AIX-MARSEILLE UNIVERSITÉ AND CA' FOSCARI UNIVERSITY OF VENICE

Double Degree Master Dissertation

Economics, Econometrics and Finance (MEEF) and
Management Des Risques Financiers (MRF)

Chinese Monetary Policy and Corporate Bond Term Structure

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Academic Year: 2022/2023

Introduction

The study of the interconnection between monetary policy and yields has been and still is one of the most investigated relationships in economics. The ability of Central Banks to influence the borrowing costs of countries and corporations is of vital importance and its study could lead to a better understanding of the consequences of monetary interventions and their influence on the economy as a whole. The overall question concerns whether this alleged effect can be identified and satisfactorily studied for China, whose monetary and fixed-income frameworks are among the most peculiar in the world.

China's bond market, in fact, has experienced exceptional growth during the past two decades, becoming one of the largest and fastest-growing fixed-income markets in the world.

Historically speaking, the country has maintained relatively strict capital controls, limiting the ability of foreign investors to access its financial markets. While these controls have been gradually eased, they have contributed to the distinct development of the Chinese bond market.

While there has been extensive research on the country's treasury bond market, few empirical studies have targeted the role and the behavior that their corporate counterpart exerts on the economy (as in Cassola and Porter[2], Krolzig and Sserwanja[17], and Girardin *et al.*[9]). Corporate bonds can, in fact, better represent the real borrowing costs of corporations since their associated yields more reliably express the cost of money of this financing means. Moreover, it is believed that investors treat the default risk of corporate bonds as similar to that of Treasury bonds, and benefit from the high corporate spread since there have been very few default occasions during the last two decades.

On the other hand, past publications have put great stress on the comprehension and interpretation of China's monetary policy stance (He and Pauwels[14], Xiong[26], Pauwels[21], and Girardin *et al.*[10]). The country's monetary authority, the People's Bank of China (PBoC) possesses a wide roster of tools to intervene in monetary policy. This makes the analysis of the monetary stance a nontrivial duty since the instruments at disposal are either continuous or discrete and

pertain to very different scales and units of measurement.
As will be presented in deeper detail in the following sections, the PBoC can influence the monetary framework of the country by relying on a set of price, quantity, and administrative instruments. Among the first category, one can find deposit and lending rates, the interest rate charges on required and excess reserves, and the lending rate on PBoC's refinancing; as far as quantity-based tools are concerned, the Reserve Requirement Ratio (RRR) and Open Market Operations (OMOs) can be found; and finally, an unquantifiable variable known as window guidance belongs to the administrative category. The manipulation of the above-mentioned instruments allows the Chinese monetary authority to steer from a hawkish policy to a dovish one, and vice versa. Usually, such kind of manipulations are shown to occur in the same direction for many of the tools, in order to strengthen the effectiveness of monetary interventions.

Finally, this study tries to establish a common ground between the two research streams in order to investigate possible links and the associated macro-financial implications between the country's corporate yields and PBoC's interventions.
First, the study aims at extracting the usual three common factors defining the fixed-income term structure in order to identify alleged cross-effects between short, medium, and long-term parameters; and second, it investigates the relationship between the yields and a suitable indicator of Chinese monetary policy. The rationale behind the analysis is to create a statistical framework capable of capturing and quantitatively expressing the one-sided effect of the latter on the latent factors defining the evolving yield curve. The sample spans from January 2009 to December 2019, covering almost 11 years. This choice was made in order to minimize the probability of incurring in structural breaks that could have been caused by the Great Financial Crisis (GFC) or by the Covid-19 pandemic.
The dissertation will be divided into chapters. Chapter 1 will present the state of the art of the most relevant publications about both the Chinese monetary policy situation and the pertinent studies on the term structure of yields. Chapter 2, on the other hand, will present in a quantitative manner the Chinese policy framework, the relevant data series, and the choice and construction of the overall model. Finally, Chapter 4 will present the economic interpretation and implications of the results, paired with a set of tests to ensure the robustness of the econometric approach adopted.

To my grandfather Antonio,
you would be proud.

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Chapter 1

Literature review

The following dissertation will mainly focus on and establish a common ground between two fronts of macro-econometric analysis.
The first (and less explored) deals with the creation of an indicator for Chinese monetary policy, whereas the second concerns methods and procedures for the term structure parametrization into explanatory latent factors.

1.1 Modeling China's Monetary Policy stance

The quest for creating an indicator capable of capturing the Chinese monetary policy stance has shown to be a tedious challenge.
The source of difficulty lies in the fact that the Chinese government exploits a wide roster of instruments and tools to manipulate the country's monetary policy.
The devices at the disposal can be classified into three main categories:

1. Price instruments.
2. Quantity-based instruments.
3. Administrative tools.

Among the first set, one can distinguish the banks' deposit and lending rates, the interest rates charged on required and excess reserves, and finally the lending rate on PBoC refinancing.
Quantity-based instruments, on the other hand, are comprised of the Reserve Requirement Ratio (RRR) and PBoC's Open Market Operations (OMO).
The only administrative tool is known as window guidance, which resembles the issuance of informal instructions or suggestions from regulatory authorities to financial institutions, usually conveyed through meetings or other communication channels.
The above-mentioned multitude of instruments makes the creation of an unambiguous monetary

policy indicator a strenuous duty since the tools are either of continuous or discrete-jump nature.

The first relevant study on the evaluation of China's monetary policy was carried out by Liu and Zhang (2007)[18] who represented it through a Neo-Keynesian model including a forward-looking Phillips curve, an IS curve, and a monetary policy reaction function based on a monetary policy rule.
The first two were estimated via a Generalized Method of Moments (GMM) on quarterly data ranging from 1990 Q2 to 2005 Q4.
They evaluated the interest rate gap and concluded that China's monetary policy was likely too tight at the beginning of the 1990s, too loose in 1994-1996 with run-away inflation, and in the period of 2004-2006, the monetary policy seemed to be accommodative.
The resulting model heavily relied upon lagged and leading inflation, output (gap), and changes in the real exchange rate and in the money supply.
The two authors recognized a likely effect of the United States on Chinese monetary policy decisions by including in the equations the real exchange rate RMB/USD, which has shown to be statistically significant at the 1% level and to have a macro-financial influence on inflation and output.

Liu's and Zhang's study was indeed insightful to assess the appropriateness of Chinese monetary policy, however, it did not focus on constructing a comprehensive measure of how to detect it.
The first approach to creating a Monetary Policy Indicator (MPI) can be traced back to D. He and L.L. Pauwels (2008)[14] who, through a discrete-choice model, were the first to pave the way for such an analysis.
Their "triple choice" indicator variable ranging from 1997 to 2007 focused on (changes of) the Required Reserve Ratio (RRR), commercial bank 1-year deposit and lending rates, and changes in the outstanding net amount of central bank bills. More specifically, they translated variations above (below) an arbitrary set of thresholds adjusted for the sample length into tightening (loosening) policy measures.
They attributed an equal weight for all policy instruments and, very importantly, supposed that simultaneous opposite signals would offset each other. This last assumption was used extensively in the remaining literature on the topic, which will be presented shortly.
Despite being a simple approach, He and Pauwels opened the way to a series of attempts at Chinese monetary policy modeling.

The next and more comprehensive study on the creation of a suitable Chinese MPI can be attributed to W. Xiong (2012)[26] who adopted an ordered discrete-choice probit model whose inputs were quarterly observations from 1986 Q4 to 2010 Q3 of lagged changes in the real GDP, inflation, money supply (M1) and finally the nominal effective exchange rate (NEER).

The analysis closely resembles He's and Pauwels'[14] since it modeled the MPI in a similar fashion. The output of the model was a series of either unitary or null impulses which defined the monetary policy stance. Such impulses were classified by comparing them to a set of pre-specified arbitrary thresholds.

A notable upgrade made by Xiong[26] to He's and Pauwels'[14] procedure lay first in a lengthier sample covering more than 30 years and second in being the earliest example of a comprehensive monetary policy indicator created as the cumulative sum of all the impulses given by the ordered probit model.

This breakthrough made the visualization of an exhaustive MPI possible and hence brought the quest for the creation of a Chinese monetary policy indicator one step forward.

Moreover, Xiong's instrument seems to share the properties of other monetary policy stance indicators around the globe, like a significant increase during the Great Financial Crisis (GFC).

The next remarkable progress in the analysis and design of an MPI is accredited to S. Lunven (2015)[20], E. Girardin *et al.* (2017)[10].

The authors managed to upgrade the instrument's state of the art at that time by managing to express the unitary impulses into more meaningful moves of 27, 54, and 81 basis points (bps).

The sample spanned from January 1993 to May 2013 and, contrary to previously mentioned studies, it also included the unobservable administrative tool known as window guidance.

The other inputs, on the other hand, mimicked the pre-existing literature, hence including *price instruments* like bank deposit and lending rates, interest rates on required and excess reserves, and the lending rate on PBoC refinancing; and *quantity* ones like the RRR, and OMOs.

The construction of Lunven and Girardin's *et al.* MPI relied on translating the inputs' monthly changes into 27bps equivalents, aggregating them, correcting for administrative interventions and for the Chinese New Year's abnormal liquidity injections, and finally, cumulating the results. This has been a huge step forward since the resulting MPI could now be compared to other monetary policy stances and also resembled more realistic Central Banks' interventions since in periods of turmoil policy-makers could decide to manipulate the rates by their magnitude of choice.

This last study preserved some features recognized and accepted in the literature. The instruments used as inputs are still weighted equally so that it is still possible for one tool to offset another. Moreover, the study kept He and Pauwels'[14] OMOs boundaries and converted them into basis points movements. The conversion was made such that an amount of CNY 200 billion was equivalent to a 27 bps change, while CNY 350 billion corresponded to a 54 bps change, and a CNY 500

billion move to an 81 bps change.
The main issue with such an approach lay in the time-invariance of the thresholds.
The magnitude of PBoC's OMOs needs to be adjusted to a factor that reflects the economic expansion of the country. This issue will be addressed in this dissertation and will concern Chinese CPI as the adjusting variable.
Lastly, Standing Lending Facilities (SLF) are not taken into account either by Lunven or by Girardin *et al.* since their study's sample stopped in May of 2013.

An important contribution to window guidance identification was performed by M. Petreski and B. Jovanovic (2013)[22], then refined by P.G. Egan and A.J. Leddin (2016)[5] who coped with such signal problem by applying a Kalman filter[16] with an autoregressive dynamic for the unobserved component.
Despite their scope of work being different from the one of this dissertation, they managed to model a seemingly unquantifiable variable by using signal extraction methods. In both publications, the resulting window guidance responds to macroeconomic events like monetary shocks and other relevant occurrences.
These can be said to be two of the few studies that surprisingly managed to obtain a satisfying result in modeling such a shady but essential tool among the Chinese monetary policy instruments.

The quest for the MPI and the study of its inputs has had great developments since its inception, characterized by continuous improvements and refinements throughout the years.
One of the main issues with Lunven's and Girardin's *et al.* studies was linked to the static nature of some of its thresholds, as said before.
The problem was addressed by L.L. Pauwels (2019)[21] in one of his latest publications, in which he adopted an analogous approach to He and Pauwels (2008)[14] but updated it by attributing time-varying weights to predictors that demonstrated greater forecasting accuracy, according to Vasnev scoring functions.
Moreover, he proposed a change in the mix of Chinese policy tools by incorporating the 7-day reverse repurchase rate at the expense of the benchmark interest rates; and finally, he purposely decided to exclude PBoC's OMOs.
Concluding, despite the deteriorating forecasting performance signaling possible breaks, Pauwels found that China continued to track the USD, and the strength of the USD had a major influence on monetary policy decisions in China.

The last remarkable attempt at modeling China's monetary policy stance was conducted by M. Funke and A. Tsang in two publications that followed each other in 2020[8] and in 2021[7] which

relied on the same approach.
The authors modeled the variable through a Dynamic Factor Model (DFM) since the monetary policy stance can be regarded as a common element for the movements of different monetary policy instruments that can be captured by a single underlying, unobservable variable.
The resulting MPI, contrary to almost all previous ones, is not characterized by discrete jumps but is of a rather continuous nature.
The advantage of Funke and Tsang's model is that it is very concise and straightforward in capturing dovish and hawkish tendencies in PBoC's decisions. The main drawback, on the other hand, is the fact that it was constructed to be standardized between $[-2, +2]$, hence excluding the possibility of comparing it to other country's policy stances.

This dissertation will embrace the discrete-jump MPIs, mainly pertaining to the features of Xiong's[26], Lunven's[20], Girardin's *et al.*[10] and Pauwels'[14][21] works.
The choice of this school of thought over others like the ones of Liu and Zhang or Funke and Tsang is linked to the various advantages that Lunven's, Girardin's, He's, and Pauwels' frameworks have.
First of all, their models are based on a comprehensive roster of the instruments at China's disposal to influence monetary policy, such as all the main price, quantity, and even administrative tools. Second, either by unitary impulses or by basis points equivalents, their findings are often coherent with the maneuvers of other Central Banks, and most importantly, the trends and overall behaviors of their instruments react cleverly in conditions of macroeconomic turmoil, like during the *dotcom* bubble or during the GFC.

1.2 Bond Term Structure and Link to Monetary Policy

Compared to Chinese monetary policy modeling, term structure analysis is a far wider branch of econometrics.
Many statistical models have followed one another throughout the years, having as a likely starting point one of the most widely recognized masterpieces in term structure parametrization by C.R. Nelson and A.F. Siegel in 1988[25], which allowed for yield curve modeling through three latent factors called level, slope, and curvature, that represented the long, short, and medium terms of the yield curve itself.
Despite not being an always arbitrage-free specification, the Nelson-Siegel model started a fruitful series of term structure analyses and forecasting algorithms, that ultimately made the study of the interconnection between fixed-income securities and macroeconomic variables possible.
This model has been later extended in such a way that time series data could be extracted from

reiterating the parametrization, like in Diebold-Li[4].

A noticeably interesting study conducted on the effects of Chinese monetary policy on Chinese bond term structure was performed by N. Cassola and N. Porter in 2011[2].
They discovered that the country's fixed-income securities represented a proper transmission channel for policy decisions.
The authors focused on a wide range of bonds, looking beyond sovereign yields, and considering quasi-sovereign as well as corporate bonds of AAA firms.
The monetary decisions were modeled by both lending and deposit rates which are periodically set by the PBoC.
Specifically, the authors found that the short-term drivers of yields (slope) responded most to the post-crisis policy stimulus and that the regulated structure of benchmark retail interest rates had a significant impact on the structure of all bond yields. They also assessed the macro-financial implications, predictive power of yields, and efficiency of the term structure.
Their study was one of the few investigating the interrelatedness between the Chinese monetary policy stance and the fixed-income market.

Not focused on China, a remarkable study on the relationship between corporate bond yields and monetary policy interventions can be attributed to H.M. Krolzig and I. Sserwanja in late 2015.[17].
They analyzed over 40 years of quarterly data of both US treasury and corporate bonds of different ratings, to assess if the yields reacted to monetary policy shocks caused by the Federal Reserve.
They relied on a 6-dimensional structural VECM and found that corporate bonds reacted both in the long and short run to such shocks at several lags, moreover, they discovered that the influence of the securities manifested faster and deeper than their government counterpart.
This study appears relevant to this dissertation since it grants a proper and analogous starting framework for the analysis. The family of vector autoregressions contains powerful tools to explain the relationship between several variables. They allow for the inclusion of non-stationary variables and for the computation of Impulse Response Functions (IRFs) which are vital for the understanding of the consequences of perturbations in the setup.

Finally, the study performed by M. Guidolin, A.G. Orlov, and M. Pediotakes[12] took one step forward in inspecting the repercussions of the Fed's monetary policy (both conventional and unconventional) on corporate bonds' term structures from late 2004 to the end of 2012.
Even though the study did not concern China or any other Asian country, it is still very relevant since it proposed an approach to deal with regime switches concerning monetary policy and

fixed-income securities.

The publication applied a 3-state Markov switching intercept autoregressive heteroskedastic model, or simply a $MSIAH(k, p)$.

$k = 3$ was selected by the authors since the study aimed at analyzing three monetary policy scenarios: conventional monetary expansion, quantitative easing (QE), and the maturity extension program (MEP); whereas the decision of the number of lags p was based on three information criteria: the Akaike information criterion, the Bayes-Schwarz criterion, and the Hannan-Quinn criterion.

