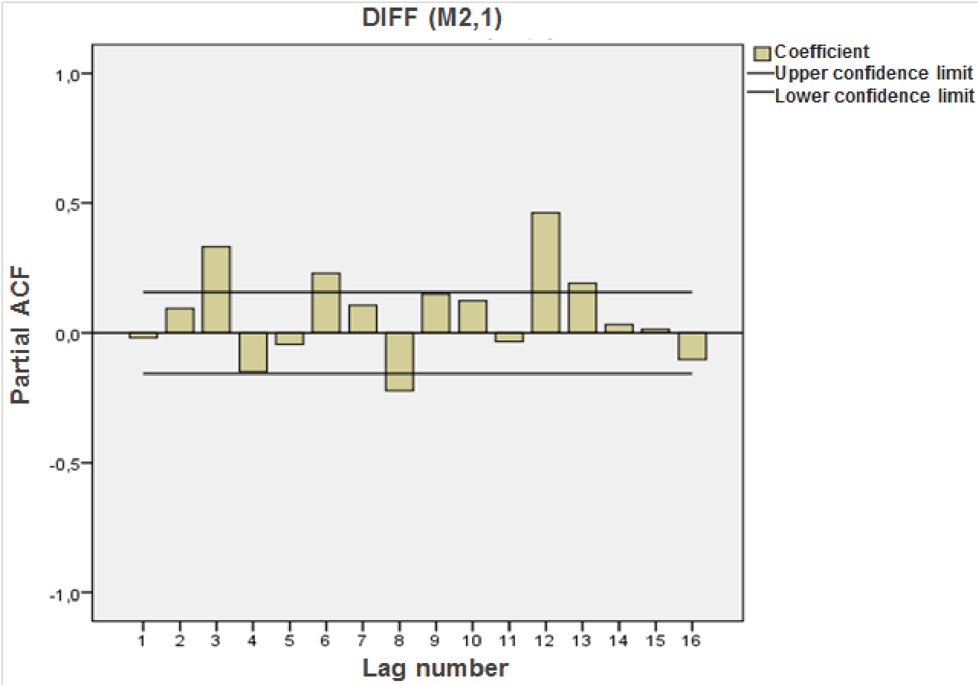
Annex 13: Box-Ljung statistic for seasonally-adjusted CHIBOR

Auto-correlation

Time series: Seasonally adjusted DIFF (CHIBOR,1)

Lag	Auto-correlation	Standard error	Box-Ljung statistic		
			Value	df	Sig.
1	,008	,078	,010	1	,922
2	-,056	,078	,525	2	,769
3	-,050	,077	,937	3	,817
4	-,027	,077	1,060	4	,901
5	,002	,077	1,061	5	,957
6	,039	,077	1,324	6	,970
7	,025	,076	1,431	7	,985
8	-,024	,076	1,531	8	,992
9	,033	,076	1,717	9	,995
10	,015	,076	1,756	10	,998
11	,069	,075	2,586	11	,995
12	,025	,075	2,693	12	,997
13	-,053	,075	3,202	13	,997
14	-,007	,075	3,211	14	,999
15	-,069	,074	4,073	15	,997
16	-,094	,074	5,669	16	,991

Annex 14: PACF of M2



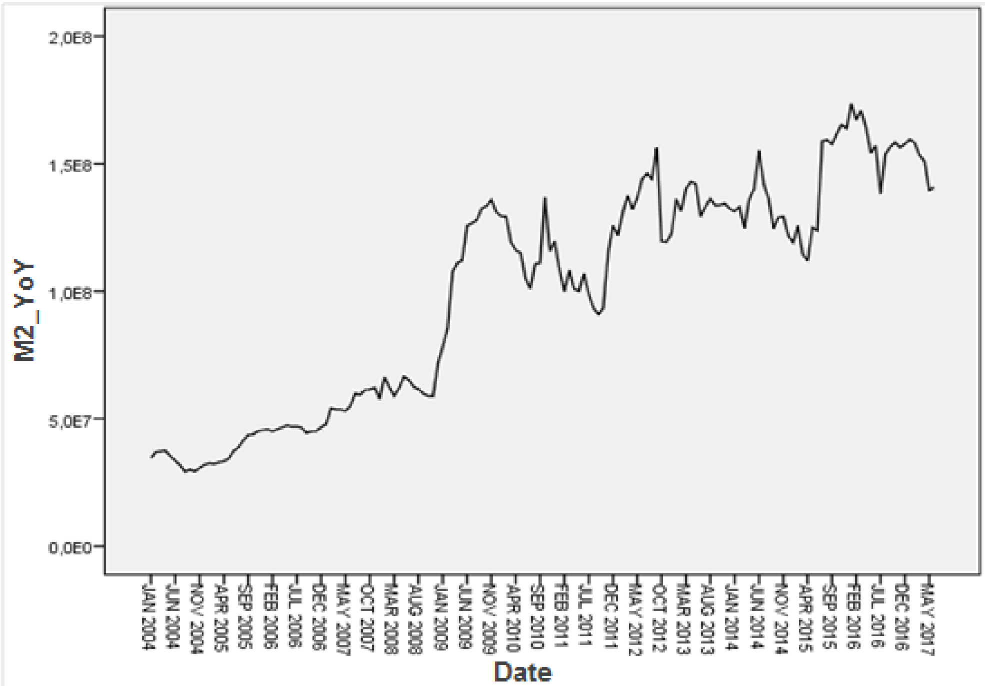
Annex 15: Box-Ljung statistic for seasonally-adjusted M2

Auto-correlation

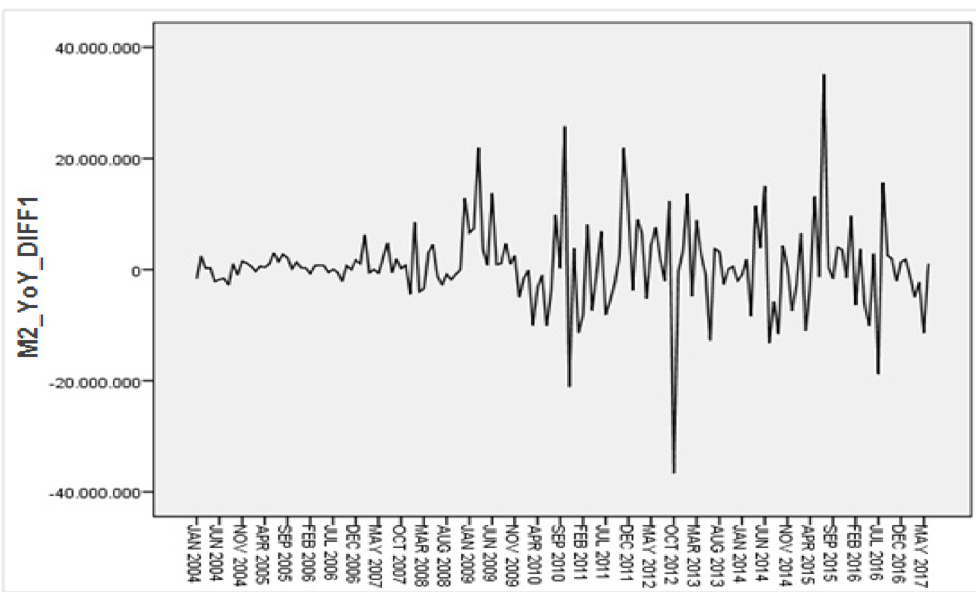
Time series: Seasonally adjusted DIFF (M2,1)

Lag	Auto-correlation	Standard error	Box-Ljung statistic Value	df	Sig.
1	-,032	,078	,168	1	,681
2	,035	,078	,370	2	,831
3	-,017	,077	,416	3	,937
4	-,017	,077	,464	4	,977
5	,007	,077	,473	5	,993
6	,005	,077	,477	6	,998
7	-,031	,076	,644	7	,999
8	,006	,076	,650	8	1,000
9	-,107	,076	2,632	9	,977
10	-,043	,076	2,957	10	,982
11	-,041	,075	3,251	11	,987
12	-,011	,075	3,273	12	,993
13	,050	,075	3,718	13	,994
14	,020	,075	3,792	14	,997
15	,149	,074	7,789	15	,932
16	-,023	,074	7,882	16	,952

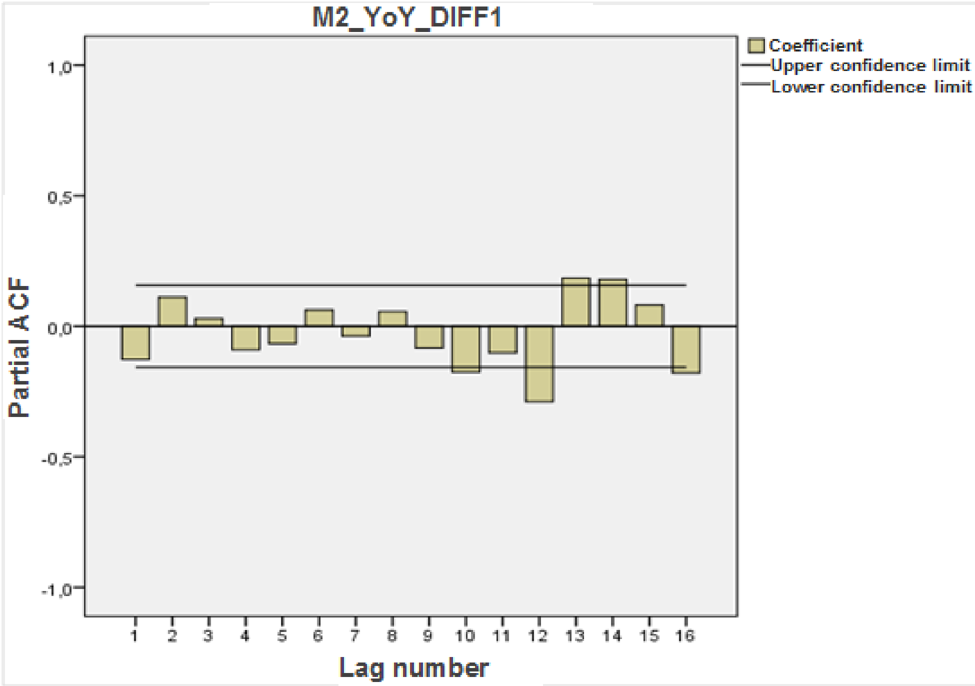
Annex 16: Plot of M2 YoY from January 2004 to June 2017