The data used, consisted of four series of weekly yields. The observations were divided into 4 portfolios according to their ratings and maturity, the classifications concerned non- and investment-grade securities either of short or long-term durations.

This publication can also be labeled as relevant because of its methodology. The authors recognized that the sample was characterized by a period of economic uncertainty with multiple monetary policy interventions and was hence organized such that different *regimes* could be analyzed at once by relying on one single comprehensive multivariate time series model.

The reliability and robustness of such an approach provided important insights into how to conduct the analysis throughout the dissertation.

The literature that has been presented was chosen based on different criteria. Those criteria mainly concerned the importance and pertinence of the publications' findings and also the usefulness of their methodology.

The branch of literature centered around term structure parametrization is undoubtedly wider when compared to Chinese monetary policy modeling, however it still offers crucial insights that will be adopted and refined throughout this dissertation.

The aim and contribution of this work will be the one of creating a link between the body of literature concerning the creation of a Chinese MPI and, if possible, study its effect on Chinese corporate yield, since empirical evidence has shown that not only treasuries react to policy shifts.

Chapter 2

Data

In order to perform the analysis, end-of-month data was chosen spanning from January 2009 to December 2019. The study covers more than ten years and begins after the Great Financial Crisis (GFC) to the pre-Covid-19 period.
This choice has been made in order to avoid important structural breaks in parameters that could have been caused by instances of economic turmoil.
The consequences of such a decision are also reflected in the following sections. The absence of nonlinear relationships presumably arising from breaks and changes in regimes allowed the study to be conducted by adopting more naive but still valid econometric techniques that could be solved by simple OLS.
Since the sample was purposely chosen to avoid recessions and alleged economic downturns the methodology did not have to rely on unnecessarily complex frameworks to get the sought results.
Concerning the sources, yield data belonged to the CEIC Global Economic Database, and all other relevant macroeconomic variables, like Reserve Requirements Ratio (RRR), PBoC's Open Market Operations (OMOs), lending and deposit rates, bank credit, etc. were retrieved from Refinitiv Eikon Datastream.

2.1 Macroeconomic Variables:

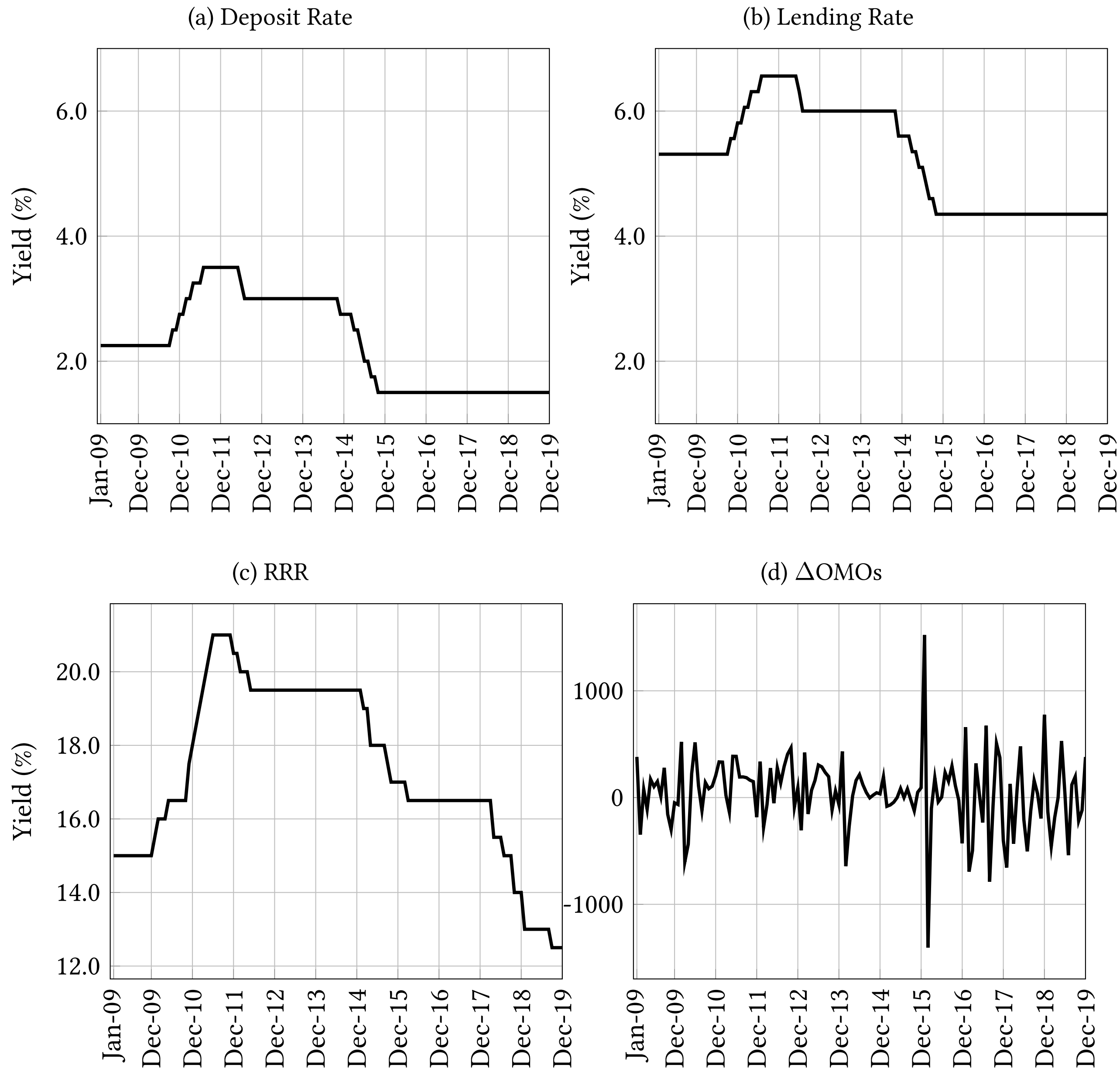
The macroeconomic variables that were taken into account for the computations belong to the set of tools at the disposal of the PBoC for monetary interventions.
As mentioned in the previous sections, the observable instruments fall either within the price or quantity categories and present different features from one tool to the other.
Here below, in Figure 2.1, will be presented the main components of monetary policy in China. The regulated interest rate corridor is presented in the upmost pictures, whereas on the bottom

charts the RRR and change in OMOs are displayed.
The figures are undoubtedly of different natures, all of them are characterized by discrete jumps, with the exception of the PBoC's Open Market Operations since they are a continuous measure. These time series will be used shortly in conjunction with the corporate bond yield data to investigate macro-financial linkages between such macroeconomic figures and fixed-income securities. Focusing on 2.1a, 2.1b, and 2.1c, one notices that all such rates have seen a substantial increase from late 2009 to late 2010 and a negative trend starting in late 2014 onward, which for the RRR continued until the end of the sample. Their behavior can be attributed with certainty to the restrictive measures first and accommodative measures then in response to the GFC.
On the other hand, the changes in OMOs reported in 2.1d show an important spike coinciding with the end of 2015 and the beginning of 2016. No unusual behavior seems to be present in correspondence to the introduction of Standing Lending Facilities (SLF) in mid-2013.
Finally, always concerning the monetary aspect of China, one last vital variable must be included, the (growth in) bank credit. Bank credit is the set of financial services provided by commercial banks to individuals, businesses, and other entities in the form of loans or credit facilities. It plays a crucial role in facilitating economic growth, investment, and consumption in the country.
It has been shown that this measure is capable of, in a sense, capturing window guidance, a qualitative-only unobservable component that consists of informal guidance or policy communication that aims to steer the direction of credit allocation and overall monetary policy. It is not a legally binding regulation but carries significant weight due to the influence and control exerted by the Chinese government over the banking system. It is typically conveyed through meetings, discussions, and instructions issued by regulatory authorities to commercial bank executives.
The growth in bank credit is plotted in Figure 2.2

2.2 Descriptive Statistics of Bond Yields:

The yields' maturities comprise financial instruments whose durations are 1, 2, 3, 5, 7, 10, 15, 20, and 30 years, or alternatively 12, 24, 36, 60, 84, 120, 180, 240, and 360 months.
Descriptive statistics tables and plots will follow in order to make possible a visual assessment of the yields.
As clearly visible, measures of central tendency like the mean and the median increase monotonically with maturity. Dispersion, on the other hand, captured by the standard deviation in the rightmost column of table 2.1 has an inverse relationship with maturity, signaling that on average shorter maturities experience more volatility than longer ones.
This phenomenon can be attributed to their enhanced responsiveness to macroeconomic news/shocks

Figure 2.1: Chinese Monetary Policy Instruments



and to the expectation theory of the term structure.

Decreasing standard deviation can be better visually captured by inspecting Figure 2.3, which shows one boxplot for each security.

The dispersion measure is indeed lower for longer-duration instruments, as a matter of fact, the whiskers of the boxplots shrink from the 10-year bond and remain substantially constant after-

Figure 2.2: Growth in Bank Credit

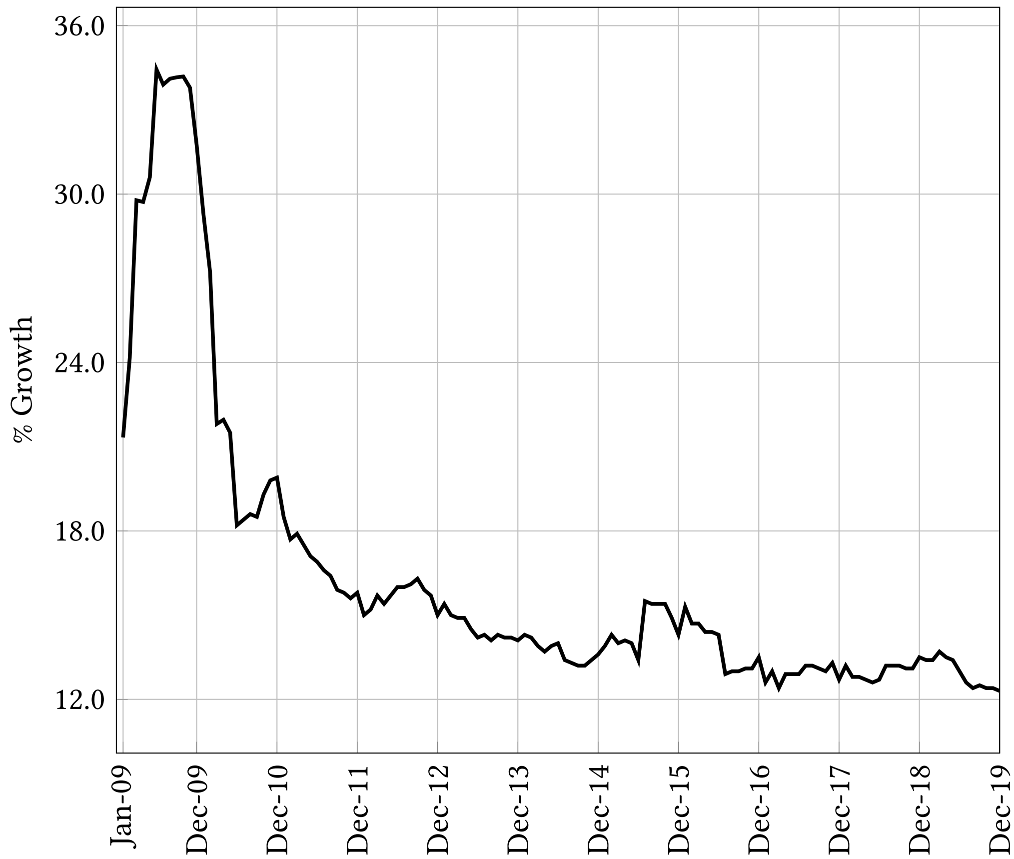


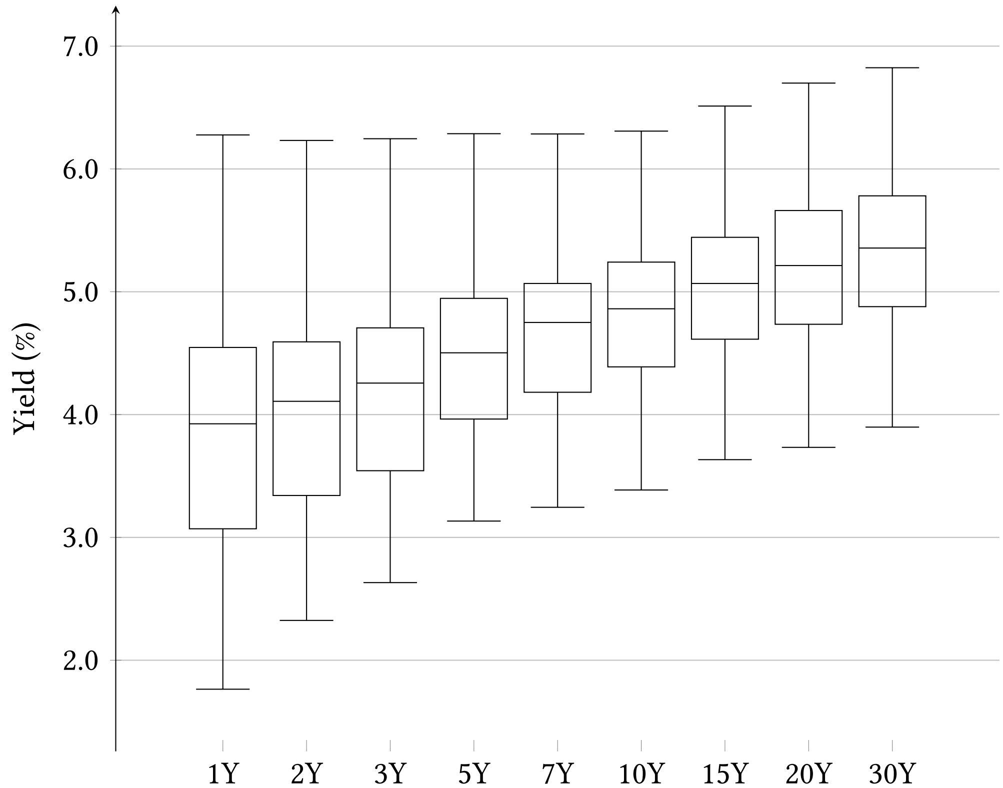
Table 2.1: Descriptive statistics of Chinese corporate bond yields

Maturity	Min	Max	Mean	Median	Standard Deviation
1Y	1.7638	6.2772	3.8418	3.4314	0.98412
2Y	2.0671	6.2324	4.053	3.6982	0.86047
3Y	2.3318	6.2469	4.2067	3.8929	0.79936
5Y	2.9036	6.2874	4.4866	4.2465	0.70542
7Y	3.1860	6.2855	4.7006	4.4815	0.65130
10Y	3.3868	6.3080	4.8605	4.6430	0.62806
15Y	3.6336	6.5126	5.0696	4.8843	0.60732
20Y	3.7338	6.6998	5.2196	5.0090	0.64395
30Y	3.8478	6.8248	5.3511	5.0971	0.62773

ward.
Moreover, an overall reduction in the InterQuartile Range (IQR) can also be seen.

As far as the evolution of yields over time is concerned, in Figure 2.4 a first look at a cross-section of the yields is plotted.

Figure 2.3: Boxplot of Chinese corporate bond yields



It is evident that despite the different maturities, such securities react similarly to macroeconomic events since their trends and oscillations move together.

In general, the analysis of bond yields can uncover insightful details. It is widely known that the so-called *yield curve inversions* act as a bad omen on the economy of a country. Such *inversions* usually consist of the 2-year yield surpassing the 10-year one and since bonds help reflect the expectations of players in financial markets, a higher interest rate in short-term instruments may signify great uncertainty and/or an incoming recession.

Historically speaking, yield curve inversions have successfully predicted recessions in the span of just one year both in developed and in developing countries.

For the sample in analysis, no inversions have been detected.

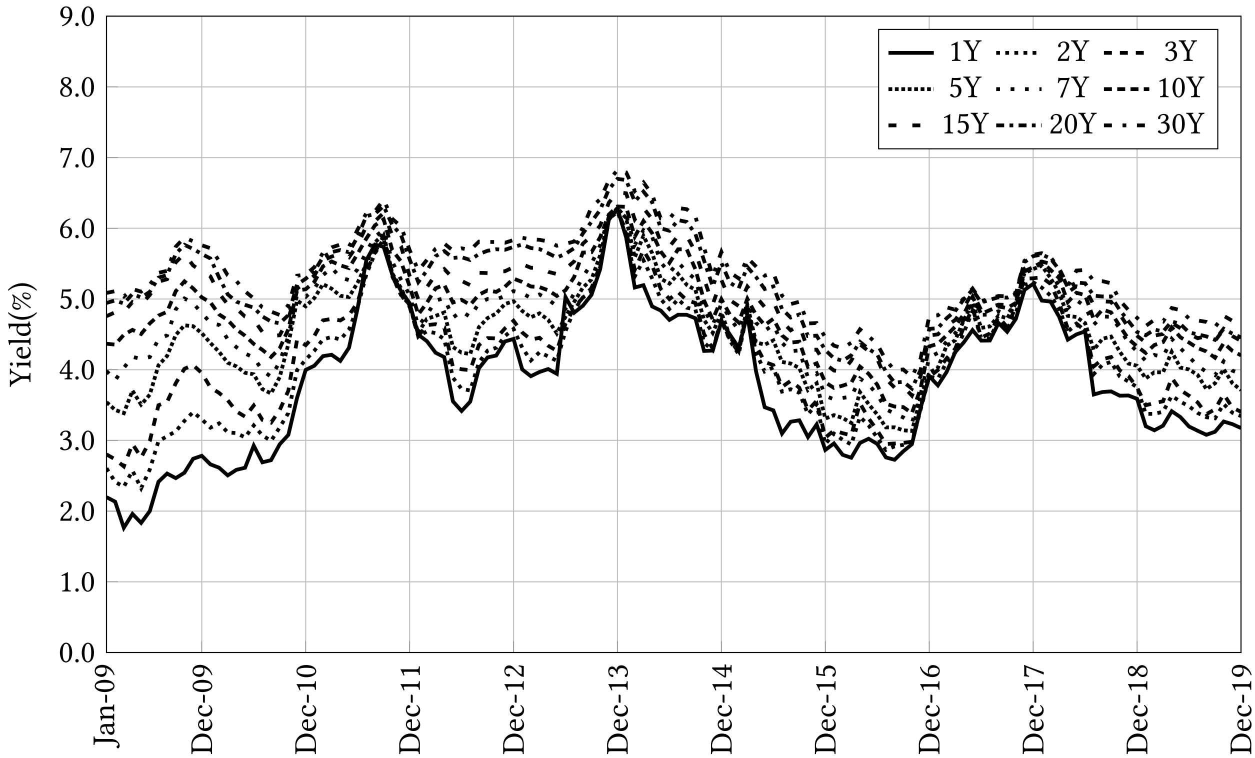
Finally, a perhaps more meaningful representation of the yields would be a chart containing the entirety of their term structure.

Figure 2.5 is capable of capturing the evolution of the term structure as time progresses.

The picture displays the different maturities on the in-depth axis, whereas on the horizontal axis, time t is placed.

It is evident that the yields have not experienced any inversions and have remained distant from the Zero Lower Bound (ZLB), which is a feature typical of corporate bonds, especially in emerging

Figure 2.4: Cross-section of Chinese Corporate Bond Yields

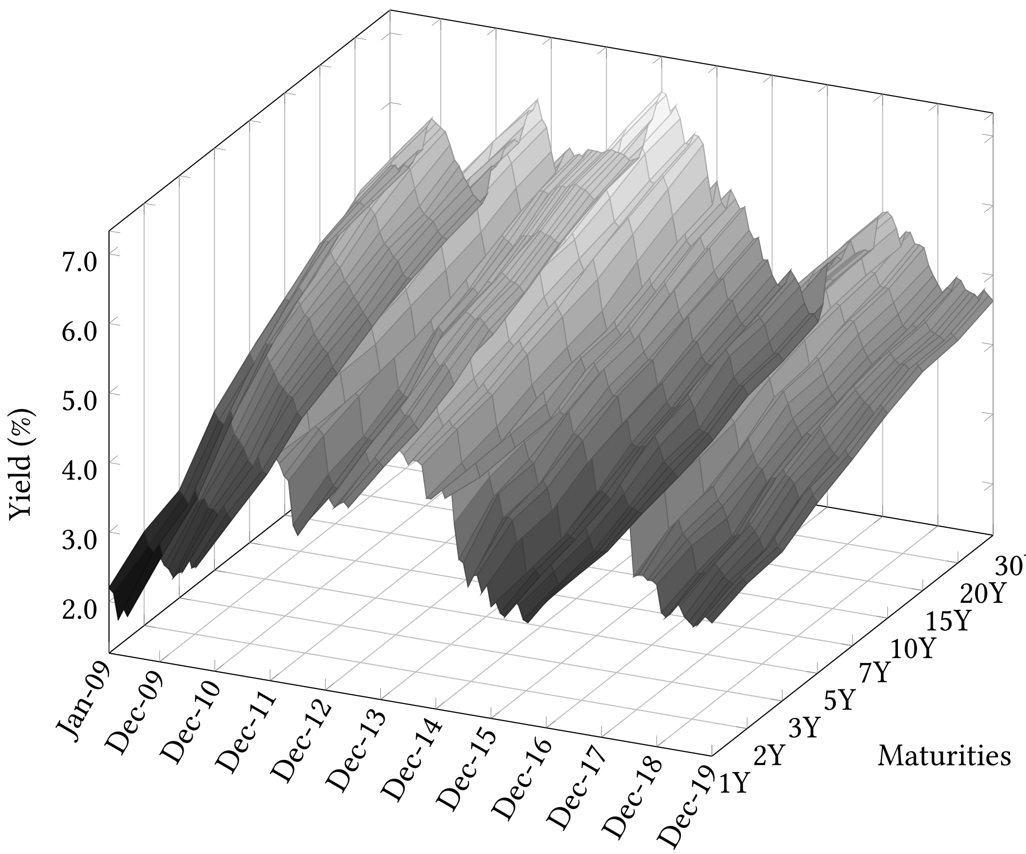


economies.

Bond yields reflect the riskiness of their corresponding instrument. High returns almost certainly arise from greater levels of risk that can be linked to, for instance, the security maturity, the entity that emits it, or other contractual obligations.

In the fixed-income market, it is rare to stumble upon corporate bonds with close to null yields since the issuer is a company that seeks financing and hence is regarded as less reliable, less stable, and more prone to default/bankruptcy than countries.

Figure 2.5: Term structure surface of Chinese corporate bonds



Chapter 3

Methodology

3.1 Term Structure Parametrization:

The scope of this dissertation revolves around the study of the effect of Chinese monetary interventions on the term structure of their corporate bonds. It is hence necessary to rely on a term structure parametrization technique in order to convert the several yields into more meaningful and analyzable variables.

For this purpose, the approach that was adopted consisted of a dynamic Nelson-Siegel model[25], theorized and applied by F.X. Diebold and C. Li[4].

The model consists of reiterating the usual Nelson-Siegel parametrization for each time instant whose output results in three time series of the latent factors that describe the term structure, called level, slope, and curvature.

The level corresponds to the long-term parameter, the slope to the short-term one, and the curvature to the medium-term factor.

This approach has shown to be a very powerful and reliable technique to parametrize a term structure of fixed-income securities and is widely used both in the literature and by policy-makers.

The dynamic Nelson-Siegel model is of the form:

$$r_t(\tau) = L_t + S_t\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) + C_t\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right) \tag{3.1}$$

$\ldots$ where $r_t(\tau)$ is the yield of the bond with maturity τ at time t, L_t is the level factor, S_t is the slope, C_t the curvature, and λ is the parameters that governs how much the slope and curvature factors contribute to the yield curve relative to the level.

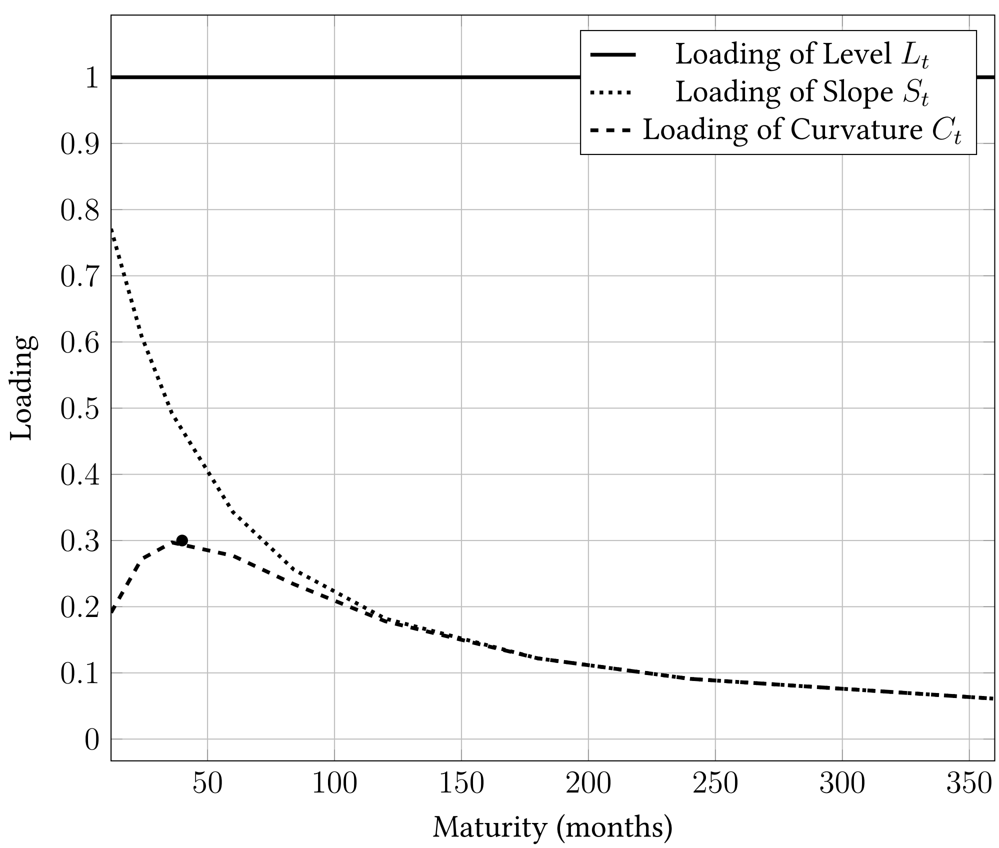
Throughout this dissertation, λ has been chosen to be equal to $\lambda = 0.0454$, because of two main reasons, the first is because that value maximizes the loading on the medium-term factor C_t at

40 months and is hence consistent with the works of Girardin *et al.*[10] and Lunven[20]; and the second is because by fixing the λ parameter, it transforms the problem from a nonlinear fitting to a simple linear regression, which is far more computationally efficient.
Concerning this last part, since Equation (3.1) reduces to a simple OLS, the overall equality becomes:

$$\begin{bmatrix} r_{\tau_1,t} \\ r_{\tau_2,t} \\ \vdots \\ r_{\tau_N,t} \end{bmatrix} = \begin{bmatrix} 1 & \frac{1-e^{-\lambda\tau_1}}{\lambda\tau_1} & \frac{1-e^{-\lambda\tau_1}}{\lambda\tau_1} - e^{-\lambda\tau_1} \\ 1 & \frac{1-e^{-\lambda\tau_2}}{\lambda\tau_2} & \frac{1-e^{-\lambda\tau_2}}{\lambda\tau_2} - e^{-\lambda\tau_2} \\ \vdots & \vdots & \vdots \\ 1 & \frac{1-e^{-\lambda\tau_N}}{\lambda\tau_N} & \frac{1-e^{-\lambda\tau_N}}{\lambda\tau_N} - e^{-\lambda\tau_N} \end{bmatrix} \begin{bmatrix} L_t \\ S_t \\ C_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{\tau_1,t} \\ \varepsilon_{\tau_2,t} \\ \vdots \\ \varepsilon_{\tau_N,t} \end{bmatrix} \tag{3.2}$$

By imposing that $\lambda = 0.0454$, the factor loadings behavior for the dynamic Nelson-Siegel model becomes as follows:

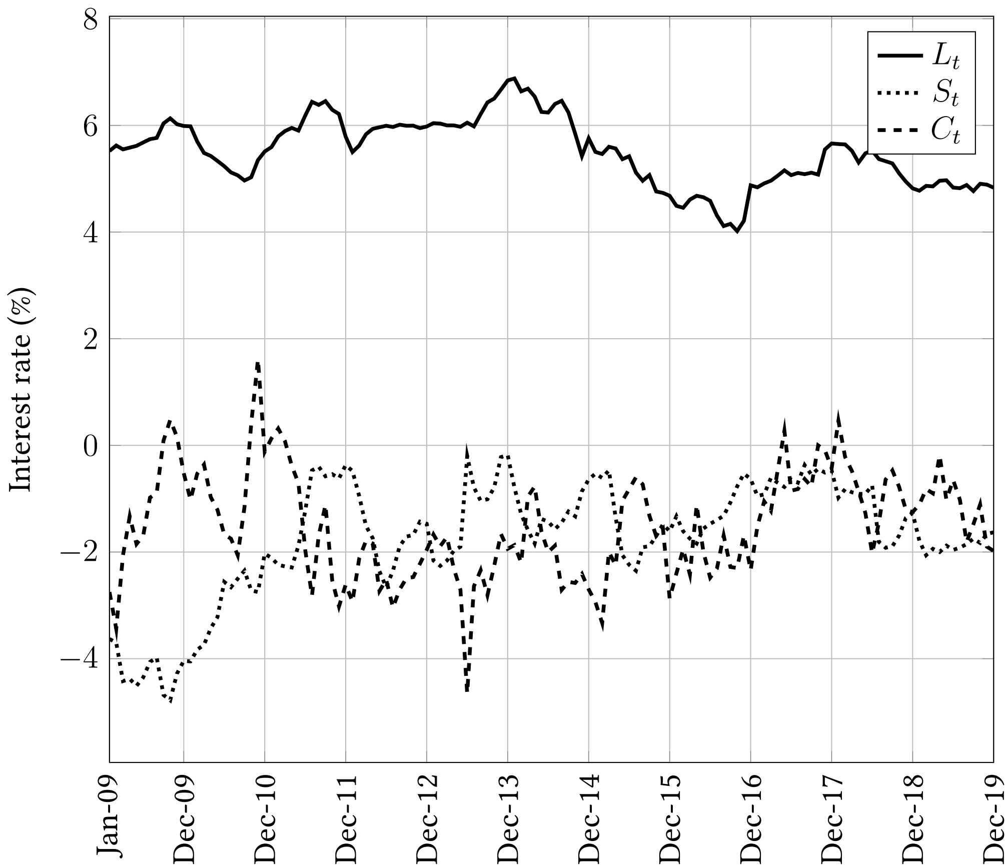
Figure 3.1: Factor Loading for Dynamic Nelson-Siegel Model



It is clear from Figure 3.1 that λ indeed maximizes the loading on the curvature C_t as visible by the dot in correspondence of the 40-month maturity.

The resulting time series of the latent factors are plotted in Figure 3.2.