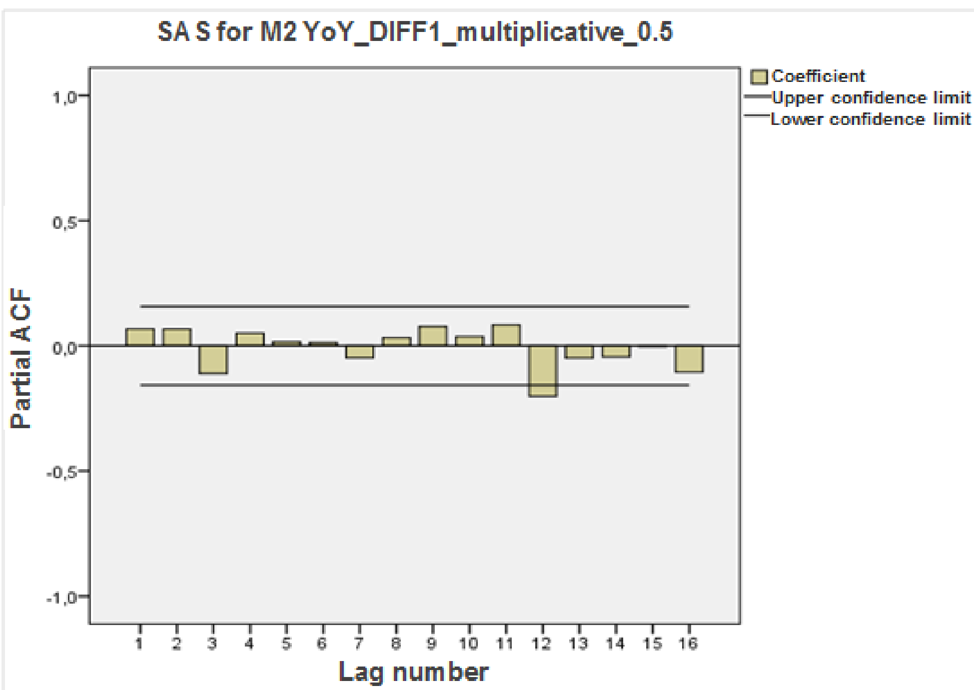
Annex 17: Non-seasonal first-order differencing of M2 YoY



Annex 18: PACF of M2 YoY



Annex 19: PACF of seasonally-adjusted M2 YoY

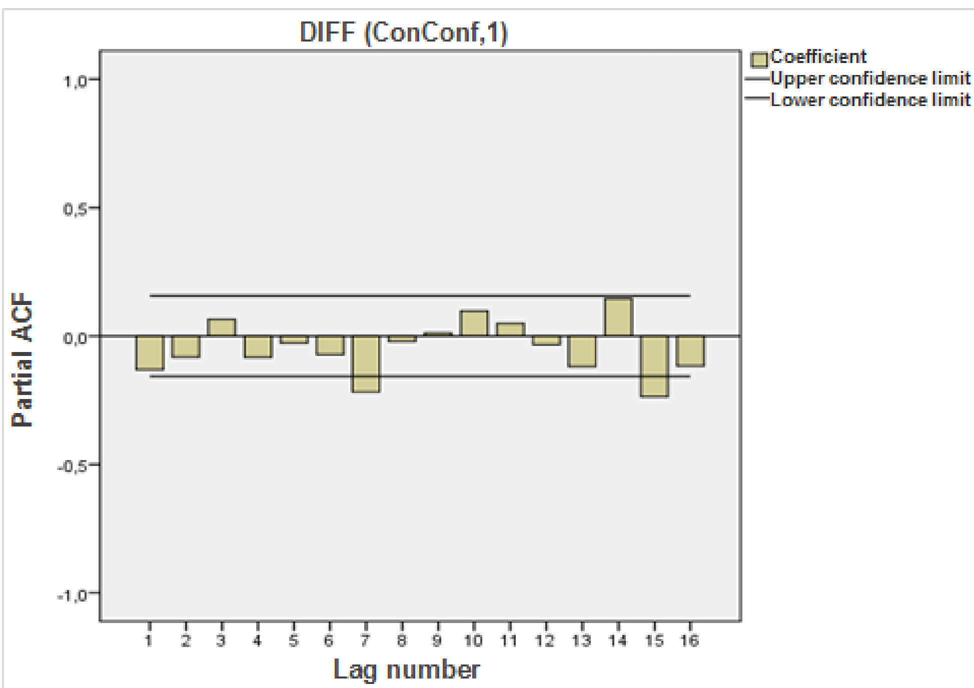


Annex 20: Box-Ljung statistic for seasonally-adjusted M2 YoY

Auto-correlation
Time series: Seasonally adjusted DIFF (M2 YoY,1)

Lag	Auto-correlation	Standard error	Box-Ljung statistic Value	df	Sig.
1	,068	,078	,753	1	,386
2	,072	,078	1,602	2	,449
3	-,101	,077	3,308	3	,347
4	,040	,077	3,581	4	,466
5	,006	,077	3,588	5	,610
6	,032	,077	3,762	6	,709
7	-,052	,076	4,229	7	,753
8	,027	,076	4,354	8	,824
9	,068	,076	5,162	9	,820
10	,064	,076	5,872	10	,826
11	,089	,075	7,272	11	,777
12	-,187	,075	13,462	12	,336
13	-,069	,075	14,306	13	,353
14	-,086	,075	15,643	14	,336
15	,025	,074	15,758	15	,398
16	-,112	,074	18,030	16	,322

Annex 21: PACF of ConConf



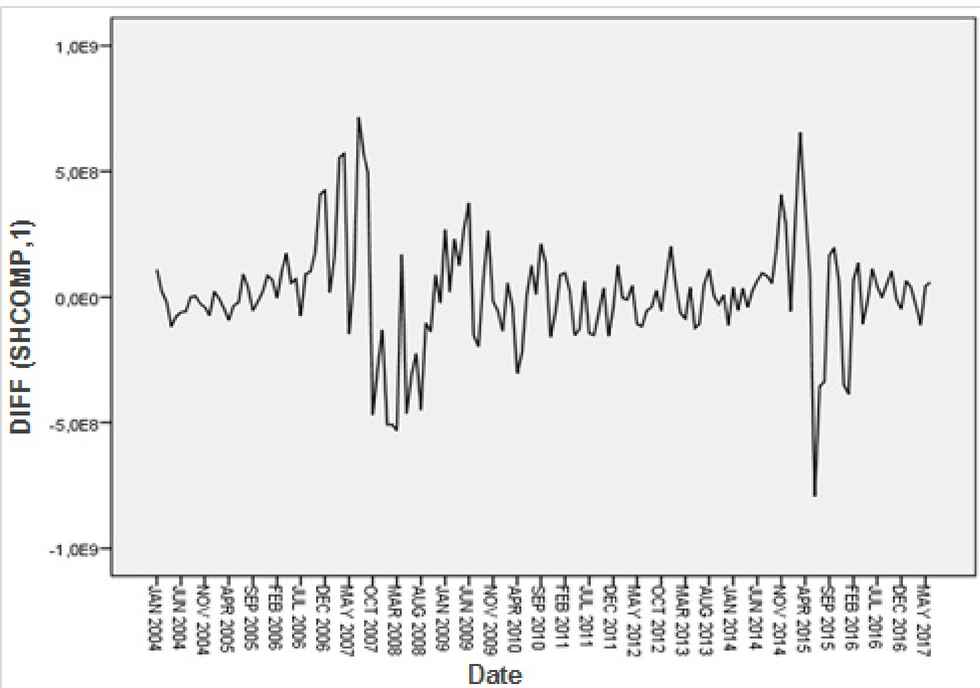
Annex 22: Box-Ljung statistic for seasonally-adjusted ConConf

Auto-correlation

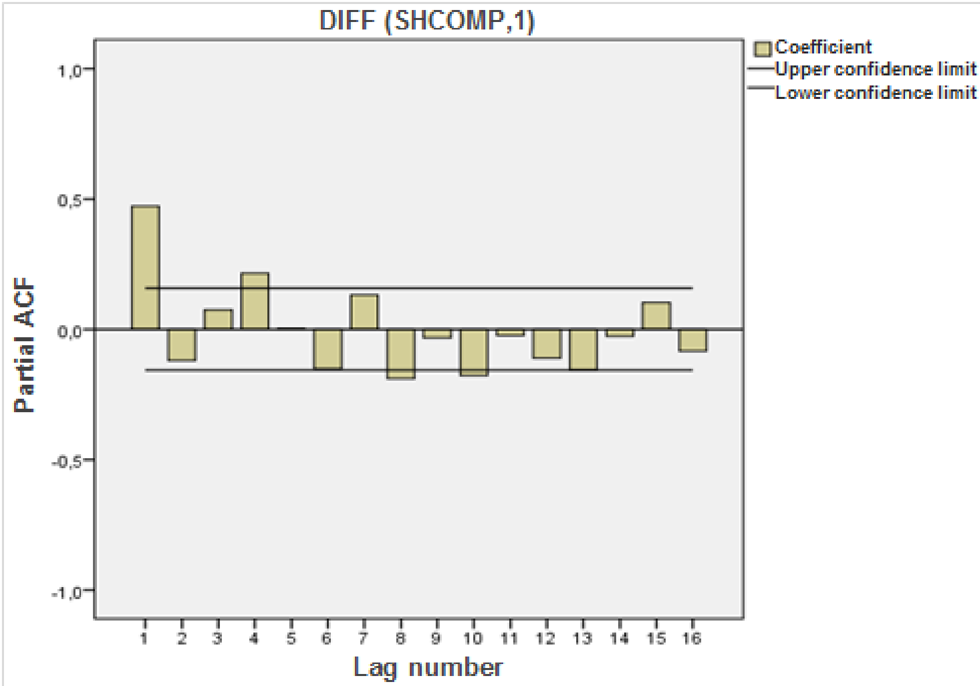
Time series: Seasonally adjusted DIFF (ConConf,1)