Figure 3.2: Level, Slope, and Curvature

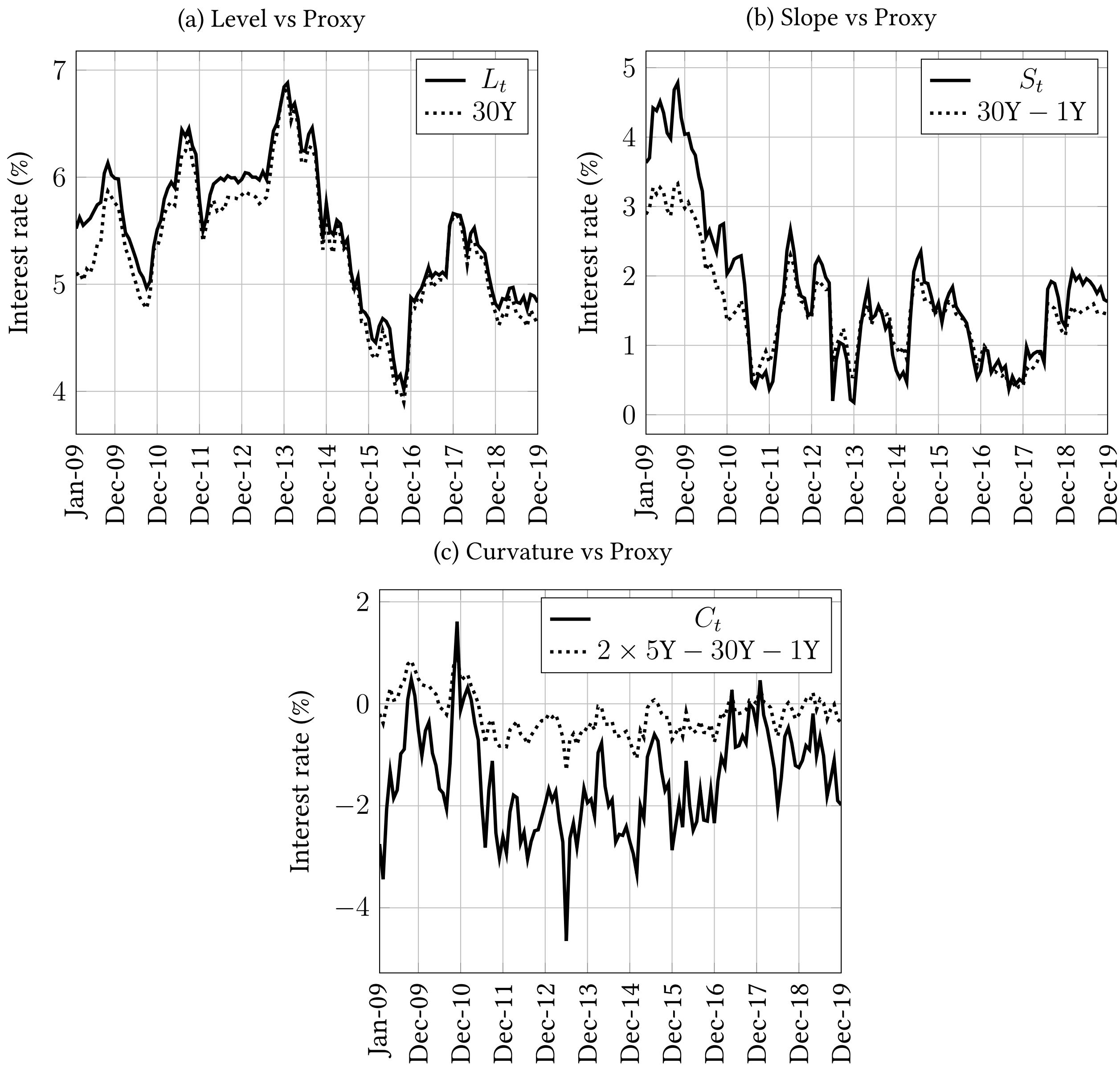


As already stated, the dynamic Nelson-Siegel model extracts three latent factors describing the term structure regardless of the number of securities and maturities present, one for the short, one for the medium, and finally one for the long term.
Once obtained, it is wise to compare such variables with widely used empirical proxies.
In this case, the empirical proxies to be compared with the latent factors are:

- The 30-year yield as the long-term proxy;
- The spread between the 30-year and the 1-year yields as a proxy for the short term;
- The difference between twice the 5-year yield and the sum between the 30-year and 1-year yields as the proxy for the medium term.

These proxies are widely used in the literature and help reflect the goodness of fit of the dynamic Nelson-Siegel model, hence a visual comparison is advisable, as in Figure 3.3.

Figure 3.3: Comparison between Term Structure Latent Factor and their Empirical Proxies

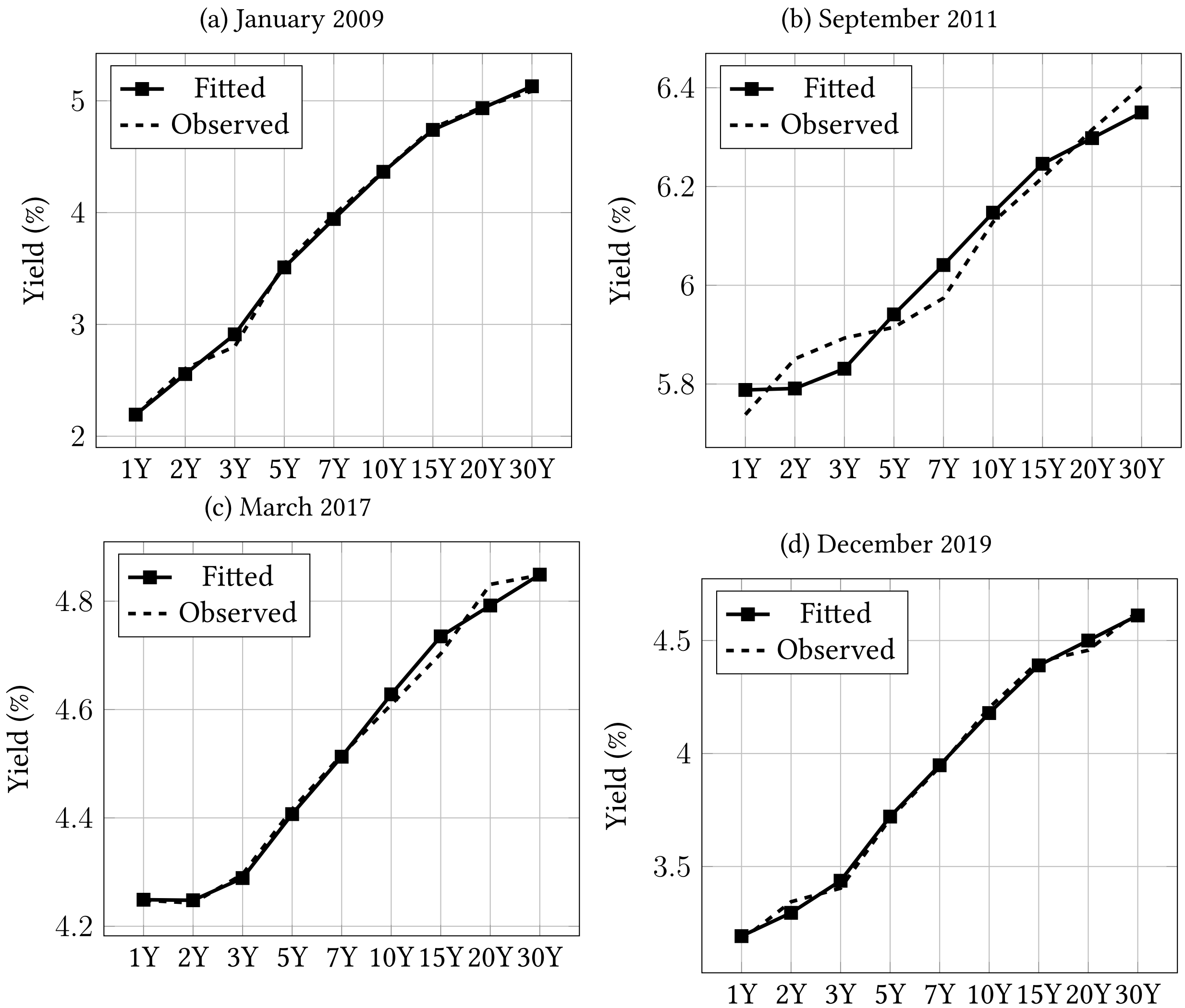


They shows that the comparison is satisfactory overall. The latent factors hug their correspondent empirical proxies, especially the level L_t and slope S_t. Curvature C_t, on the other hand, departs significantly from its proxy, however, empirical evidence has proven that this parameter is less capable of capturing the medium-term securities of the term structure.

Finally, before proceeding with the section it is noteworthy to inspect the model fit for specific dates throughout the sample. The fit is shown in Figure 3.4.

The sample dates were taken respectively at the beginning, first and third fourths, and end of the

Figure 3.4: Comparison of Model Fit vs Sample Dates



sample.

The model behaves in a such satisfactory way that for some of the plots, the results of the regression are almost indistinguishable from the observed values.

It is noteworthy to point out that given the low liquidity of the Chinese corporate bond market, the parametrization usually loses accuracy for financial instruments of longer maturities, as clearly noticeable in the rightmost part of 3.4c.

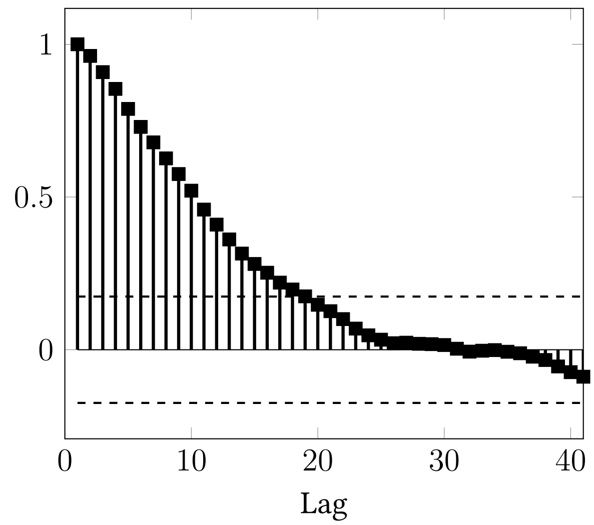
Overall, the parameters in Figure 3.2 seem stable over time, however before proceeding with the model, it is compulsory to test for their stationarity since OLS estimation and inference does not allow for $I(d)$ with $d > 1$ processes.

Stationarity has been assessed both visually with the aid of autocorrelation functions (ACFs) and with widely-used statistical tests.

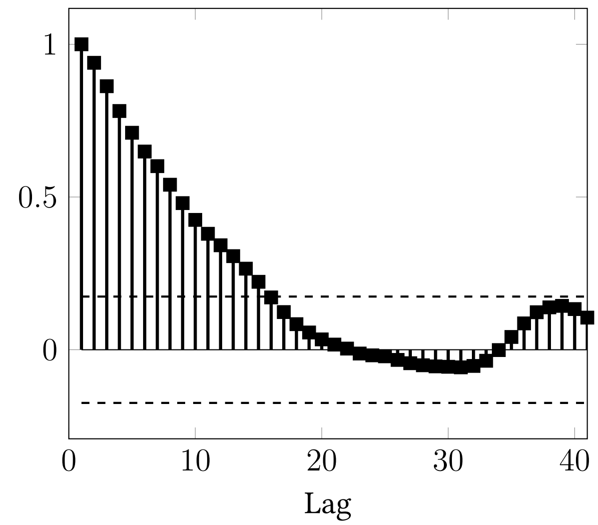
The ACFs for the latent factors are shown in Figure 3.5.

Figure 3.5: ACFs for Term Structure Latent Factors

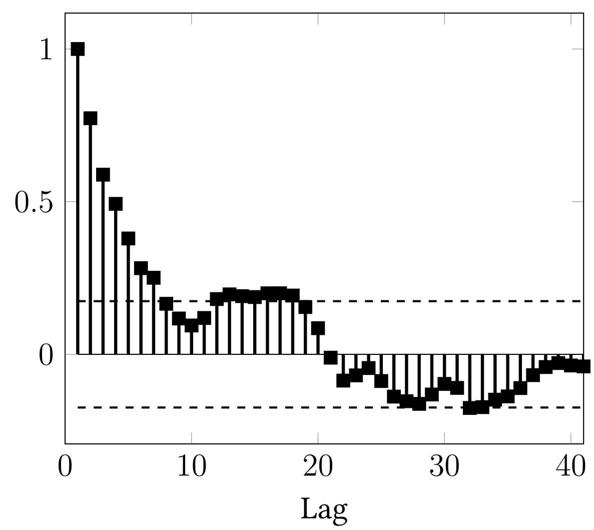
(a) ACF of L_t



(b) ACF of S_t



(c) ACF of C_t



The slowly decaying behaviour of the ACFs suggest that the latent factors might be non-stationary, especially the level in 3.5a and the slope in 3.5b. On the other hand, it is not completely clear as far as curvature is concerned, as visible in 3.5c.

To further deepen the understanding, the statistical tests applied were the Augmented Dickey-Fuller[3] and Phillips–Perron[23] tests, whose coinciding outputs are reported in Table 3.1.

The results reveal that the level (L_t in Figure 3.2) and slope (S_t in Figure 3.2) are not stationary, hence the first differences of all factors had to be computed in order to also better focus on the

Table 3.1: Output of ADF and Phillips-Perron tests for unit root on parameters' levels

Time Series	Hypothesis to retain	*p-value*	Test Statistic	Critical Value
L_t	H_0	0.4630	-0.5110	-1.9432
S_t	H_0	0.1015	-1.6081	-1.9432
C_t	H_1	0.0233	-2.2641	-1.9432

dynamics of the system.

Figure 3.6: ΔLevel, ΔSlope, and ΔCurvature

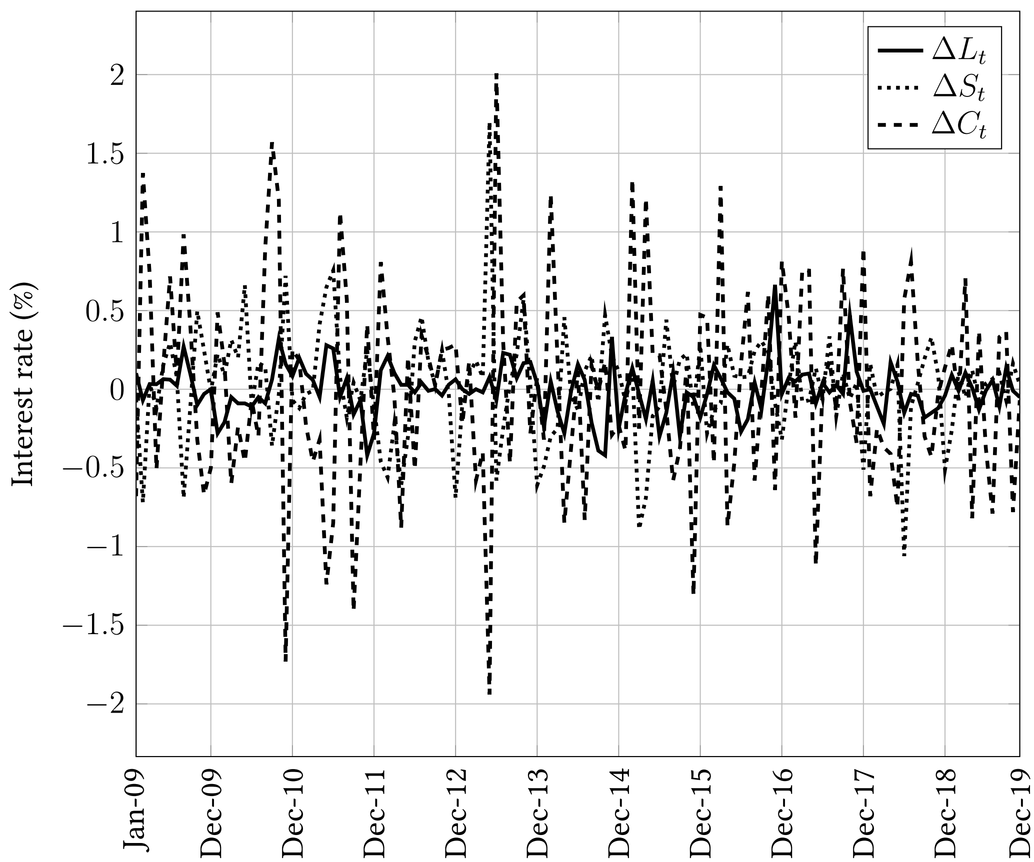


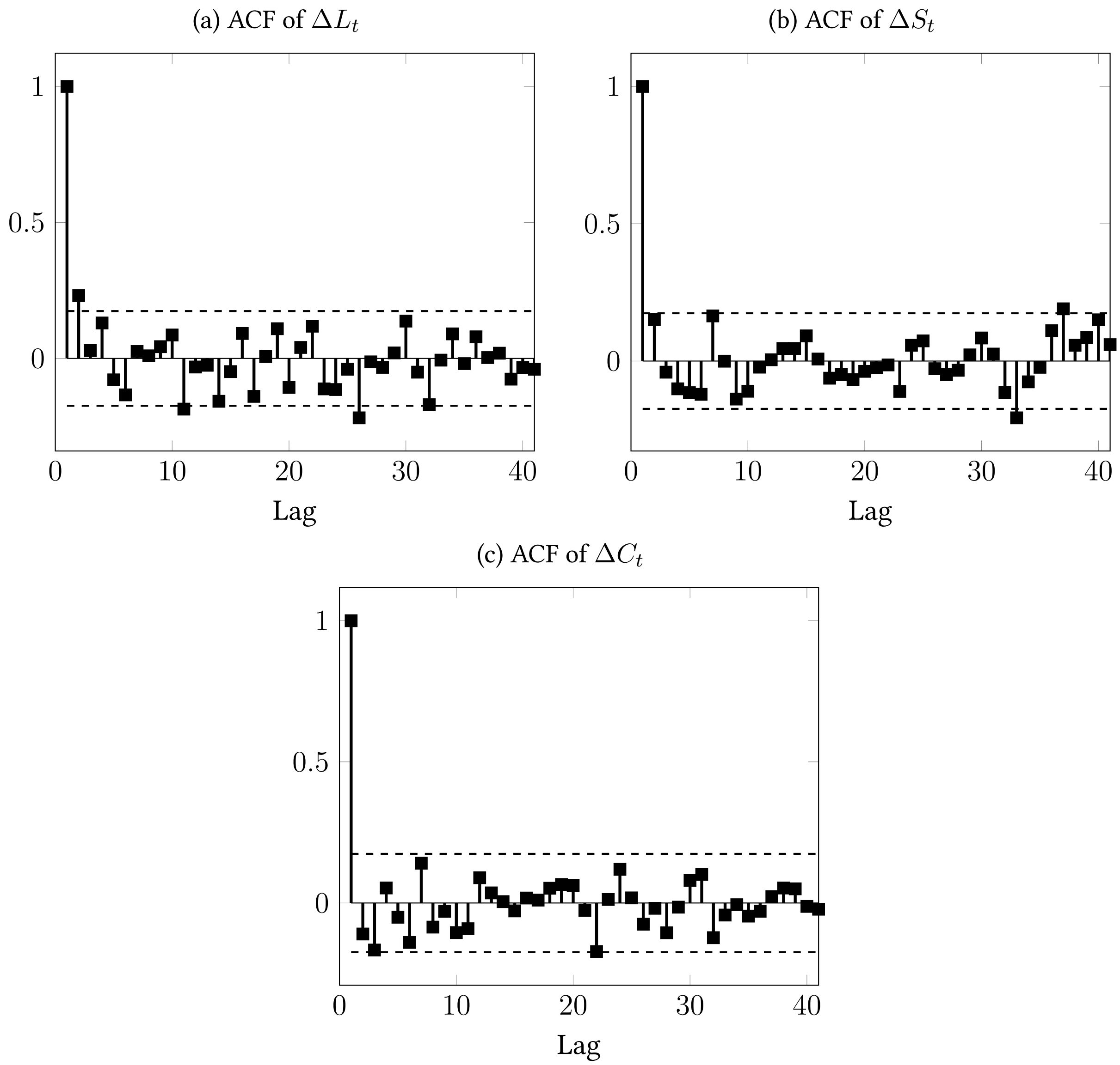
Figure 3.6 shows the behavior of the latent factors' first differences through time. It is now time to assess if such time series are stationary, so that the model can finally be fit.

Once again, the autocorrelation functions are provided and the same statistical tests as for the parameters in level are performed.

One can see by inspecting Figure 3.7 that once differenced, the variables ACFs hardly show persistent autocorrelation through time, but on the contrary, decay significantly fast, which is a sign typical of stationary time series.

Finally, both the ADF and Phillips-Perron tests are repeated and their coinciding outputs are

Figure 3.7: ACFs for First-Differenced Term Structure Latent Factors



shown in Table 3.2.

Table 3.2: Output of ADF and Phillips-Perron tests for unit root on parameters' first differences

Time Series	Hypothesis to retain	*p-value*	Test Statistic	Critical Value
ΔL_t	H_1	0.0010	-8.9788	-1.9433
ΔS_t	H_1	0.0010	-9.7372	-1.9433
ΔC_t	H_1	0.0010	-12.7316	-1.9433

The tests for unit root identification, paired with the ACFs, now ensure that the first difference of the term structure parameters are weakly stationary, hence making the OLS estimation possible.

The scope of the dissertation is undoubtedly to discover if Chinese monetary policy had an effect on such parameters, however, it is insightful to uncover whether throughout the sample the parameters had significant cross-effects. According to the expectation theory of the term structure, long-term interest rates are an average of current and future expected short-term interest rates. In other words, the yield on a long-term bond can be viewed as the average of the expected short-term interest rates over the bond's maturity period, hence shifts in shorter maturity securities might influence longer maturity ones.
According to such rationale, a Granger causality test[11] was performed to assess whether cross-parameter effects were significant. It is said that a time series variable X_1 Granger-causes another time-evolving variable X_2 if predictions of the value of X_2 based on its own past values and on the past values of X_1 are better than predictions of X_2 based only on X_2's own past values.
The results of such test are shown in Table 3.3.

Table 3.3: Granger Causality Test Output on Parameters' First Differences

H_0	Hypothesis to Retain	Test Statistic	*p-value*	Critical Value
Exclude all but lagged L_t	H_1	13.869	0.0010	5.9915
Exclude all but lagged S_t	H_0	0.6361	0.7276	5.9915
Exclude all but lagged C_t	H_0	0.9931	0.6086	5.9915

As reported in the first line of the output table, the rejection of H_0 means that lagged values of the slope S_t and of the curvature C_t indeed Granger-cause the level L_t.
This phenomenon can be interpreted as the *flow* of shocks from the short and medium term yields to the ones of longest maturity, in accordance with expectation theory of the yield curve.
On the other hand, there does not seem to be an effect of past values of curvature and level on slope and of lags of slope and level on curvature, in favor of, once again expectation theory of yields.

The output of Table 3.3 is also insightful because it paves the way for the main model selection of the study. Since it has been shown that the first differences of the term structure parameters are indeed stationary (Figure 3.7 and Table 3.2), that there are significant cross-parameter effects (Table 3.3), and that a proxy for Chinese monetary policy must be considered, that brings to the choice of a multivariate time series model whose inputs are stationary, hence the best trade-off between precision and complexity lead the decision to fall on a Vector Autoregressive model, also known as VAR(p), to which has been added an exogenous regressor representing the country's monetary policy stance, hence obtaining a VARX(p, b).

3.2 VARX(p,b) Model:

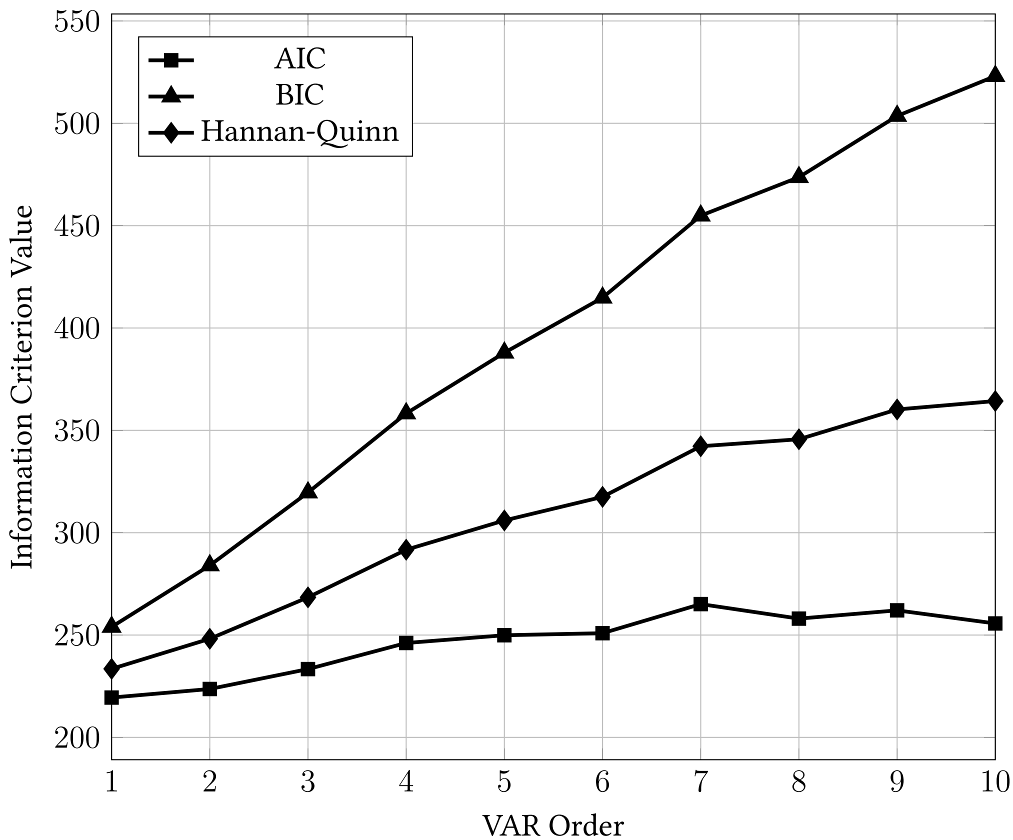
The choice of a Vector Autoregressive (VAR) model has many advantages, like the ease of interpretation of results, however, it requires some additional considerations.
First of all, the model needs to be correctly specified. The order p of a VAR model consists of the number of past lags to consider. An educated guess for the best order relies on observing the Information Criteria (IC).
The information criteria are used in statistical model selection to balance model complexity and goodness-of-fit. They penalize models for having more parameters, promoting the selection of simpler models that still explain the data well.
The theory states that a lower value of an information criterion is preferable to a higher one.
The most commonly used ICs are Akaike's[1], Bayes'[24], and Hannan-Quinn's[13], of the form:

$$\begin{aligned}
\text{AIC} &= -2\log(L) + 2k \\
\text{BIC} &= -2\log(L) + k\log(n) \\
\text{HQ} &= -2\log(L) + 2k\log(\log(n))
\end{aligned}$$

... with L being the value of the maximum likelihood function, k the number of parameters of the model, and n the length of the time series.
The penalty term in these criteria accounts for the number of parameters in the model, with Bayes' Information Criterion being the one with the most stringent penalties for complexity.
Concerning the model fit, as clear from Figure 3.8 the best choice is undoubtedly a VAR(1) since all information criteria determine that the order for the autoregressive process must be equal to 1. This choice prevents any issues related to the degrees of freedom. Some multivariate time series models suffer from the drawback of being highly parametrized making estimation difficult and not reliable for small samples. The VAR(p) model parameters grow according to a second-order polynomial of form $k + pk^2$, hence the lower p, the more preferable it is.

Since the scope of the dissertation is to study the effect of Chinese monetary policy on the country's corporate yields, it is mandatory to include a proxy for the monetary stance.
Since China's monetary authority, or more specifically, the PBoC possesses a wide range of tools to intervene in monetary policy, the choice of the proxy fell on the growth of bank credit, previously reported in Figure 2.2.
This decision was influenced by several reasons. First, bank credit is of vital importance to the Chinese economy because it fosters the development of the country, second, this measure is centralized since it is controlled by the government which issues directives and credit quotas, and

Figure 3.8: Information Criteria for VAR(p) Order Choice



finally, as explained in the previous chapter it encompasses the unquantifiable meetings, discussions, and instructions issued by regulatory authorities to commercial bank executives, also known as window guidance.

Hence (the growth of) bank credit has been chosen as the exogenous variable for the regression because exogenous variables by construction are able to influence the endogenous ones, without being affected, and hence reliably mimicking the cause-effect relationship between monetary interventions and term structure.

Most importantly, this setup allows for the estimation not only of parameter interdependence already investigated via the Granger causality test but also of the effects of the proxy for monetary policy on such factors.

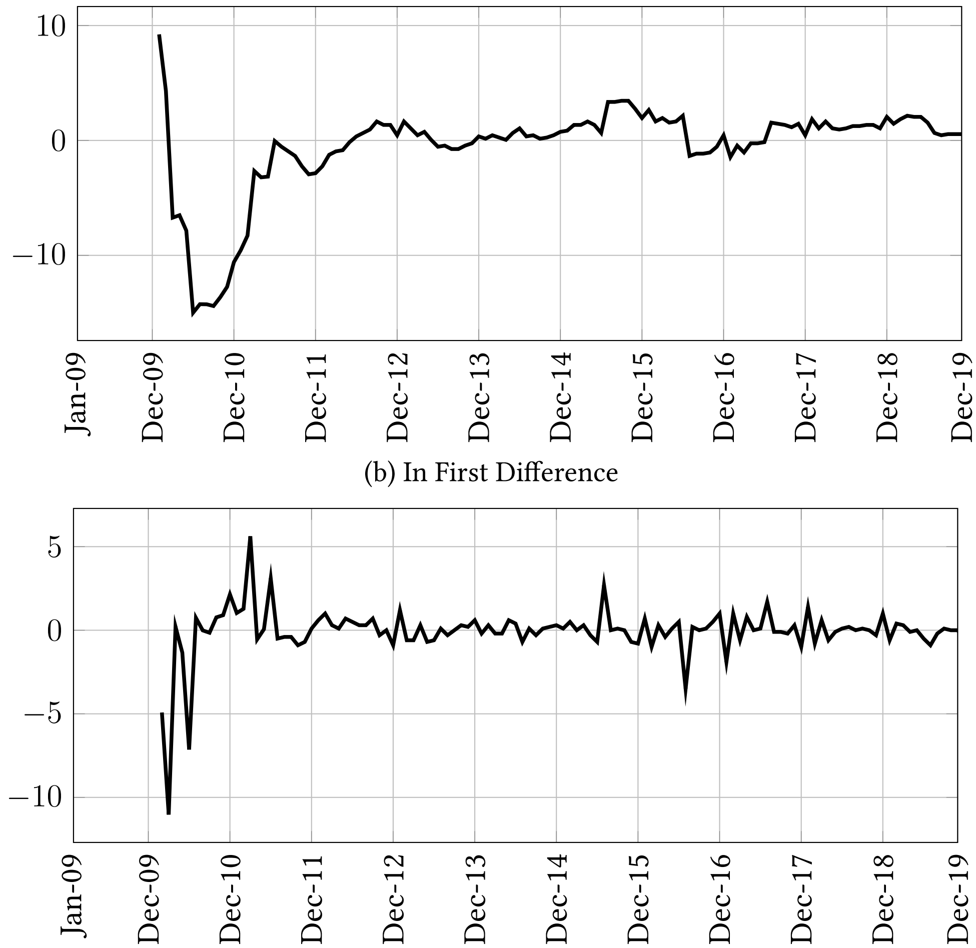
Bank credit has been detrended since it displayed a deterministic trend and seasonally adjusted, obtaining the time series in Figure 3.9a. Since however, the study has a major focus on the dynamic of the system instead of performing an in-level analysis, the data has been first differenced, also ensuring stationarity, as reported in Figure 3.9b.

Stationarity is evaluated statistically once again with the ADF and Phillips-Perron tests. The out-

Figure 3.9: Detrended, Seasonally-Adjusted Bank Credit and its First Difference

(a) In Level

(b) In First Difference



puts coincide once again seemingly because of the very low *p-value*, as shown in Table 3.4.

Table 3.4: Output of ADF and Phillips-Perron tests for unit root on bank credit first difference

Time Series	Hypothesis to retain	*p-value*	Test Statistic	Critical Value
ΔBank Credit	H_1	0.0010	-9.4738	-1.9437

After having ensured the stationarity of both the differenced Nelson-Siegel latent factors and of the differenced bank credit, the VARX(p, b) model is ready to be fit.

One last consideration before proceeding concerns the responsiveness of the term structure to credit impulses. Empirical evidence has shown that there exists a link between bank credit and yields, however, the timeliness with which the latter reacts can span from a semester to a whole year. For this sample, in particular, it has been shown that no effect of the growth in bank credit is significant before the tenth-month mark, hence requiring the regression to include distant lags in time of the exogenous regressor. The lags that were selected for the exogenous variable in the

VARX model coincided with $t-10$, $t-11$, and $t-12$. Other model configurations were proposed and the outputs can be found in Appendix A.3.