Lag	Auto-correlation	Standard error	Box-Ljung statistic Value	df	Sig.
1	-,005	,078	,004	1	,951
2	-,008	,078	,015	2	,993
3	-,069	,077	,813	3	,846
4	-,025	,077	,914	4	,923
5	,066	,077	1,656	5	,894
6	,058	,077	2,233	6	,897
7	,092	,076	3,683	7	,815
8	-,029	,076	3,825	8	,873
9	-,061	,076	4,462	9	,878
10	,028	,076	4,602	10	,916
11	,135	,075	7,826	11	,729
12	-,010	,075	7,843	12	,797
13	-,048	,075	8,254	13	,827
14	-,103	,075	10,141	14	,752
15	-,064	,074	10,883	15	,761
16	,034	,074	11,089	16	,804

Annex 23: Non-seasonal first-order differencing of SHCOMP



Annex 24: PACF of SHCOMP



Annex 25: Box-Ljung statistic for seasonally-adjusted SHCOMP

Auto-correlation

Time series: Seasonally adjusted DIFF (SHCOMP,1)

Lag	Auto-correlation	Standard error	Box-Ljung statistic Value	df	Sig.
1	-,043	,078	,299	1	,584
2	-,010	,078	,317	2	,853
3	,271	,077	12,609	3	,006
4	-,053	,077	13,085	4	,011
5	-,009	,077	13,098	5	,022
6	-,008	,077	13,108	6	,041
7	-,012	,076	13,131	7	,069
8	,011	,076	13,154	8	,107
9	-,113	,076	15,384	9	,081
10	,009	,076	15,397	10	,118
11	,012	,075	15,423	11	,164
12	-,194	,075	22,057	12	,037
13	,018	,075	22,113	13	,054
14	,012	,075	22,138	14	,076
15	-,142	,074	25,766	15	,041
16	,012	,074	25,793	16	,057

Annex 26: ADF test for entire set of time series-related indicators

```
> adf.test(daten$PVsales_ZSAS_1)

        Augmented Dickey-Fuller Test

data:  daten$PVsales_ZSAS_1
Dickey-Fuller = -5.4624, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

Warnmeldung:
In adf.test(daten$PVsales_ZSAS_1) : p-value smaller than printed p-value
> adf.test(daten$CHIBOR_ZSAS_2)

        Augmented Dickey-Fuller Test

data:  daten$CHIBOR_ZSAS_2
Dickey-Fuller = -5.0282, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

Warnmeldung:
In adf.test(daten$CHIBOR_ZSAS_2) : p-value smaller than printed p-value
> adf.test(daten$ConConf_ZSAS_3)

        Augmented Dickey-Fuller Test

data:  daten$ConConf_ZSAS_3
Dickey-Fuller = -5.0439, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

Warnmeldung:
In adf.test(daten$ConConf_ZSAS_3) : p-value smaller than printed p-value
> adf.test(daten$M2_YoY_ZSAS_5)

        Augmented Dickey-Fuller Test

data:  daten$M2_YoY_ZSAS_5
Dickey-Fuller = -4.7857, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

```
> adf.test(daten$M2_YoY_ZSAS_5)

        Augmented Dickey-Fuller Test

data:  daten$M2_YoY_ZSAS_5
Dickey-Fuller = -4.7857, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

Warnmeldung:
In adf.test(daten$M2_YoY_ZSAS_5) : p-value smaller than printed p-value
> adf.test(daten$ZSHCOMP_SAS_6)

        Augmented Dickey-Fuller Test

data:  daten$ZSHCOMP_SAS_6
Dickey-Fuller = -4.9076, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

Warnmeldung:
In adf.test(daten$ZSHCOMP_SAS_6) : p-value smaller than printed p-value
```

Annex 27: Derivation of MAPE in validation set (2014)

Date	Actual PV sales	Forecasted PV sales	Unsigned percentage error	MAPE
Jan 2014	1.738.459,00	1.436.425,19	17,4%	
Feb 2014	1.048.318,00	1.084.626,59	3,5%	
Mar 2014	1.447.575,00	1.443.052,30	0,3%	2.3%
Apr 2014	1.399.329,00	1.466.144,99	4,8%	
May 2014	1.440.206,00	1.430.288,58	0,7%	
Jun 2014	1.394.054,00	1.188.711,30	14,7%	9.5%
Jul 2014	1.265.765,00	1.213.128,16	4,2%	
Aug 2014	1.380.593,00	1.297.686,32	6,0%	
Sep 2014	1.584.866,00	1.346.688,29	15,0%	
Oct 2014	1.583.695,00	1.379.418,77	12,9%	
Nov 2014	1.642.328,00	1.292.765,92	21,3%	
Dec 2014	1.903.942,00	1.649.264,79	13,4%	

Literature citations

Adamowski, Jan; Karapataki, Christina (2010): “Comparison of Multivariate Regression and Artificial Neural Networks for Peak Urban Water-Demand Forecasting: Evaluation of Different ANN Learning Algorithms”. In: Journal of Hydrologic Engineering, vol. 15, pp. 729-743

Ahrens, Joachim (1999): ”Toward a Post-Washington Consensus: The Importance of Governance Structures in Less Developed Countries and Economies in Transition”. In: Journal for institutional innovation, development and transition, vol. 4 (2000), pp. 78-86

Akerlof, George A. (1970): “The Market for “Lemons”: Quality Uncertainty and the Market Mechanism”. In: The Quarterly Journal of Economics, vol. 84, no. 3, pp. 488-500

Alabi, M.A.; Issa, S.; Afolayan, R.B. (2013): “An Application of Artificial Intelligent Neural Network and Discriminant Analyses on Credit Scoring”. In: Mathematical Theory and Modeling, vol. 3, no. 11, pp. 20-28

Alavi, Maryam; Leidner, Dorthy E. (2001): “Review: Knowledge management and knowledge management systems: Conceptual foundations and research issues”. In: MIS Quarterly, pp. 107-136

Anders, Ulrich; Korn, Olaf (1999): “Model selection in neural networks”. In: Neural Networks, vol. 12, issue 2, pp. 309-323

Andreou, Elena; Ghysels Eric; Kourtellos, Andros (2011): “Forecasting with Mixed-Frequency Data”, The Oxford Handbook of Economic Forecasting, Oxford University Press, Oxford, pp. 225-246

Armesto, Michelle T. (2010): “Forecasting with Mixed Frequencies”. In: Federal Reserve Bank of St. Louis Review, November/December 2010, vol. 92, issue 6, pp. 521-536

Armstrong, J. Scott (2001): “Principles of Forecasting. A Handbook for Researchers and Practitioners”, Springer, New York

Arrow, Kenneth J. (1969): “The Organization of Economic Activity: Issues Pertinent to the Choice of Market Versus Nonmarket Allocation.” In: The Analysis of and Evaluation of Public Expenditure: The PPB System, vol. 1, Washington D.C., pp. 39-73

Aryeetey, Ernest (2004): A Development-Focused Allocation of the Special Drawing Rights. In: Atkinson, Anthony Barnes (ed.) “New Sources of Development Finance”, Oxford University Press, Oxford, pp. 90-109

Aschinger, Gerhard (2002):”Currency Board, Dollarisation or Flexible Exchange Rates for Emerging Economies? Reflections on Argentina”. In: Intereconomics: Review of European Economic Policy, March/April 2002, vol. 37, issue 2, pp. 110-115. Available on the Internet. URL: https://rd.springer.com/article/10.1007/BF02930159 [2019-07-16]

Backhaus, Klaus; Erichson, Bernd; Plinke, Wulff et al. (2018): “Multivariate Analysemethoden. Eine anwendungsorientierte Einführung”, 15th edition, Springer, Berlin

Backus, David K.; Kehoe, Patrick J.; Kydland, Finn E. (1992): “International Real Business Cycles”. In: The Journal of Political Economy, vol. 100, issue 4, pp. 745-775

Baer, Werner (1972):”Import Substitution and Industrialization in Latin America: Experiences and Interpretations”. In: Latin American Research Review, vol. 7, no. 1, pp. 95-122

Bareev, Timur (2014): “Application of different cluster typologies in Russian’s automotive cluster analysis”. In: Procedia Economics and Finance, vol. 14, pp. 42-48

Barkley Rosser, John Jr.; Rosser, Marina V. (2018): “Comparative Economics in a Transforming World Economy”, 3rd edition, The MIT Press, Cambridge, Massachusetts

Barnes, Tom (2018): “Making Cars in the New India: Industry, Precarity and Informality”, Cambridge University Press, Cambridge

Barney, Jay B. (1991): “Firm Resources and Sustained Competitive Advantage”. In: Journal of Management, vol. 17, no. 1, pp- 99-120

Barney, Jay B.; Wright, Mike; Ketchen, David J. Jr. (2001): “The resource-based view of the firm: Ten years after 1991”. In: Journal of Management, vol. 27, pp. 625-641

Beifuss, Annika (2015): “Leverage is a Double-Edged Sword”. In: Business Journal of the German Chamber of Commerce in China, October-November 2015, issue 5, pp. 24-25

Ben-Porath, Y. (1980): “The F-Connection: Families, Friends, and Firms and the Organization of Exchange”. In: Population and Development Review, vol. 6, pp. 1-30

Biesta, Gert (2012): “Mixed methods”. In: Arthur, James (ed.) “Research Methods and Methodologies in Education”, SAGE, Thousand Oaks, California, pp. 147-152

Bishop, Christopher M. (1996): “Neural Networks for Pattern Recognition”, Oxford University Press, Cambridge

Bresser-Pereira; Luiz Carlos; Gala, Paulo (2008): “Foreign savings, insufficiency of demand, and low growth”. In: Journal of Post Keynesian Economics, vol. 30, no. 3, pp. 315-334

Bresser-Pereira; Luiz Carlos; Nakano, Yoshiaki (2003):”Economic growth with foreign savings?” In: Brazilian Journal of Political Economy, vol. 23, no. 2, April-June 2003, pp. 3-27

Brooks, Chris (2014): “Introductory Econometrics For Finance”, 3rd edition, Cambridge University Press, Cambridge

Bryman, Alan (2009): “Mixed Methods in Organizational Research”. In: Buchanan, David A; Bryman, Alan (eds.) “The Sage Handbook of Organizational Research Methods”, Sage, London

Bryman, Alan; Bell, Emma (2015): “Business Research Methods”, 4th edition, Oxford University Press, Oxford

Bu, Qingxiu (2011): "Danone v. Wahaha: Who Laughs Last". In: Business Law Review, issue 6, pp. 140-147

Buckley, Peter J.; Casson, Marc C. (1991): "The future of the multinational enterprise", 2nd edition, The Macmillan Press, London

Cameron, John D. (2004): "The World Bank and the New Institutional Economics". Contradictions and Implications for Development Policy in Latin America. In: Latin American Perspectives, vol. 31, no. 4, pp. 97-103

Camm, Jeffrey D. (2015): "Essentials of Business Analytics", Cengage Learning, Connecticut, Stamford

Carayannis, Elias G. (2012): "Absorptive Capacity and Organizational Learning". In: Encyclopedia of the Sciences of Learning, Springer, Boston, Massachusetts, pp. 25-27

Carlson, Sune (1966): "Internationalization business research", Uppsala

Carnot, Nicolas; Koen, Vincent; Tissot, Bruno (2011): "Economic Forecasting and Policy", 2nd edition, Palgrave Macmillan, Basingstoke, Hampshire

Carrithers, David W. (2001): "Montesquieu and the Liberal Philosophy of Juris-prudence". In: Montesquieu's Science of Politics. Essays on The Spirit of Laws, Rowman & Littlefield, Lanham, Maryland, pp. 291-334

Chang, Crystal (2016): "China's 13th Five-Year Plan: Implications for the Automobile Industry". Paper published for Testimony before the U.S.-China Economic and Security Review Commission Hearing on China's 13th Five Year Plan, pp. 1-17. Available on the Internet. URL: https://www.uscc.gov/sites/default/files/Crystal%20Chang_Written%20Testimony%20042716.pdf [2019-07-16]

Chatterjee, Sheshadri; Kar, A.K. (2018): "Readiness of Smart City: Emerging Economy Perspective" In: Clement, Marc; Dwivedi, Yogesh K.; Lal, Banita et al. "Emerging Markets from a Multidisciplinary Perspective. Challenges, Opportunities and Research Agenda", Springer International Publishing, Cham

Chen, An-Sing; Leung, Mark T.; Daouk, Hazem (2003): "Application of neural networks to an emerging financial market: forecasting and trading the Taiwan Stock Index". In: Computers & Operations Research, vol. 30, pp. 901-923

Chen, Zhiyuan; Liu, Bing (2018): "Lifelong Machine Learning", 2nd edition, Morgan & Claypool Publishers, San Rafael, California

Chin, Gregory T. (2013): "Understanding Currency Policy and Central Banking in China". In: The Journal of Asian Studies, vol. 72, no. 3, pp. 519-538

Chow, G.C. (1986): "Chinese statistics". In: The American Statistician, vol. 40, issue 3, pp. 191-196

Christensen, Ronald (2001): "Advanced Linear Modelling. Multivariate, Time Series, and Spatial Data; Nonparametric Regression and Response Surface Maximization", 2nd edition, Springer, New York

Coase, R.H. (1988): “The Firm, the Market, and the Law”, The University of Chicago Press, Chicago

Coase, Ronald (1998): “The New Institutional Economics”. In: The American economic review, vol. 88, pp. 72-74

Coase, Ronald (2012): “Saving Economics from the Economists”. In: Harvard Business Review, December 2012 issue. Available on the Internet. URL: http://hbr.org/2012/12/saving-economics-from-the-economists/ar/1 [2019-07-16]

Coase, Ronald H. (1960): “The Problem of Social Cost”. In: Journal of Law and Economics, vol. 3, pp. 1-44

Cohn, Theodore H. (2016): “Global Political Economy. Theory and Practice”, 7th edition, Routledge, New York

Colton, Luke S.; Morrison, Wayne M. (1997): “The Chinese Transportation System: A Bottleneck or an Engine of Growth?”. In: China’s Economic Future: Challenges to U.S. Policy, M.E. Sharpe, New York, pp. 280-319

Comin, Diego; Gertler, Mark (2006): “Medium-term Business Cycles”. In: American Economic Review, vol. 96, issue 3, pp. 523-551

Confucius Institute Headquarter (n.d.). Available on the Internet. URL: http://www.chinesetest.cn/gosign.do?lid=0# [2019-07-16]

Corrigan, Michael W.; Grove, Doug; Vincent, Philipp F. (2011) : “Multi-Dimensional Education. A Common Sense Approach to Data-Driven Thinking”, SAGE, Thousand Oaks, California

Crowe, Michael; Sheppard, Lorraine (2012): “Mind mapping research methods”. In: Quality and Quantity, vol. 46, issue 5, pp. 1493-1504

Dahlmann, Carl J. (1979): “The Problem of Externality”. In: The Journal of Law and Economics, vol. 22, no. 1, pp. 141-162

Dai, Xiudian (2013): “Politics of digital development: informatization and governance in China”. In: Gashenko, Irina V.; Zima, Yulia S; Davidyan, Armenak V. (eds.) “Digital World: Connectivity, Creativity and Rights”, Routledge, Abingdon, Oxfordshire, pp. 34-51

Davidson, Paul (2002): “Financial Markets, Money and the Real World”, Edward Elgar, Cheltenham, Gloucestershire