The resulting VARX$(1,3)$ model can be represented with its extended form as:

$$\begin{bmatrix} \Delta L_t \\ \Delta S_t \\ \Delta C_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} + \begin{bmatrix} \phi_{11} & \phi_{12} & \phi_{13} \\ \phi_{21} & \phi_{22} & \phi_{23} \\ \phi_{31} & \phi_{32} & \phi_{33} \end{bmatrix} \begin{bmatrix} \Delta L_{t-1} \\ \Delta S_{t-1} \\ \Delta C_{t-1} \end{bmatrix} + \dots$$
$$\dots + \begin{bmatrix} \Delta BC_{t-10} & 0 & 0 \\ 0 & \Delta BC_{t-10} & 0 \\ 0 & 0 & \Delta BC_{t-10} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} + \begin{bmatrix} \Delta BC_{t-11} & 0 & 0 \\ 0 & \Delta BC_{t-11} & 0 \\ 0 & 0 & \Delta BC_{t-11} \end{bmatrix} \begin{bmatrix} \beta_4 \\ \beta_5 \\ \beta_6 \end{bmatrix} + \dots$$
$$\dots + \begin{bmatrix} \Delta BC_{t-12} & 0 & 0 \\ 0 & \Delta BC_{t-12} & 0 \\ 0 & 0 & \Delta BC_{t-12} \end{bmatrix} \begin{bmatrix} \beta_7 \\ \beta_8 \\ \beta_9 \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix} \qquad \text{with } \varepsilon_{it} \overset{iid}{\sim} N(0, \sigma_i^2) \quad (3.3)$$

It can be rewritten in matrix form as:

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \boldsymbol{\Phi} \boldsymbol{y_{t-1}} + \boldsymbol{\Delta BC_{t-10}} \boldsymbol{\beta_1} + \boldsymbol{\Delta BC_{t-11}} \boldsymbol{\beta_2} + \boldsymbol{\Delta BC_{t-12}} \boldsymbol{\beta_3} + \boldsymbol{\varepsilon_t} \qquad \text{with } \boldsymbol{\varepsilon_t} \overset{iid}{\sim} N(0, \boldsymbol{\Sigma}) \quad (3.4)$$

$\dots$ where $\boldsymbol{y_t}$ and $\boldsymbol{y_{t-1}}$ are the $n \times 3$ and $(n-1) \times 3$ matrices of the not lagged and lagged differenced Nelson-Siegel endogenous factors, respectively, $\boldsymbol{\mu}$ is the 3×1 vector of intercepts, $\boldsymbol{\Phi}$ the 3×3 matrix of autoregressive coefficients, and $\boldsymbol{\beta_i}$ with $b = 1, 2, 3$ being the 3×1 vectors of coefficients linking the effects of the exogenous lagged differenced bank credit on term structure parameters.
$\boldsymbol{\Delta BC_{t-b}}$ matrices with $b = 10,\ 11,\ 12$ are constructed in such a way that their off-diagonal elements are null so that the influence of Nelson-Siegel factors on bank credit is neglected, only letting the diagonal entries affect the latter.

Chapter 4

The Effect of Bank Credit on the Term Structure

4.1 Model Results and Comments

The VARX(1,3) model referring to Equation 3.4 has been fit to the data and yields the output shown in Table 4.1.

The asterisks next to a coefficient signal its significance level: $(*)$ at 10%, $(**)$ at 5%, and $(***)$ at 1%.

The results in Table 4.1 show that the cross-parameter effects indeed persist and are significant. What was previously suggested by the Granger causality test is now confirmed, hence the slope S_t and the curvature C_t positively influence the behavior of the level L_t at $t-1$, whose effects are found to be significant at the 5% and 1% levels.

More in detail, for a unitary increase in the short and medium-term parameters, there corresponds to an increase of 0.0958 and of 0.0877 in the long-term factor, respectively. Moreover, two Nelson-Siegel factors, the slope and the curvature, display persistent self-dynamics given by their statistically significant autoregressive coefficients. The former is positively influenced by its past lags, and the latter on the contrary is negatively affected by its corresponding ones.

Focusing on the effect of the monetary policy proxy on the Chinese corporate bond term structure, one can assess that the long-term factor L_t is negatively affected by the growth in the country's bank credit at lag $t-10$ and that the short-term one is also negatively affected by it at $t-11$ and $t-12$ lags.

These results are consistent with the hypothesis of the non-timeliness response of the yield curve to credit shocks. As a matter of fact, the latent factors react at very distant past lags and always

Table 4.1: VARX(1,3) Output

Parameter	Estimated Value	Standard Error	Test Statistic	*p-value*
μ_1	-0.0057	0.0149	-0.3811	0.7031
μ_2	0.0060	0.0319	0.1883	0.8507
μ_3	-0.0222	0.0606	-0.3654	0.7149
$\phi_{1,1}$	0.1907	0.0906	2.1045	$0.0353^{(**)}$
$\phi_{2,1}$	-0.2866	0.1939	-1.478	0.1394
$\phi_{3,1}$	-0.1054	0.3687	-0.2858	0.7751
$\phi_{1,2}$	0.0958	0.0474	2.0218	$0.0432^{(**)}$
$\phi_{2,2}$	0.1258	0.1014	1.2399	0.2150
$\phi_{3,2}$	-0.0713	0.1928	-0.3697	0.7116
$\phi_{1,3}$	0.0877	0.0257	3.4123	$0.0006^{(***)}$
$\phi_{2,3}$	-0.0383	0.0550	-0.6968	0.4860
$\phi_{3,3}$	-0.1905	0.1046	-1.8209	$0.0686^{(*)}$
β_1	-0.0256	0.0127	-2.0216	$0.0432^{(**)}$
β_2	0.0133	0.0271	0.4916	0.6230
β_3	-0.0465	0.0515	-0.9032	0.3664
β_4	0.0125	0.0126	0.9896	0.3224
β_5	-0.0693	0.0270	-2.562	$0.0104^{(**)}$
β_6	0.0136	0.0514	0.2653	0.7908
β_7	-0.0097	0.0094	-1.0363	0.3001
β_8	-0.0388	0.0201	-1.9301	$0.0536^{(*)}$
β_9	0.0462	0.0382	1.2105	0.2261

with a negative sign.
The negative sign of the estimated coefficients can be interpreted as a parallel downward shift of the entire term structure when the Chinese credit base expands.

Once having obtained the estimated parameters of the VARX$(1,3)$ model, it is wise to assess its stationarity.
Stationarity is ensured if and only if the absolute values of the eigenvalues of the matrix $\mathbf{\Phi}$ lie within the unit circle in the complex plane.
Eigenvalues provide valuable insights into the behavior of linear transformations and can help determine stability, convergence, and other properties of systems described by matrices. They can be found by solving the characteristic equation:

$$\det(\mathbf{\Phi} - \boldsymbol{\lambda}\boldsymbol{I}) = 0$$

... det() represents the determinant, $\mathbf{\Phi}$ is the autoregressive coefficient square matrix, $\boldsymbol{\lambda}$ is the eigenvalue vector, and $\boldsymbol{I}$ is the identity matrix of the same size as $\mathbf{\Phi}$. Such figures are found to be:

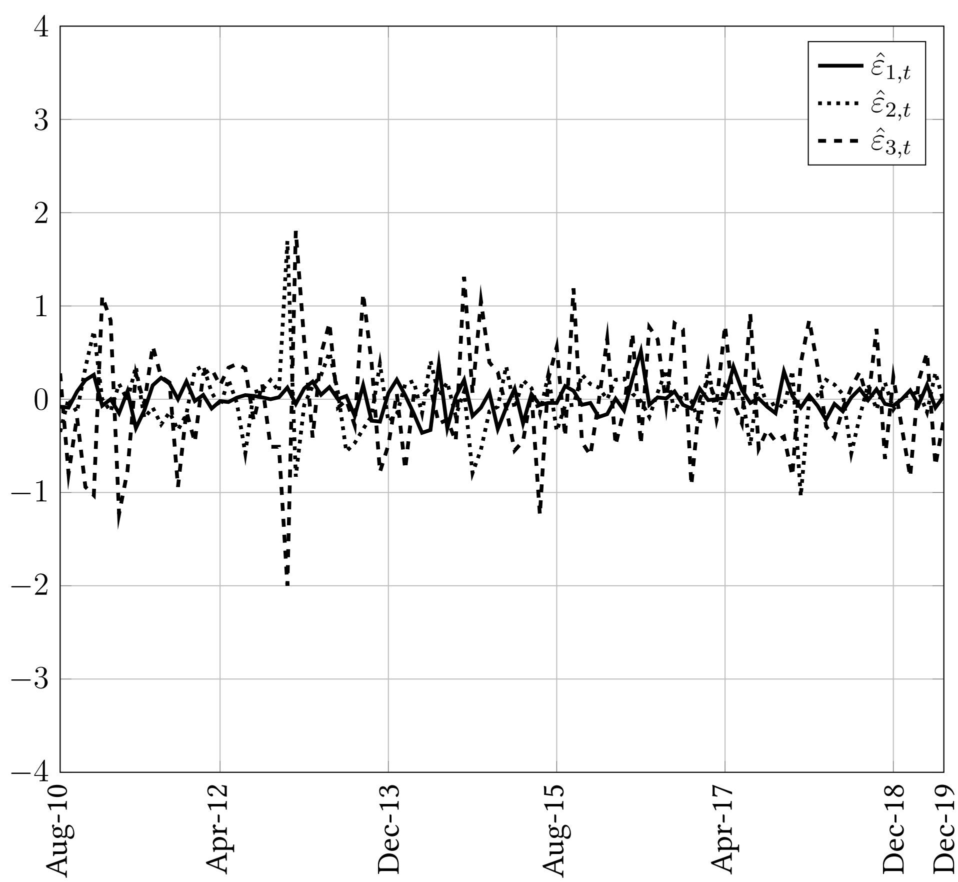
$$\boldsymbol{\lambda} = \begin{bmatrix} 0.209 \\ 0.209 \\ 0.160 \end{bmatrix}$$

Since the magnitude of all $\boldsymbol{\lambda}$ entries is less than 1, one can conclude that the multivariate model is stationary.

4.2 Residuals Diagnostics

Residual diagnostics is a crucial phase for the assessment of whether the model was specified correctly. A proper behavior like the absence of autocorrelation and heteroskedasticity is vital to ensure the robustness of the model. The resulting time series are shown in Figure 4.1 and do not

Figure 4.1: VARX$(1, 3)$ residuals



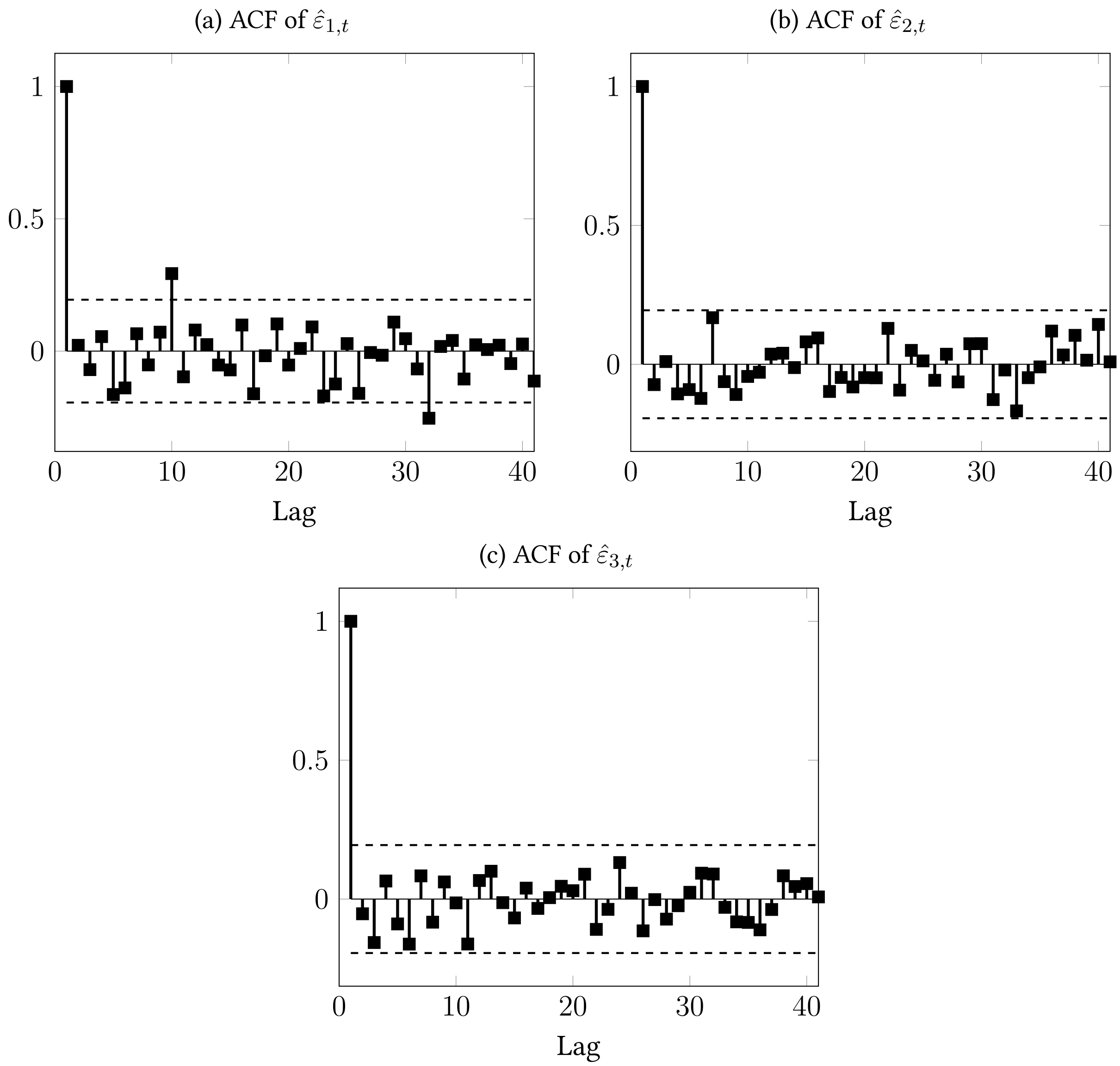
display erratic conduct.
The lack of serial correlation in the residuals is important for the validity of a regression model for several reasons. First of all, autocorrelation violates one of the fundamental assumptions of linear regression, namely the independence assumption. When there is autocorrelation in the residuals, it indicates that the current value of the dependent variable is correlated with previous values. This correlation can lead to biased and inefficient parameter estimates, making it difficult to accurately estimate the relationships between the independent variables and the dependent variable. Second of all, it can affect the validity of statistical inference and hypothesis tests. The standard errors of the estimated coefficients may be underestimated, leading to incorrect *p-values* and confidence intervals. This, in turn, can result in erroneous conclusions about the statistical significance of the independent variables and the overall model. It can mask or distort the true relationships between the variables in the regression model. It becomes challenging to interpret the individual coefficient estimates and understand the true impact of the independent variables on the dependent variable. It may also lead to misleading interpretations of the model's goodness of fit measures. Finally, serial correlation indicates that there is information in past observations that is not captured by the current set of independent variables, and in forecasting scenarios, this can lead to less accurate predictions as the model fails to account for the systematic patterns and dependencies present in the data.
Residuals' serial correlation is hence investigated both via visual and statistical tools.
Their autocorrelation functions are provided in Figure 4.2.
Their ACFs behavior resembles the one of a white noise, with no significant autocorrelation lags after $p = 1$, however in order to ensure such a claim, also the output of Ljung-Box tests[19] for autocorrelation is reported in Table 4.2:

Table 4.2: Ljung-Box Tests on Model Residuals

Residual Time Series	Hypothesis to Retain	*p-value*	Test Statistic	Critical Value
$\hat{\varepsilon}_{1,t}$	H_0	0.1371	26.9343	31.4104
$\hat{\varepsilon}_{2,t}$	H_0	0.7656	15.1866	31.4104
$\hat{\varepsilon}_{3,t}$	H_0	0.6725	16.6976	31.4104

Finally, one can conclude that the VARX(1,3) model residuals are not autocorrelated, in favor of the suitability of the overall setup. The high *p-values* signal the failure to reject the null hypothesis of no significant autocorrelation for the first 20 lags, hence such a claim can be confirmed.
Finally, residuals' heteroskedasticity must be addressed because it violates the assumption of constant variance of the residuals across all levels of the independent variables. In case of heteroskedasticity in the residuals, the standard errors of the estimated coefficients may be biased and inefficient. This could lead to incorrect inference, including inaccurate *p-values* and confidence

Figure 4.2: ACFs of Model Residuals



intervals. Inefficient parameter estimates reduce the precision and reliability of the estimated relationships between the independent variables and the dependent variable. Moreover, if present it could also be the cause of biased coefficient estimates. When the variability of the residuals differs across different levels of the independent variables, the model may assign excessive weight to observations with higher variances and less weight to observations with lower ones. As a result, the estimated coefficients may be biased towards the groups or observations with higher variances. In order to address such concern, the ACFs of squares residuals are provided in Figure 4.3 jointly with the results of the Ljung-Box and Engle's ARCH[6] tests in Table 4.3 and Table 4.4, respectively.