Day, Iris (2017): “Underlying Consumer Price Inflation in China”. In: RBA Bulletin, Reserve Bank of Australia, pp. 29-36. Available on the Internet. URL: https://www.rba.gov.au/publications/bulletin/2017/dec/pdf/bu-1217-4-underlying-consumer-price-inflation-in-china.pdf [2019-07-16]

De Veaux, Richard D.; Ungar, Lyle H. (1994): “Multicollinearity: A tale of two nonparametric regressions”. In: Cheeseman, Peter; Oldford, R. Wayne (eds.) “Selecting Models from Data. Artificial Intelligence and Statistics IV”, Springer, New York, pp. 393-402

Detienne, Kristen Bell; Detienne, David H.; Joshi, Shirish A. (2003): "Neural Networks as Statistical Tools for Business Researchers", Organizational Research Methods, vol. 6, issue 2, pp. 236-265

Devlin, Robert; Ffrench-Davis, Ricardo (1995): "The great Latin America crisis: a decade of asymmetric adjustment". In: Revista de Economica Politica, vol. 15, no. 3 (59), pp. 117-142

Devore, Jay (2015): "Probability and Statistics for Engineering and the Sciences", 9th edition, Brooks/Cole Publishing, Pacific Grove, California

Du, Jiangze; Wang, Jying-Nan; Lai Kin Keung et al. (2018): "Chinese currency exchange rates analysis: risk management, forecasting and hedging strategies", Routledge, New York

Du, Ke-Lin; Swamy, M.N.S. (2014): "Neural Networks and Statistical Learning", Springer, London

Dunning, John H. (2001): "The eclectic (OLI) paradigm of international production: past, present and future". In: International Journal of the Economics of Business, vol. 8, issue 2, pp. 173-190

Durbin, James; Koopmann, Siem Jan (2012): "Time Series Analysis by State Space Methods", 2nd edition, Oxford University Press, Oxford

Edwards, Sebastian (2009): "Forty Years of Latin America's Economic Development: From The Alliance For Progress To The Washington Progress", National Bureau Of Economic Research NBER Working Paper Series, working paper 15190. Available on the Internet. URL: http://www.nber.org/papers/w15190 [2019-07-16]

Enderwick, Peter (2007): "Understanding Emerging Markets: China and India", Routledge, New York

Epstein, Gerald; Grabel, Ilene; Jomo, K.S. (2008): "Capital Management Techniques in Developing Countries: Managing Capital Flows in Malaysia, India, and China". In: Ocampo, Jose Antonio; Stiglitz, Joseph E. (eds.) "Capital Market Liberalization and Development", Oxford University Press, New York, pp. 139-169

Ermis, Murat; Sahingoz, Ozgur K.; Ulengin, Fusun (2004): "An Agent Based Supply Chain System with Neural Network Controlled Processes". In: Zhang Jun; He, Ji-Huan; Fu, Yuxi (eds.) "Computational and Information Science", CIS 2004, Lecture Notes in Computer Science, vol. 3314, Springer, Berlin, pp. 837-846

Estey, J.A. (1936): "Orthodox Economic Theory: A Defense". In: Journal of Political Economy, vol. 44, no. 6, pp. 791-802

Fantazzini, Dean; Toktamysova, Zhamal (2015): "Forecasting German car sales using Google data and multivariate models". In: International Journal of Production Economics, vol. 170, pp. 97-135

Fantom, Neil; Serajuddin, Umar (2016): "The World Bank's Classification of Countries by Income", World Bank Policy Research Working Paper, no. 7528, Washington DC

Faulkner, David (2006): “Cooperative Strategy Strategic Alliances and Networks”. In The Oxford Handbook of Strategy: A Strategy Overview and Competitive Strategy, Oxford University Press, New York, pp. 610-650

Feldstein, Martin (2017): “Underestimating the Real Growth of GDP, Personal Income, and Productivity”. In: Journal of Economic Perspectives, vol. 31, no. 2, pp. 145-164

Feng, Qiushi (2018): “Variety of Development. Chinese Automakers in Market Reform and Globalization”, Palgrave Macmillan, Singapore

Fischer, Doris (2015): “Like an Athlete on Dope. China’s Economy in 2015 and its Detoxification”. In: Business Journal of the German Chamber of Commerce in China, October-November 2015, issue 5, pp. 18-19

Fredriksson, Gustav; Roth, Alexander; Tagliapietra, Simone (2018): “Is the European automotive industry ready for the global electric vehicle revolution?”. In: Policy Contribution, issue no. 26, pp. 1-21. Available on the Internet. URL: http://bruegel.org/wp-content/uploads/2018/12/PC-26_2018_1.pdf [2019-07-16]

Frumkin, Norman (2015): “Guide to Economic Indicators”, 4th edition, Routledge, Abingdon, Oxfordshire

Furubotn, Eirik G.; Richter, Rudolf (2000): “Institutions and Economic Theory. The Contribution of the New Institutional Economics”, The University of Michigan Press, Ann Arbor, Michigan

Gallegati, Marco (2014): “Early Warning Signals of Financial Stress: A “Wavelet-Based” Composite Indicators Approach. In: Advances in Non-linear Economic Modeling: Theory and Applications, pp. 115-138

Gao, Junjie; Xie, Yanan; Cui, Xiaomin et al. (2018): “Chinese automobile sales forecasting using economic indicators and typical domestic brand automobile sales data: A method based on econometric model”. In: Advances in Mechanical Engineering, vol. 10, no. 2, pp. 1-11

George, Frank H. (1984): “The Science of Investment”, Routledge, Abingdon, Oxfordshire

Ghysels, Eric; Osborn, Denise R. (2001): “The Econometric Analysis Of Seasonal Time Series”, Cambridge University Press, Cambridge

Gilad, Benjamin (2004): “Early warning: using competitive intelligence to anticipate market shifts, control risk, and create powerful strategies”, Amacom Books, New York

Glowik, Mario (2016): “Market Entry Strategies: Internationalization Theories, Concepts and Cases of Asian High-Technology Firms”, 2nd edition, De Gruyter Oldenbourg, München

Glowik, Mario; Bruhs, Sarah Maria (2014): “Business-To-Business. A global network perspective”, Routledge, New York

Glowik, Mario; Smyczek, Slawomir (2011): “International Marketing Management: Strategies, Concepts and Cases in Europe”, Oldenbourg Wissenschaftsverlag, München

Godfrey, Richard (2016): “Strategic Management. A critical introduction”, Routledge, Abingdon, Oxfordshire

Gonzalez-Rivera, Gloria (2016): “Forecasting for Economics and Business”, Routledge, New York

Grant, Robert M. (2015): “Foundations of Strategy”, 2nd edition, John Wiley & Sons, West Sussex, Chichester

Guo, Grace Chun; Jiang, Crystal X.; Yang, Qin (2017): "The Effect of Government Involvement on Chinese Firms’ Corporate Entrepreneurial Activities: The Case of Chinese Automobile Industry". In: New England Journal of Entrepreneurship: vol. 20, no. 1, pp. 6-16

Hair, Joseph F.; Celsi, Mary W; Money, Arthur H. et al. (2015): “Essentials of Business Research Methods”, 2nd edition, Routledge, New York

Halawi, Leila A.; Aronson, Jay E.; McCarthy, Richard V. (2005): “Resource-Based View of Knowledge Management for Competitive Advantage”. In: The Electronic Journal of Knowledge Management, vol. 3, issue 2, pp. 75-86

Han, Jiawei; Kamber, Micheline; Pei, Jian (2012): “Data Mining: Concepts and Techniques”, 3rd edition, Elsevier, Oxford

Haykin, Simon (2009): “Neural Networks and Learning Machines“, 3rd edition, Pearson Prentice Hall, New Jersey, Upper Saddle River

Haynes, Jeffrey (2008):”Development Studies”, Polity Press, Cambridge

Henry, Anthony E. (2018): “Understanding Strategic Management”, Oxford University Press, 3rd edition, New York

Herr, Hansjörg; Priewe, Jan (2005): “Beyond the “Washington Consensus”: Macroeconomic Policies for Development”. In: International Politics and Society, 2/2005, pp. 72-97

Herr, Hansjörg; Ruoff, Bea (2018): “Insufficient economic convergence in the world economy: How do economists explain why too many countries do not catch up?” In: Agrarian South: Journal of Political Economy, pp. 1-27

Herrmann, Andreas; Brenner, Walter; Stadler, Rupert (2018): “Autonomous Driving. How the Driverless Revolution Will Change the World”, Emerald Publishing, Bingley, West Yorkshire

Hitt, Michael A.; Ireland, R. Duane; Hoskisson, Robert E. (2016): ”Strategic Management: Competitiveness & Globalization: Concepts and Cases, 12th edition, Cengage Learning, Boston, Massachusetts

Holweg, Oliver N.; Luo, Jianxi; Oliver, Nick (2009): „The past, present and future of China’s automotive industry: a value chain perspective“. In: International Journal of Technological Learning, Innovation and Development, vol. 2, no. 1-2, pp. 76-118

Holz, Carsten A. (2014): “The quality of China’s GDP statistics”. In: China Economic Review, vol. 30, pp. 309-338

Hott, Christian; Kunkel, A.; Nerb, G. (2007): “The Accuracy of Turning Point Predictions with the Ifo Business Climate”. In: Goldrian, Georg (ed.) ”Handbook of Survey-Based Business Cycle Analysis”, Edward Elgar, Northampton, Massachusetts, pp. 175-196

Huang, Wei; Lai, Kin Keung; Nakamori, Yoshiteru (2007): “Neural Networks in Finance and Economics Forecasting”. In: International Journal of Information Technology & Decision Making, vol. 6, no. 1, pp. 113-140

Huang, Yiping; Wang, Xun; Wang Bijun et al. (2013): “Financial Reform in China. Progress and Challenges.” In: Park, Yung Chul; Patrick, Hugh; Meissner, Larry (eds.) “How Finance Is Shaping the Economies of China, Japan and Korea, Columbia”, University Press, New York

Hülsmann, Marco; Borscheid, Detlef; Friedrich, Christoph M. et al. (2012): “General Sales Forecast Models for Automobile Markets and their Analysis”. In: Transactions on Machine Learning and Data Mining, vol. 5, no. 2, pp. 65-86

Hymer, Stephen H. (1976): “The international operations of national firms. A study of foreign direct investment”, The MIT Press, Cambridge, Massachusetts

International Energy Agency (2018): “Global EV Outlook 2018: Towards cross-modal electrification”. Available on the Internet. URL: http://centrodeinnovacion.uc.cl/assets/uploads/2018/12/global_ev_outlook_2018.pdf [2019-07-16]

International Monetary Fund (2015): “World Economic Outlook: Uneven Growth. Short- and Long-Term Factors”, Washington, pp. 1-230. Available on the Internet. URL: http://www.imf.org/external/pubs/ft/weo/2015/01/ [2019-07-16]

International Monetary Fund (2017): “Argentina. Staff report for the 2017 Article IV consultation”. Available on the Internet. URL: https://www.imf.org/~/media/Files/Publications/CR/2017/cr17409.ashx [2019-07-16]

International Monetary Fund (2018): “World Economic Outlook: Cyclical Upswing, Structural Change”, Washington DC. Available on the Internet. URL: https://www.imf.org/en/Publications/WEO/Issues/2018/03/20/world-economic-outlook-april-2018 [2019-07-16]

International Monetary Fund (n.d.; a): “IMF DataMapper: GDP current prices”. Available on the Internet. URL: http://www.imf.org/external/datamapper/NGDPD@WEO/OEMDC/ADVEC/WEOWORLD [2019-07-16]

Izenman, Alan J. (2008): “Modern Multivariate Statistical Techniques: Regression, Classification, and Manifold Learning”, Springer Science+Business Media, New York

Jiang, Dou (2016): “Inflation and inflation uncertainty in China”. In: Applied Economics, vol. 48, no. 41, pp. 3935-3943

Johanson, Jan; Mattson, Lars-Gunnar (1988): “Internationalization in industrial systems – a network approach”. In: Hood Neil; Vahlne, Jan-Erik (eds.) “Strategies in Global Competition”, Croom Helm, New York

Johnstone, Karla; Gramling, Audrey; Rittenberg, Larry E.: (2013): ”Auditing: A Risk-Based Approach to Conducting a Quality Audit”, 9th edition, Cengage Learning, University of Wisconsin, Madison, Wisconsin

Juselius, Katarina (2009): “The Long Swings Puzzle: What the Data Tell When Allowed to Speak Freely”. In: Mills, Terence C; Patterson, Kerry (eds.) “Palgrave Handbook of Econometrics”, vol. 2: Palgrave Macmillan, London pp. 349-384

Kaastra, Iebeling; Boyd, Milton (1996): “Designing a neural network for forecasting financial and economic time series”. In: Neurocomputing, vol. 10, pp. 215-236

Kaminsky, Graciela L.; Reinhart, Carmen M.; Vegh, Carlos A. (2004).: “When It Rains, It Pours: Procyclical Capital Flows and Macroeconomic Policies”, NBER working paper, no. 10780, pp. 1-58

Kelleher, John D.; D`Arcy, Aoife; Namee, Brian Mac (2015): “Fundamentals of Machine Learning for Predictive Data Analytics: Algorithms, Worked Examples, and Case Studies”, The MIT Press, Cambridge, Massachusetts

Kendall, Maurice G.; Ord, J. Keith (1990): “Time series”, 3rd edition, Hodder Arnold, London

Kennedy, Peter (2003): A Guide to Econometrics, 5th edition, The MIT Press, Cambridge, Massachusetts

Khanna, Tarun; Palepu, Krishna G. (2010): “Winning in Emerging Markets: A Road Map for Strategy and Execution”, Harvard Business Press, Boston

Koch-Weser, Iacob N. (2013): “The Reliability of China’s Economic Data: An Analysis of National Output”, U.S.-China Economic and Security Review Commission Staff Research Project, pp. 1-44. Available on the Internet. URL: https://www.uscc.gov/sites/default/files/Research/TheReliabilityofChina%27sEconomicData.pdf [2018-08-19]

Konar, Amit; Bhattacharya, Diptendu (2017): “Time-series Prediction and Applications: A Machine Intelligence Approach”, Springer International Publishing, Cham

Koopmans, Tjalling C. (1957): “Three Essays on the State of Economic Science”, McGraw-Hill, New York

Kotz, David M. (2004): "The 'Uzbek Growth Puzzle' and the Washington Consensus". At: the Allied Social Science Associations Convention, San Diego, California

Kouneva-Loewenthal, Neli; Vojvodic, Goran (2012): “Corruption and its Effect on Foreign Direct Investment in the Energy Sector of Emerging and Developing economies”. In: Van Tulder, Rob; Verbeke, Alain; Voinea, Liviu (eds.) “New Policy Challenges for European Multinationals, Progress in International Business Research”, vol. 7, Emerald Group Publishing, pp. 339-363

Kregel, Jan (2008):"The Discrete Charm of the Washington Consensus". In: Journal of Post Keynesian Economics, vol. 30, no. 4, pp. 541- 560

Kruse, Rudolf; Borgelt, Christian; Klawonn, Frank et al. (2016): "Computational Intelligence: A Methodological Introduction", 2nd edition, Springer, London

Kumar, Anoop S.; Kamaiah, Bandi (2017): "Co-movement among Asian Forex Markets: Evidence from Wavelet Methods". In: Current Issues in Economics and Finance, Springer Nature Singapore, pp. 53-63

Kuvulmaz, Janset; Usanmaz, Serkan; Engin, Seref Naci (2005): "Time series Forecasting by Means of Linear and Nonlinear Models". In: 4th Mexican International Conference on Artificial Intelligence, Springer, Berlin, pp. 504-513

Kvintradze, Eteri (2010):"Russia's Output Collapse and Recovery: Evidence from the Post-Soviet Transition". In: IMF Working Paper, Strategy, Policy, and Review Department. Available on the Internet. URL: http://www.imf.org/external/pubs/ft/wp/2010/wp1089.pdf [2019-07-16]

Law, Rob; Pine, Ray (2004): "Tourism Demand Forecasting for the Tourism Industry: A Neural Network Approach". In: Zhang, Peter G. (ed.) "Neural Networks in Business Forecasting", Idea Group Publishing, Hershey, Pennsylvania, pp. 121-141

Layton, Allan P. (1991): "Some Australian experience with leading indicators". In: Lahiri, Kajal; Moore, Geoffrey H. (eds.) "Leading economic indicators. New approaches and forecasting records", Cambridge University Press, Cambridge, pp. 211-230

Li, He; Yu, Zhixiang; Zhang, Chuanjie et al. (2017): "Determination of China's foreign exchange intervention: evidence from the Yuan/Dollar market". In: Studies in Economics and Finance, vol. 34, issue 1, pp. 62-81

Li, Hongxing; Chen, C.L. Philip; Huang, Han-Pang (2000): "Fuzzy Neural Intelligent Systems: Mathematical Foundation and the Applications in Engineering", CRC Press, Boca Raton, Florida

Li, Jieyin (2009): "Factors affecting international commercial dispute – resolution negotiations in China". In: ADR Bulletin, vol. 11, no. 3, article 5, pp. 56-61

Li, Ziran (2015): "Emergence of China's 2006-2007 Stock Market Bubble and Its Burst". In: Cheng, Siwei; Li, Ziran (eds.) "The Chinese Stock Market Volume II: Evaluation and Prospects", Palgrave Macmillan, Basingstoke, Hampshire, pp. 61-124

Liang, Priscilla; Ouyang, Alice; Willet, Thomas D. (2009): "The RMB Debate and International Influences on China's Money and Financial Markets". In: Barth, James R; Tatom, John A.; Yago, Glenn (eds.) "China's Emerging Financial Markets: Challenges and Opportunities", Springer, New York, pp. 267-301

Liu, Fang; Zhang, Jun; Zhu, Tian (2016): "How much can we trust China's investment statistics?" In: Journal of Chinese Economic and Business Studies, vol. 14, pp. 215-228

Lu, Wen-Min; Hung, Shiu-Wan; Kweh, Qian Long et al. (2014): "Production and Marketing Efficiencies of the U.S. Airline Industry: A Two-Stage Network DEA Approach. In: Cook, Wade; Zhu, Joe (eds.) "Data Envelopment Analysis: A Handbook of Modeling Internal Structure and Network", Springer, New York, pp. 537-568

Maciel, Leandro S.; Ballini, Rosangela (2010): "Neural Networks Applied to Stock Market Forecasting: An Empirical Analysis". In: Journal of the Brazilian Neural Network Society, vol. 8, issue 1, pp. 3-22

Magnani, Giovanna; Zucchella, Antonella; Floriani, Dinora (2018): "The logic behind foreign market selection: Objective distance dimensions vs. strategic objectives and psychic distance". In: International Business Review, vol. 27, pp. 1-20

Mahadevan, B. (2010): "Operations Management: Theory & Practice", 2nd edition, Pearson Education, New Delhi

Mak, Wendy (2009): "Forecasting the sustainability of China's economic performance: early twenty-first century and beyond". In: Klein, Lawrence R. (ed.) "The Making of National Economic Forecasts", Edward Elgar, Cheltenham, Gloucestershire, pp. 27-68

Mani, Sunil (2017): "Leadership in the automobile industry: the case of India's Tata Motors". In: Malerba, Franco; Mani, Sunil; Adams, Pamela (eds.) "The Rise to Market Leadership. New Leading Firms from Emerging Countries", Edward Elgar, Cheltenham, Gloucestershire, pp. 68-98

Mankiw, N. Gregory (1987): "The Optimal Collection of Seigniorage. Theory and Evidence". In: Journal of Monetary Economics, vol. 20, pp. 327-341

Marangos, John (2007):"What happened to the Washington Consensus? The evolution of international development policy" In: The Journal of Socio Economics 38 (2009), pp. 197-208

Mashrgy, Mohamed Al; Bouguila, Nizar, Daoudi (2011): "A Robust Approach for Multivariate Binary Vectors Clustering and Feature Selection". In: Lu, Bao-Liang; Zhang, Liqing; Kwok, James (eds.) "Neural Information Processing", Springer, Berlin, pp. 125-133

McCaffrey, James (2015): "Gradient Descent Training Using C#". In: The Microsoft Journal for Developers, vol. 30, no. 3, March 2015, pp. 68-73. Available on the Internet. URL: https://msdn.microsoft.com/en-us/magazine/dn913188 [2019-07-16]

McGranahan, Donald (1972): "Development indicators and development models". In: The Journal of Development Studies, vol. 8, issue 3, pp. 91-102

McLeod, Gordon (1983): "Box-Jenkins In Practice. Univariate Stochastic and Transfer Function / Intervention Analysis", section 5, GJP Publication, Lancaster

McNelis, Paul D. (2005): "Neural Networks in Finance: Gaining Predictive Edge in the Market", Elsevier Academic Press, Burlington, Massachusetts

Medeiros, Carlos Aguiar de (2008): "Financial dependency and growth cycles in Latin American countries". In: Journal of Post-Keynesian Economics, vol. 31, no. 1, pp. 79-99

Milton, John; Ohira, Toru (2014): “Mathematics as a Laboratory Tool. Dynamics, Delays and Noise”, Springer, New York

Ministry of Commerce of the People’s Republic of China (1994): “Formal Policy on Development of Automotive Industry”. Available on the Internet. URL: http://english.mofcom.gov.cn/aarticle/lawsdata/chineselaw/200211/20021100053370.html [2019-07-16]

Ministry of Commerce of the People’s Republic of China (n.d.). Available on the Internet. URL: http://english.mofcom.gov.cn/article/newsrelease/significantnews/201707/20170702607364.shtml [2019-07-16]

Mishra, R.K., Zhou Shaopeng (2011): “Economic Reforms in India and China”, Allied Publishers, New Delhi

Mody, Ashoka (2004): “What is an Emerging Market”, IMF Working Paper, no. 4/177, pp. 1-24. Available on the Internet. URL: https://www.imf.org/en/Publications/WP/Issues/2016/12/31/What-is-An-Emerging-Market-17598 [2019-07-16]

Moody’s Investors Service (2018): “Volkswagen Aktiengesellschaft: Credit Opinion Update Following Outlook Change to Stable. Available on the Internet. URL: https://www.volkswagenag.com/presence/investorrelation/publications/fixed-income/rating/2018/2018%2003%2028%20Moody%27s%20Credit%20Opinion.pdf [2019-07-16]

Moore, Basil J. (2006): “Shaking the Invisible Hand. Complexity, Endogenous Money and Exogenous Interest Rates”, Palgrave Macmillan, New York

Moosmayer, Dirk C.; Chong, Alain Yee-Loong; Liu, Martin J. (2013): “A neural network approach to predicting price negotiation outcomes in business-to-business contexts”. In: Expert Systems with Applications, pp. 3028-3035