Figure 4.3: ACFs of Squared Model Residuals

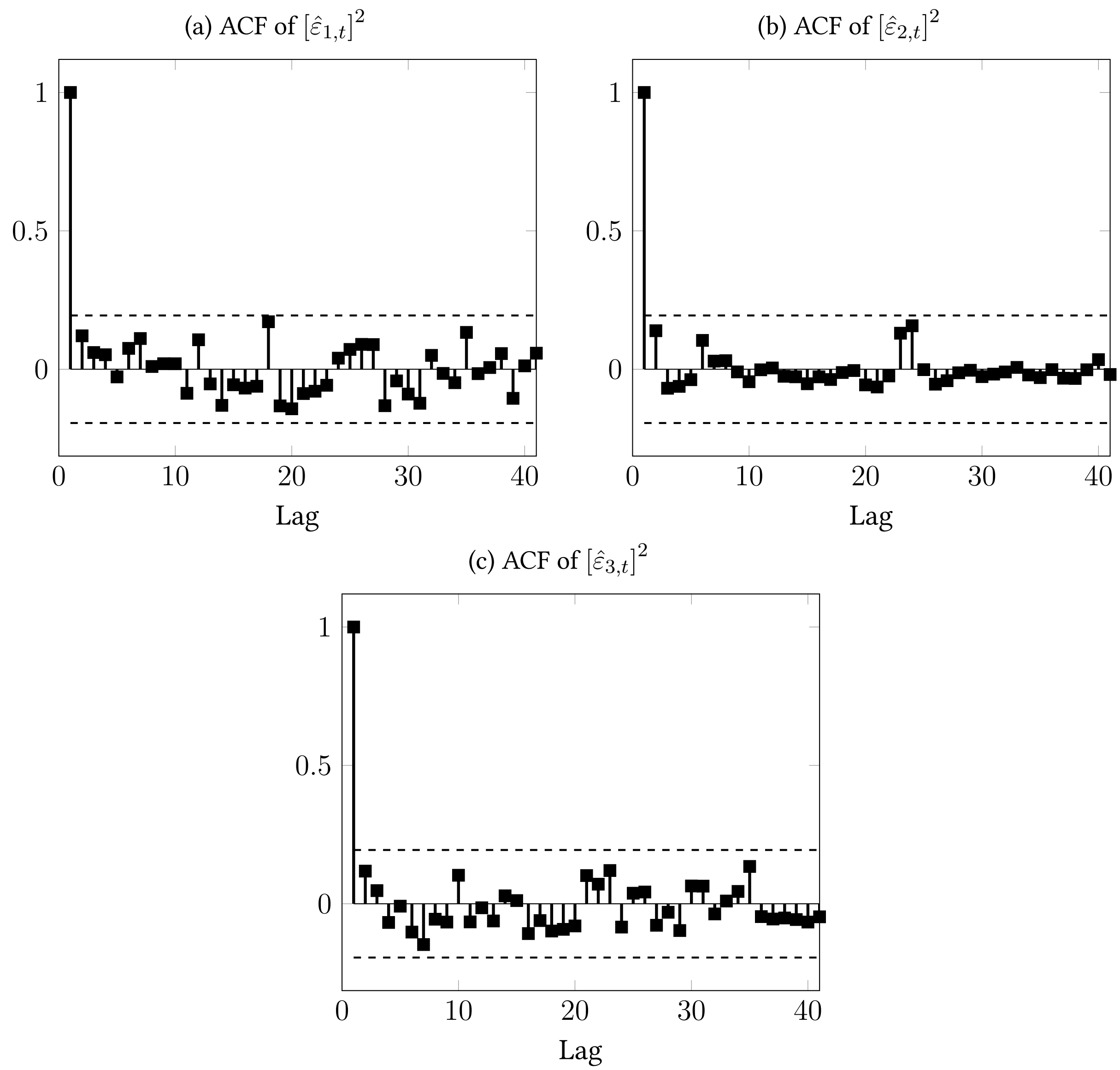


Table 4.3: Ljung-Box Tests on Squared Model Residuals

Residual Time Series	Hypothesis to Retain	*p-value*	Test Statistic	Critical Value
$[\hat{\varepsilon}_{1,t}]^2$	H_0	0.4394	40.7012	55.7585
$[\hat{\varepsilon}_{2,t}]^2$	H_0	0.9999	14.1731	55.7585
$[\hat{\varepsilon}_{3,t}]^2$	H_0	0.2280	48.7123	55.7585

Engle's ARCH test is a powerful tool used to assess the presence of non-constant variance in a time series, which is crucial in residual diagnostic. It tests whether squared residuals follow an autoregressive process and checks the joint non-significance of such AR coefficients, as below:

$$H_0 : \alpha_1 = \alpha_2 = \cdots = \alpha_p = 0$$
$$H_1 : \varepsilon_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 + u_t$$

Table 4.4: Engle's ARCH Test on Model Residuals

Residual Time Series	Hypothesis to Retain	*p-value*	Test Statistic	Critical Value
$\hat{\varepsilon}_{1,t}$	H_0	0.9988	18.1537	55.7585
$\hat{\varepsilon}_{2,t}$	H_0	1.0000	8.8893	55.7585
$\hat{\varepsilon}_{3,t}$	H_0	0.7387	42.1187	55.7585

As clear, from what is being shown in 4.3, 4.3, and 4.4, the residuals do not manifest heteroskedastic behavior.

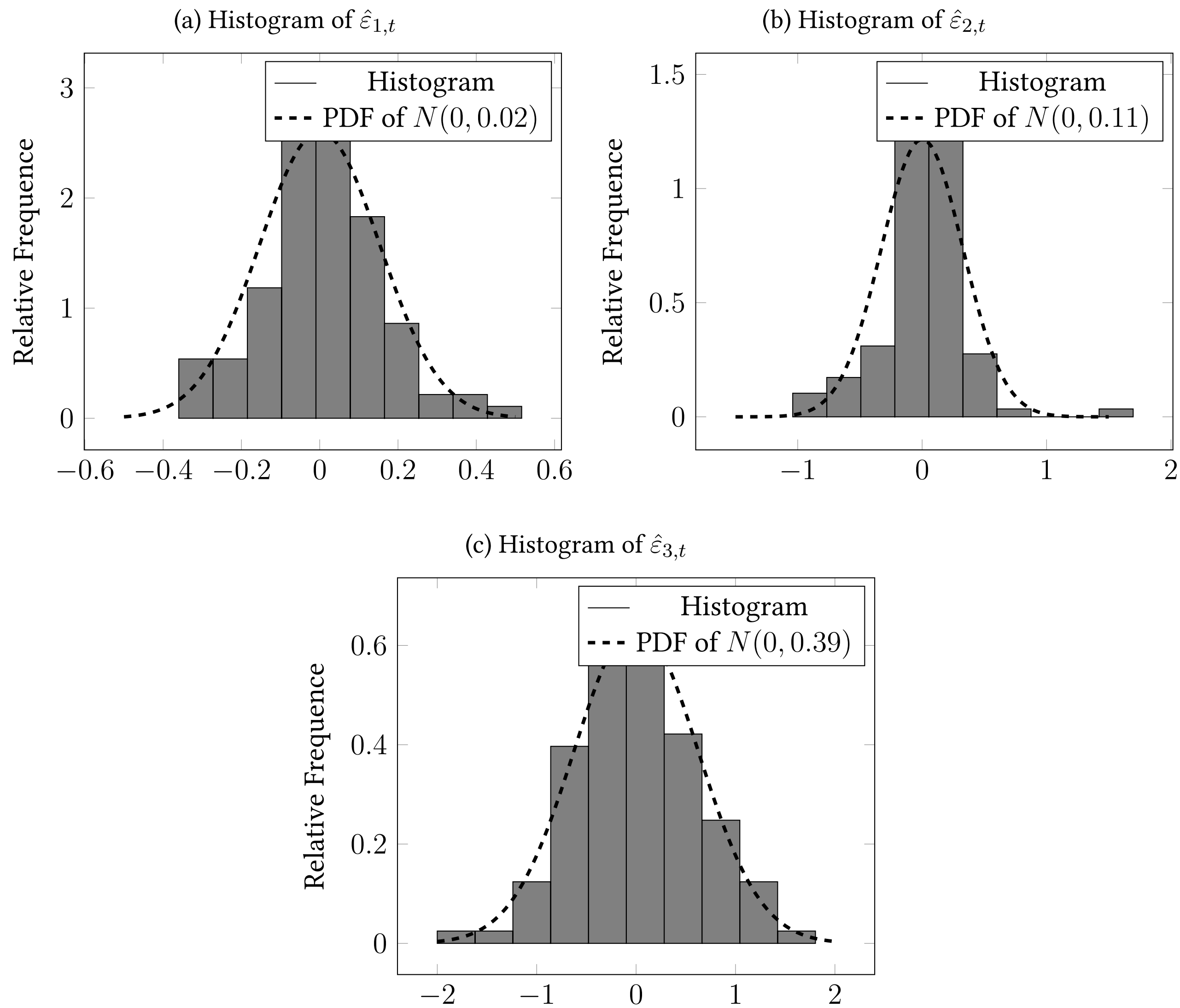
Finally, concerning the residuals' distribution, the assumption of normality must is tested, which is crucial for statistical inference and hypothesis testing. When the residuals follow a normal distribution, it enables the use of parametric tests, such as t-tests and F-tests. The histograms with a their corresponding superimposed normal distribution are shown in Figure 4.4, paired with the results of the Jarque-Bera test for normality[15].

Table 4.5: Jarque-Bera Test on Model Residuals

Residual Time Series	Hypothesis to Retain	*p-value*	Test Statistic	Critical Value
$\hat{\varepsilon}_{1,t}$	H_0	0.1885	1.9728	5.4584
$\hat{\varepsilon}_{2,t}$	H_0	0.1410	3.6752	5.4584
$\hat{\varepsilon}_{3,t}$	H_0	0.5000	0.6830	5.4584

In conclusion, one can affirm that the overall VARX(1,3) model explaining the effect of growth in bank credit on the latent Nelson-Siegel factors describing the term structure of Chinese corporate bonds is satisfactory and pertains to the OLS assumptions.
The effect has been proven and shown in the following and previous sections. As a final consideration, it would be suitable to also assess the consequences of a shock on the endogenous variables of the term structure, hence it would require to visually assess the model's impulse response functions (IRFs). They consist of introducing an impulse or shock into the system by setting the value of a particular variable to a known value for a brief period while keeping all other variables unchanged. The response of the system, measured by the changes in the variables of interest over time, is then recorded.
The estimated IRFs show the dynamic response of the variables to the shock. They reveal how

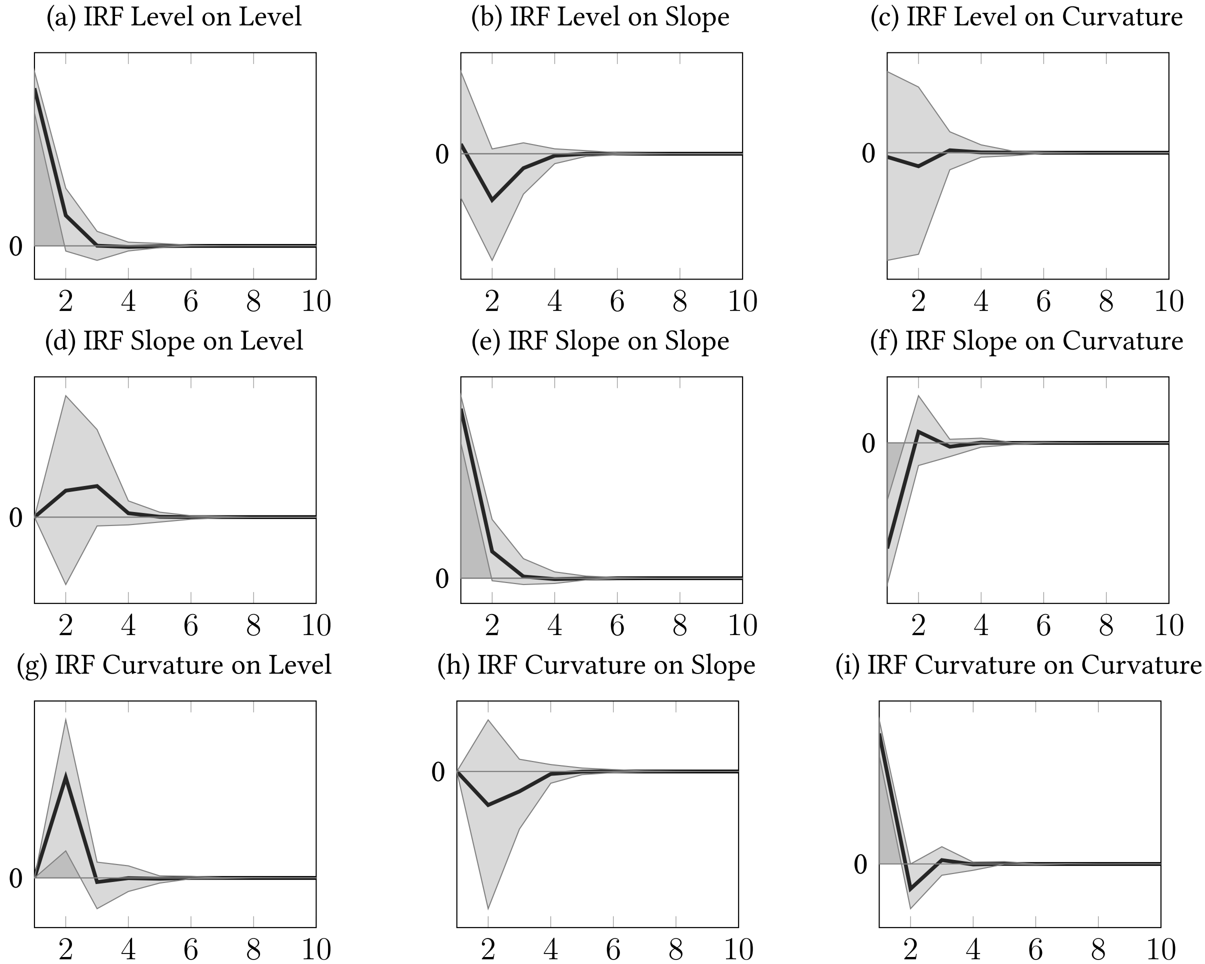
Figure 4.4: Histogram of Residuals



the initial shock propagates through the system, affecting variables at different time lags. They provide insights into the magnitude, duration, and persistence of the effects caused by the shock.

Figure 4.5 shows the different effects that a one standard deviation shock would have on the endogenous parameters of the VARX(1,3) model.
Overall, regardless of the cause or recipient of such perturbation, the impact dissipates quite quickly after 4-5 lags (months) in the future and the parameters revert to their steady states.
If one inspects the IRFs more closely, one notices on the leftmost column of the plots (4.5a, 4.5d, 4.5g) that the effect of shocks on the level L_t has a positive magnitude if caused by the slope S_t

Figure 4.5: Impulse Response Functions of Nelson-Siegel Latent Factors



(4.5d) and by the curvature C_t (4.5g).

The same cannot be stated for disturbances on the slope (middle column of 4.5) for which every coefficient causes a negative departure of S_t at the first lags before reverting to stability.

Finally, shocks on the curvature have a mixed effect depending on the *cause* variable. Level L_t has almost no consequences (4.5c), whereas the slope and the curvature on itself have mirrored outcomes, as shown in 4.5f and 4.5i, respectively.

Conclusion

The liberalization of the Chinese bond market that has taken place in the last two decades has had important implications on the interconnections between the monetary policy stance of the country and the fixed-income instruments' yields.
Corporate yields have in fact been proven to react to changes in bank credit.
Two of the three usual Nelson-Siegel parameters, the level and the slope, defining the long and short-term behavior of the term structure respectively, negatively respond to increases in the bank credit with a lagged effect of 10, 11, and 12 months.
Bank credit has been shown to be the most suitable indicator for the Chinese monetary policy stance for this sample among the ones that have been used throughout the existing literature. Its continuous path and crucial role in PBoC's decisions make it a reliable measure to represent either dovish or hawkish Chinese monetary decisions.
Moreover, bank credit is capable of capturing the unobservable component known as window guidance, which consists of a series of informal guidelines issued by the PBoC to the most relevant credit institutions in the country about to what extent to stimulate the economy.
Finally, it is considered a suitable proxy since it is collinear with other monetary policy tools, like OMOs, regulated deposit and lending rates, and the Reserve Requirement Ratio (RRR) among others.
What is also being found is that the parameters of the dynamic Nelson-Siegel model display persistent autocorrelations and cross-parameter dependency, especially the slope and the curvature. Moreover, such short and medium-term coefficients are useful in explaining and Granger causing the long-term one, also known as the level.