Nagaraj, R. (2012): “Growth, Inequality and Social Development in India. Is Inclusive Growth Possible?”, Palgrave Macmillan, Basingstoke, Hampshire

National Development and Reform Commission of the People’s Republic of China (2004): “汽车产业发展政策 (Automobile Industry Development Policy)”. Available on the Internet. URL: http://tzs.ndrc.gov.cn/zttp/xkxmql/xkxmyj/200507/t20050719_78926.html [2019-07-16]

Naughton, Barry (2007): “The Chinese Economy. Transitions and Growth”, The MIT Press, Cambridge, Massachusetts

Naughton, Barry (2018): “The Chinese Economy: Adaptation and Growth”, The MIT Press, 2nd edition, Cambridge, Massachusetts

Nielsen, Lynge (2011): “Classification of Countries Based on Their Level of Development: How it is Done and How it Could be Done”, IMF Working Paper, no. 11/31, pp. 1-46. Available on the Internet. URL: http://www.imf.org/external/pubs/cat/longres.aspx?sk=%2024628.0 [2019-07-16]

North, Douglass C. (1990): “Institutions, institutional change and economic performance”, Cambridge University Press, Cambridge

Ocampo, Jose Antonio (2004): “Latin America’s Growth and Equity Frustrations During Structural Reforms”. In: Journal of Economic Perspectives, vol. 18, no. 2, pp. 67-88

OECD (2018): “Economic Outlook for Southeast Asia, China and India 2018 – Update: Promoting Opportunities in E-commerce”, OECD Publishing, Paris, pp. 1-106. Available on the Internet. URL: http://www.oecd.org/economy/economic-outlook-for-southeast-asia-china-and-india-2018-update-9789264302990-en.htm [2019-07-16]

Ord, Keith; Fildes, Robert (2013): “Principles of Business Forecasting. International Edition”, South-Western College Publishing, Mason, Ohio

Palley, Thomas I. (2003): ”The Economics of Exchange Rates and the Dollarization Debate”. In: International Journal of Political Economy, vol. 33, no. 1, pp. 61-82

Pan, Heping; Tilakaratne, Chandima; Yearwood, John (2005): “Predicting Australian Stock Market Index Using Neural Networks Exploiting Dynamical Swings and Intermarket Influences”. In: Journal of Research and Practice in Information Technology, vol. 37, issue 1, pp. 43-55

Pastor, Manuel Jr. (1989):”Latin America, the Debt Crisis, and the International Monetary Fund”. In: Latin American Perspectives, vol. 16, no. 1, Latin America’s Debt and the World Economic System, pp. 79-110

Patton, Michael Q. (2015): “Qualitative research & evaluation methods: integrating theory and practice”, 4th edition, SAGE Publications Inc., Thousand Oaks, California

Perry, Nathan; Schönerwald, Carlos (2012): “Institutions, Geography, and Terms of Trade in Latin America. An Evaluation of the Washington Consensus”. In: International Journal of Political Economy, vol. 41, no. 1, pp. 66-94

Peterson, Gerald E.; St. Clair, Daniel C.; Aylward, Steven R. (1995): “Using Taguchi’s Method of Experimental Design to Control Errors in Layered Perceptrons”. In: IEEE Transactions on Neural Networks, vol. 6, no. 4, pp. 949-961

Petty, J. William; Titman, Sheridan; Keown, Arthur J. et al. (2012): “Financial Management. Principles and applications”, 6th edition, Pearson, Sydney

Porter, Michael E. (1990): “The competitive advantage of nations”, The Free Press, New York

Porter, Michael E. (2008): “On competition”, Harvard Business Review Press, 2nd revised edition, Boston, Massachusetts

Porter, Nathan; Xu, TengTeng (2016): “Money-Market Rates and Retail Interest Regulation in China: The Disconnect between Interbank and Retail Credit Conditions”. In: International Journal of Central Banking, vol. 12, issue 1, pp. 143-198

Priddy, Kevin L.; Keller, Paul E. (2005): “Artificial Neural Networks. An Introduction”, SPIE – The International Society for Optical Engineering, Bellingham, Washington

Qi, Min (2001): “Predicting US recessions with leading indicators via neural network models”, In: International Journal of Forecasting, vol. 17, pp. 383-401

Qi, Min; Zhang Peter G. (2008): “Trend Time series Modeling and Forecasting With Neural Networks”. In: IEEE Transaction On Neural Networks, vol. 19, no. 5, pp. 808-816

Ranchhod, Ashok (2007): “Marketing Strategies: A contemporary approach”, 2nd edition, Pearson Education, Harlow, Essex

Rawski, T.G. (1976): “On the reliability of Chinese economic data: Discussion”. In: Journal of Development Studies, vol. 12, issue 4, pp. 438-441

Reed, Russell; Marks, Robert J. II (1999): “Neural Smithing: Supervised Learning in Feedforward Artificial Neural Networks”, The MIT Press, Cambridge, Massachusetts

Reinert, Kenneth A.; Rajan, Ramkishen S.; Glass, Amy Jocelyn (2009): ”The Princeton Encyclopedia Of The World Economy”. Princeton University Press, Princeton

Rieg, Robert (2010): “Do forecasts improve over time? A case study of the accuracy of sales forecasting at a German car manufacturer”. In: International Journal of Accounting and Information Management, vol. 18, no. 3, pp. 220-236

Roberts, Ivan (2015): “Seasonal Adjustment of Chinese Economic Statistics”, Reserve Bank of Australia Research Discussion Paper, no. rdp2015-13, pp. 1-55. Available on the Internet. URL: http://www.rba.gov.au/publications/rdp/2015/pdf/rdp2015-13.pdf [2019-07-16]

Rock, Michael T.; Toman, Michael A. (2015): “China’s Technological Catch-Up Strategy. Industrial Development, Energy Efficiency, and CO2 Emissions”, Oxford University Press, New York

Rodrik, Dani (2006): ”Goodbye Washington Consensus, Hello Washington Confusion? A Review of the World Bank’s Economic Growth in the 1990s: Learning from a Decade of Reform”. In: Journal of Economic Literature, vol. XLIV, pp. 973-987

Rojas, Raul (2013): “Neural Networks: A Systematic Introduction”, 2nd edition, Springer, Berlin

Roohi, Farhat (2013): “Artificial Neural Network Approach to Clustering”. In: The International Journal of Engineering And Science, vol. 2, issue 3, pp. 33-38

Rosen, Daniel; Bao, Beibei (2015): “Broken Abacus? A More Accurate Gauge of China’s Economy”. Center for Strategic and International Studies, Washington D.C.

Runkler, Thomas A. (2012): “Data Analytics. Models and Algorithms for Intelligent Data Analysis”, Springer Vieweg, Wiesbaden

Ruß, Georg; Kruse, Rudolf; Schneider, Martin et al. (2008): “Estimation of Neural Network Parameters for Wheat Yield Prediction”. In: Bramer, Max (ed.) “Artificial Intelligence in Theory and Practice II”, vol. 276, Springer, Boston, Massachusetts, pp. 109-118

Russow, Llyod C.; Okoroafo, Sam C. (1996): “On the way towards developing a global screening model”. In: International Marketing Review, vol. 13, issue 1, pp. 46-64

Ryan, Paul; Dundon, Tony (2008): “Case Research Interviews: Eliciting Superior Quality Data”. In: International Journal of Case Method Research & Application (2008) XX, 4, pp. 443-450. Available on the Internet. URL: http://www.wacra.org/PublicDomain/IJCRA%20xx_iv_IJCRA%20pg443-450%20Ryan.pdf [2019-07-16]

Sakarya, Sema; Eckman, Molly; Hyllegard, Karen H. (2007): “Market selection for international expansion. Assessing opportunities in emerging markets”. In: International Marketing Review, vol. 24, no. 2, pp. 208-238

Sanford, Jonathan E.; Hardt, John P.; Nanto, Dick K. et al. (2003): “IMF and World Bank activities in Russia and Asia: Some conflicting perspectives”. In: Columbus, Frank (ed.) “Russia in Transition”, vol. 1, Nova Science Publishers, New York, pp. 13-34

Schildt, Henri; Keil, Thomas; Maula, Markku (2012): ”The Temporal Effects Of Relative And Firm-Level Absorptive Capacity On Interorganizational Learning”. In: Strategic Management Journal, vol. 33, pp. 1154-1173

Schotter, Andrew (1981): “The Economic Theory of Social Institutions”, Cambridge University Press, Cambridge

Schrammel, Tine (2014): “Clusters as an instrument to bridge institutional voids in transition economies. Lessons learned from Southeast Europe”, Springer Gabler, Wiesbaden

Selviah, David R.; Shawash, Janti (2009): “Generalized Correlation Higher Order Neural Networks for Financial Time Series Prediction”. In: Zhang, Ming (ed.) “Artificial Higher Order Neural Networks for Economics and Business”, Information Science Reference, Pennsylvania, Hershey, pp. 212-249

Shahabuddin, Syed (2009): “Forecasting automobile sales”. In: Management Research News, vol. 32, issue 7, pp. 670-682

Sharma, J.K. (2007): “Business Statistics”, 2nd edition, Pearson Education, New Delhi

Shiskin, Julius; Young, Allan H.; Musgrave, John C. (1965): “The X-11 Variant Of The Census Method II Seasonal Adjustment Program”, U.S. Government Printing Office, Washington D.C.

Shoemaker, Patrick A.; Carlin, Michael J.; Shimabukuro, Randy L. (1991): “Back Propagation Learning With Trinary Quantization of Weight Updates”. In: Neural Networks, vol. 4, issue 2, pp. 231-241

Simon, Herbert (1984): “On the Behavioral and Rational Foundations of Economic Dynamics”. In: Journal of Economic Behavior and Organization, vol. 5, pp. 35-56

Sodhi, Sartaj S.; Chandra, Pravin (2013): “Interval Based Weight Initialization Method for Sigmoidal Feedforward Artificial Neural Networks”. In: AASRI Procedia, vol. 6, pp. 19-25

Stiglitz, Joseph E. (2001): ”More Instruments and Broader Goals: Moving Toward the Post-Washington Consensus”. In: Chang, Ha-Joon (ed.) “Joseph Stiglitz and the World Bank. The Rebel Within”, Anthem Press, London, pp. 17-56

Stiglitz, Joseph E. (2003a): “Globalization and growth in emerging markets and the New Economy”. In: Journal of Policy Modeling, vol. 25, pp. 505-524

Stiglitz, Joseph E. (2003b): “Whither reform? Towards a new agenda for Latin America”. In: Cepal Review, no. 80, August 2003, pp. 7-38

Stiglitz, Joseph E. (2004a): ”The Post Washington Consensus Consensus”, Columbia University Initiative for Policy Dialogue Working Paper, pp. 1-15

Stiglitz, Joseph E. (2004b): “Capital-market liberalization, globalization, and the IMF”. In: Oxford Review of Economic Policy, vol. 20, no. 1, pp. 57-71

Sun, Rongrong (2015): “What measures Chinese monetary policy?”. In: Journal of International Money and Finance, vol. 59, pp. 263-286

Supachart, Wannakomol (2019): “The Economic Policy Uncertainty in China, the United States, and Europe: The Empirical Impact on Chinese Stock Markets”. In: Applied Economics and Finance, vol. 6, no. 5, pp. 131-144

Tang, Rachel (2012): “China’s Auto Sector Development and Policies: Issues and Implications”, Congressional Research Service, pp. 1-40. Available on the Internet. URL: https://www.hsdl.org/?view&did=718658 [2019-07-16]

Tao, Mengying, Xie Yuelan, Qu, Qiang et al. (2019): “Characteristics of China’s interest rate system”. In: “Market-Based Interest Rate Reform in China”, China Finance 40 Forum Research Group, Routledge, New York, pp. 27-59

Tarassenko, Lionel (1998): “Guide to Neural Computing Applications”, Butterworth-Heinemann, Oxford

Teece, David J. (2018): “Business models and dynamic capabilities”. In: Long Range Planning, vol. 51, pp. 40-49

Teece, David J.; Pisano, Gary; Shuen Amy (1997): “Dynamic Capabilities and Strategic Management”, Strategic Management Journal, vol. 18, no. 7, pp. 509-533

Thawornwong, Suraphan; Enke, David (2004): “Forecasting Stock Returns with Artificial Neural Networks”. In: Neural Networks in Business Forecasting, Idea Group Publishing, Hershey, Pennsylvania, pp. 47-79

The Central People’s Government of the People’s Republic of China (2009): “汽车产业调整和振兴规划 (Plan on Adjusting and Revitalizing the Automotive Industry)”. Available on the Internet. URL: http://www.gov.cn/zwgk/2009-03/20/content_1264324.htm [2019-07-16]

Theodoridis, Sergios; Koutroumbas, Konstantinos (2008): “Pattern recognition”, 4th edition, Elsevier, Burlington, Massachusetts

Thomasberger, Claus (2012): "Economic imbalances, capitalism and democracy". In: Herr, Hansjörg; Niechoj, Torsten; Thomasbeger, Claus et al. (eds.) "From crisis to growth? The challenges of debt and Imbalances", Metropolis-Verlag für Ökonomie, Gesellschaft und Politik, Marburg, pp. 145-168

Tkacz, Greg; Hu, Sarah (1999): "Forecasting GDP Growth Using Artificial Neural Networks", Staff Working Papers 99-3, Bank of Canada. Available on the Internet. URL: https://www.bankofcanada.ca/wp-content/uploads/2010/05/wp99-3.pdf [2019-07-16]

Tong, Howell (2012): "Threshold Models in Non-linear Time Series Analysis". In: Lecture Notes In Statistics, vol. 21, Springer, New York

Trading Economics (n.a.): "China Shanghai Composite Stock Market Index" and "CSI 300" URL: https://tradingeconomics.com/china/stock-market [2020-02-20], URL https://tradingeconomics.com/shsz300:ind [2020-02-20]

United Nations Development Programme (2016): "Human Development Report 2016", New York. Available on the Internet. URL: http://hdr.undp.org/en/2016-report/download [2019-07-16]

United States International Trade Commission (2011): "China: Effects of Intellectual Property Infringement and Indigenous Innovation Policies on the U.S. Economy", USITC Publications. Available on the Internet. URL: https://www.usitc.gov/publications/332/pub4226.pdf [2019-07-16]

Upton, Graham; Cook, Ian (2014): "A Dictionary of Statistics", 3rd edition, Oxford University Press, Oxford

Van Drongelen, Wim (2010): "Signal Processing for Neuroscientists, A Companion Volume. Advanced Topics, Nonlinear Techniques and Multi-Channel Analysis", Elsevier, London

Venugopal, Venkataraman; Baets, Walter (1994): "Neural Networks and Statistical Techniques in Marketing Research: A Conceptual Comparison". In: Marketing Intelligence & Planning, vol. 12, issue 7, pp. 30-38

Vernon, Raymond (1966): "International investment and international trade in the product cycle". In: Quarterly Journal of Economics, vol. 80, pp. 190-207

Vernon, Raymond (1972): "International trade: the product life cycle approach". In: Wells, L.T. (ed.) "The product life cycle and international trade", Harvard University

Vu Quang Viet (2009): "GDP by production approach: A general introduction with emphasis on an integrated economic data collection framework". Published as United Nations' training material for "Statistical Capacity Development in China and Other Developing Countries in Asia", pp. 1-137. Available on the Internet. URL: https://unstats.un.org/unsd/China_UNSD_Project/GDP%20by%20production%20approach.pdf [2019-07-16]

Wang, Jue (2018): "China-IMF Collaboration: Toward the Leadership in Global Monetary Governance". In: China Political Science Review, vol. 3, issue 1, pp. 62-80

Wang, Shuai; Shang, Wei (2014): "Forecasting Direction of China Security Index 300 Movement with Least Squares Support Vector Machine". In: Procedia Computer Science, vol. 31, pp. 869-874

Warner, Rebbecca M. (1998): "Spectral Analysis of Time series Data", The Guilford Press, New York

Webster, Allen (2013): "Introductory Regression Analysis: With Computer Application for Business and Economics", Routledge, New York

Wen, Jiandong (2015): "China's strategy for reforming its RMB exchange-rate policy and macroeconomic policies in support of that strategy". In: "China's Exchange Rate Regime", China Development Research Foundation, Routledge, New York, pp. 186-219

Wilcox, Rand R. (2009): "Basic Statistics. Understanding Conventional Methods and Modern Insights", Oxford University Press, Oxford

Williamson, John (2000): "What Should the World Bank Think about the Washington Consensus?" In: The World Bank Observer, vol. 15, no. 2 (August 2000), pp. 251-264

Williamson, John (2004): "The strange history of the Washington Consensus". In: Journal of Post Keynesian Economics, winter 2004-5, vol. 27, no. 2, pp. 195-206

Williamson, John (2008): "A Short History of the Washington Consensus". In: Serra, Narcis; Stiglitz, Joseph E. (eds.) "The Washington Consensus Reconsidered. Towards a New Global Governance", Oxford University Press, Oxford, pp. 14-30

Williamson, Oliver E. (1975): "Markets and Hierarchies. Analysis and Antitrust Implications", Free Press, New York

Williamson, Oliver E. (1996): "The Mechanisms of Governance", Oxford University Press, New York

Williamson, Oliver E. (2000): "The New Institutional Economics: Taking Stock, Looking Ahead". In: Journal of Economic Literature, vol. 38, no. 3, pp. 595-613

Williamson, Oliver E. (2008a): "Transaction Cost Economics: The Precursors". In: Economic Affairs, vol. 28, issue 3, pp. 7-14

Williamson, Oliver E. (2008b): "Outsourcing: Transaction cost economics and supply chain management". In: Journal of Supply Chain Management, vol. 44, no. 2, pp. 5-16

Williamson, Oliver E. (2017): "Contract, Governance and Transaction Cost Economics", World Scientific Publishing, Hackensack, New Jersey

Wilson, Randall D.; Martinez, Tony R. (2001): "The Need for Small Learning Rates on Large Problems". In: Proceedings of the 2001 International Joint Conference on Neural Networks, (IJCNN`01), pp. 115-119

Wilson, Randall D.; Martinez, Tony R. (2003): "The general inefficiency of batch training for gradient descent learning". In: Neural Network, vol. 16, issue 10, pp. 1429-1451

Wooldridge, Jeffrey M. (2015): “Introductory Econometrics. A Modern Approach”, 6th edition , Cengage Learning, Boston, Massachusetts

World Bank (n.d.; a): “World Bank Country and Lending Groups”. Available on the Internet. URL: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups [2019-07-16]

World Bank (n.d.; b): “Time required to enforce a contract (days)”. Available on the Internet. URL:https://data.worldbank.org/indicator/IC.LGL.DURS?end=2017&locations=IN-CN-DE-RU-US-SG&name_desc=false&start=2017 [2019-07-16]

Wright, S. (2013): “Competitive Intelligence, Analysis and Strategy. Creating Organisational Agility”, Routledge, Abingdon, Oxfordshire

Yaffee, Robert A.; Mc Gee, Monnie (2000): “Introduction to Time Series Analysis and Forecasting: With Applications of SAS and SPSS”, Academic Press, San Diego, California

Yeung, Daniel S.; Cloete, Ian; Wing, W.Y. Ng (2010): “Sensitivity Analysis for Neural Networks”, Springer, Berlin

Yi, Gang; Guo, Kai (2015): “Banking and financial institutions”. In: Chow, Gregory C.; Perkins, Dwight H. (eds.) “Routledge handbook of the Chinese economy”, Routledge Taylor & Francis, London, pp. 235-254

Yim, Juliana (2002): “A Comparison of Neural Networks with Time Series Models for Forecasting Returns on a Stock Market Index”. In: Developments in Applied Artificial Intelligence, 15th International Conference on Industrial and Engineering Applications of Artificial Intelligence and Expert Systems, Springer, Berlin, pp. 25-35

You, Mingqing (2014): “Addition of PM2.5 into the National Ambient Air Quality Standards of China and the Contribution to Air Pollution Control: The Case Study of Wuhan, China”. In: The Scientific World Journal, vol. 2014, pp. 1-10

Yu, Lean (2007): “An Improved BP Algorithm with Adaptive Smoothing Momentum Terms for Foreign Exchange Rate Prediction” In: Yu, Lean; Wang, Shouyang; Lai, Kin Keung (eds.): “Foreign-Exchange-Rate Forecasting with Artificial Neural Networks”, International Series in Operations & Research, vol. 107, Springer, Boston Massachusetts, pp. 101-118

Yu, Yongding (2018): “The reform of China’s exchange rate regime”. In: Garnaut, Ross; Song, Ligang; Fang, Cai (eds.) “China’s 40 Years of Reform and Development: 1978-2018”, Australian National University Press, Acton ACT, pp. 313-328

Yu, Zhiwen; Chen, Hantao; You, Jane et al. (2015): “Adaptive FuzzY Consensus Clustering Framework for Clustering Analysis of Cancer Data”. In: IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 12, no. 4, pp. 887-901

Zaheer, Srilata; Mosakowski, Elaine (1997): “The Dynamics of the Liability of Foreignness: A Global Study of Survival in Financial Services”. In: Strategic Management Journal, vol. 18, no. 6, pp. 439-463

Zhang, Dabin; Yu, Lean; Wang, Shouyang et al. (2010): "Neural network methods for forecasting turning points in economic time series: an asymmetric verification to business cycles". In: Frontiers of Computer Science in China, vol. 4, issue 2, pp. 254-262

Zhang, Peter G. (2004a): "Neural Networks in Business Forecasting", Idea Group Publishing, Hershey, Pennsylvania

Zhang, Peter G. (2004b): "Business Forecasting with Artificial Neural Networks: An Overview". In: Zhang, Peter G. "Neural Networks in Business Forecasting", Idea Group Publishing, Hershey, Pennsylvania, pp. 1-22

Zhao, X. (2017): "Organizational Learning in the Context of Institutional Voids: Government Interventionism and Business Networks in Asia". In: Hong, Jacky; Snell, Robin; Rowley, Chris (eds.) "Organizational Learning in Asia. Issues and Challenges", Elsevier, Amsterdam, pp. 13-38

Zheng, Sheng; Cao C.X.; Singh, R.P. (2014): "Comparison of ground based indices (API and AQI) with satellite based aerosol products". In: Science of the Total Environment 488-89, pp. 398-412

Zheng, Xiaolian; Chen Ben M. (2013): "Stock Market Modeling and Forecasting. A System Adaptation Approach", Springer, London