That said, it is evident that this study is able to create a solid common ground between the Chinese corporate bond market yields and the influence that the proxy for the monetary policy stance exerts on them, which was hardly investigated in past literature, opening up to a new, more detailed field of research that links monetary decisions to the cost of money actually experienced by corporations, that ultimately reflects into the real economy.

Appendix A

Appendix

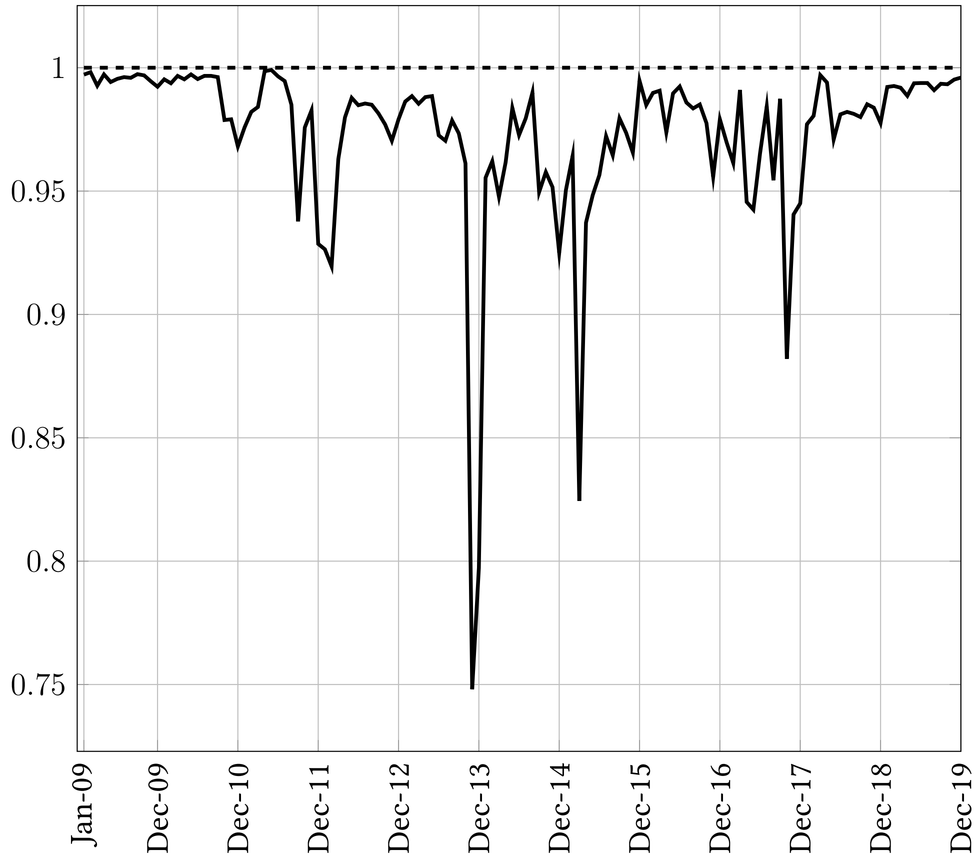
A.1 Dynamic Nelson-Siegel Model Goodness of Fit

The Diebold-Li dynamic Nelson-Siegel model adopted reiterates the parametrization of the yield curve for each t until the time series of the latent factors describing the yields are extracted.
By fixing the λ parameter one avoids a state-space specification of the model, which would have been undoubtedly more cumbersome to evaluate than a simple OLS.
Since, in fact, the output is produced by a simple linear regression, measures of goodness of fit can be computed in order to assess the goodness of fit of the overall model.
Such a figure is produced for each time instant for which the Nelson-Siegel parametrization is computed, hence a vector is produced whose dimension coincides with the length of the sample.
This brief section presents the evolution of the R^2, a well-known coefficient of determination, and is shown in Figure A.1.
The R^2 is very satisfactory, hugging closely to the 1 upper threshold and having as the global minimum a value of 0.75 in correspondence of late 2013.

A.2 Proxy Selection for the Chinese Monetary Policy Stance

The overall analysis revolved around the study of the influence that Chinese monetary policy allegedly exerted on the country's corporate yields, so the choice of a proper proxy for the monetary stance was crucial.
As previously explained in Section 2.1, China possesses a wide variety of both quantifiable and non-quantifiable instruments belonging to different categories depending on their features. This multitude of tools makes the decision on which proxy to adopt not an easy task.
Empirical studies have relied on (the growth of) PBoC's total assets to discriminate between

Figure A.1: R^2 of Dynamic Nelson-Siegel Fit



dovish and hawkish monetary interventions. The rationale lies in the fact that when a Central Bank undertakes actions such as Open Market Operations, it purchases massive amounts of mainly fixed-income securities in order to decrease their yields, lower the cost of money and eventually expand the monetary base of the country with the purpose of fostering the economic development.

On the other hand, other scholars adopted other means to model the Chinese monetary stance, such as creating actual Monetary Policy Indicators (MPIs). The development of such attempts has already been presented in the literature review, however, the most remarkable and robust experiments were performed first by Girardin *et al.*[10], who constructed such an index to mimic the features and characteristics of other countries' base rates; and by Pauwels[21], who refined his approach previously applied in another publication to generate a series of impulses of unitary magnitude.

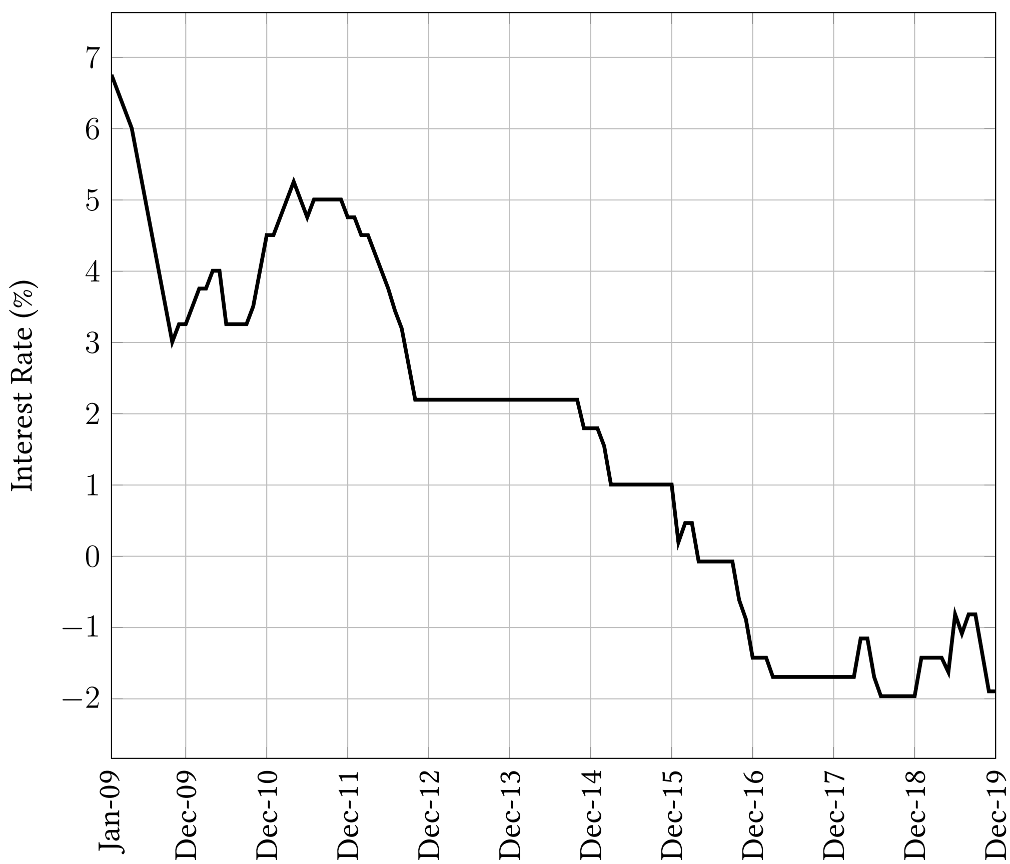
The former managed to create an indicator that pertained to the typical discrete-jump behavior of monetary policy stances which could reliably react to occurrences of economic turmoil.

Their model setup contained many of the policy tools at PBoC's disposal, even accounting for the unobservable window guidance.

Girardin's *et al.* updated MPI, however, had a major drawback. As visible in Figure A.2 from late 2016 onward it broke the Zero Lower Bound (ZLB) and kept substantially decreasing until it reached levels that were undoubtedly too low to faithfully depict a monetary policy stance.

Pauwels's indicator, on the contrary, only consisted of either hawkish or dovish impulses, hence lacking a comprehensive measure that could be applied and compared.

Figure A.2: Girardin's *et al.* Updated Monetary Policy Indicator



In order to correct for such a disadvantage, the unitary impulses were converted into 27bps equivalents and summed, so that a more comprehensive MPI could be constructed.

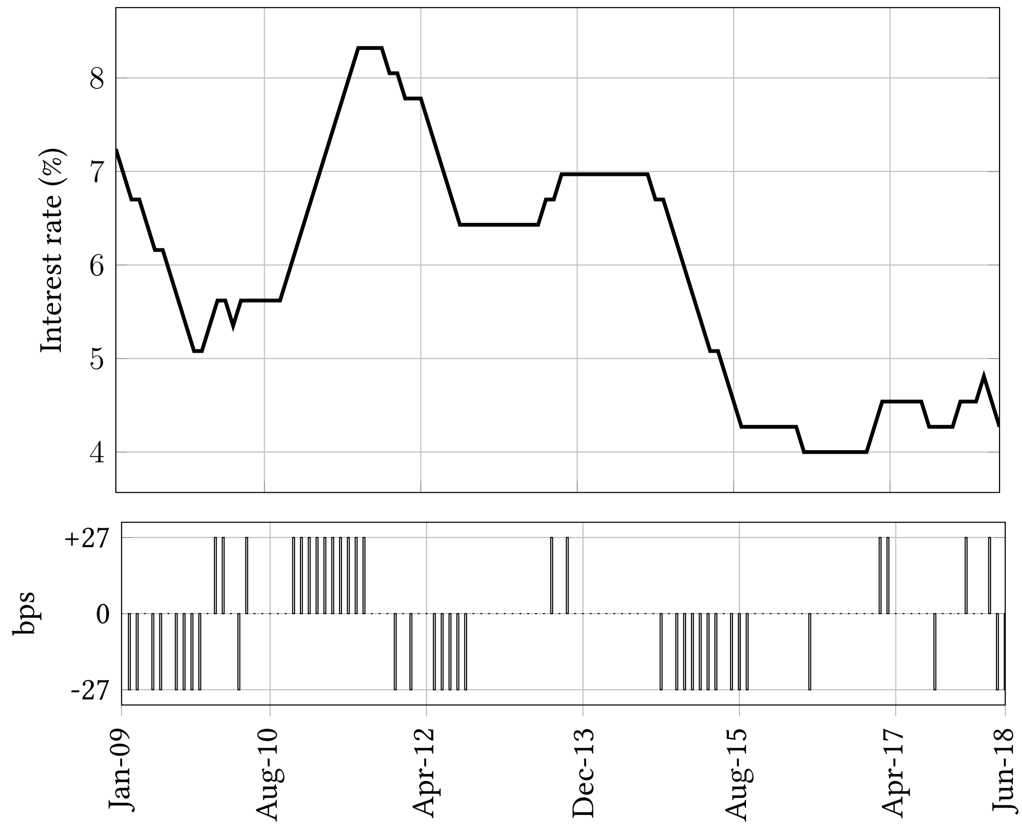
The starting point of the newly created monetary stance coincided with the value of the 3-month SHIBOR at the beginning of Pauwels' analysis, or January 2002. This value was found to be 4%.

The overall conversion of Pauwels' impulses into the corresponding MPI is presented in Figure A.3.

Visually speaking, the two charts look similar, signaling that the two different approaches were able to yield close results.

The two main differences between them can be first captured by inspecting the plots. Pauwels' study in Figure A.3 stretches until mid-2018, whereas Girardin's *et al.* manages to span until the

Figure A.3: Pauwels' Unitary Impulses (bottom) and Conversion to MPI (top)



end of 2019. Secondly, Pauwels' analysis does not include PBoC's OMOs, hence lacking a component that was instead accounted for by Girardin *et al.*, moreover the former incorporates the 7-day reverse repurchase rate at the expense of the benchmark interest rates and applies time-varying thresholds, which were neglected by the latter.

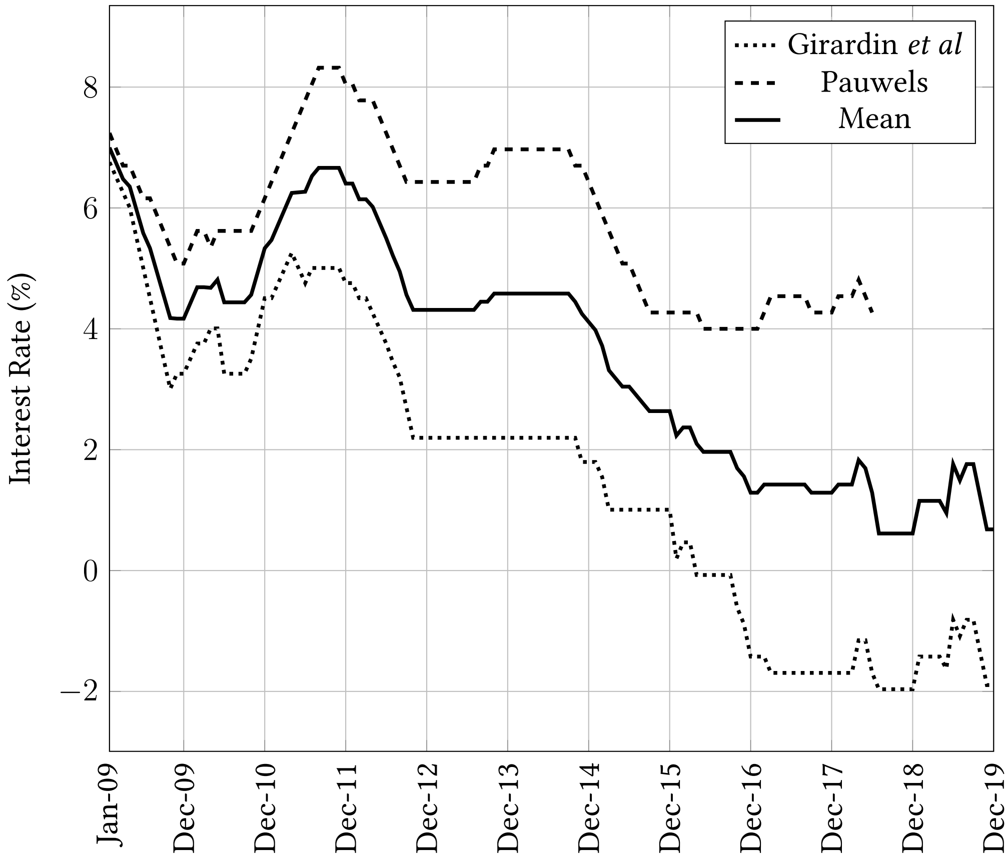
These discrepancies in their approaches tempt the reader to fuse the two MPIs by computing their average in order to find one, single, comprehensive monetary policy stance for China.

This decision leads to the middle plot in Figure A.4.

The resulting MPI is hence comprised of a more complete roster of monetary policy tools, incorporates time-sensitive thresholds, avoids the ZLB by still behaving like a base rate with discrete jumps of 27bps, and finally reacts properly to macroeconomic occurrences.

The new instrument displays a substantial decrease in correspondence to the closing instants of the GFC and a slight increase during the sovereign debt crisis. This is consistent with historical evidence since right after the Lehman Brothers bankruptcy China experienced a brief though sharp downturn in 2008, but quickly recovered and grew by 8.7% in 2009 and by 10.4% in 2010,

Figure A.4: Fused Monetary Policy Indicator



which may have caused the Chinese government to hike the rates.

The new MPI could at first be regarded as promising for the above-mentioned reasons. However, it experiences a loss of effectiveness when being used as a proxy for monetary policy to describe the effect of PBoC's decisions on the corporate bond term structure.

Some preliminary regressions were run to assess its efficacy, still pertaining to the same VARX model that has been adopted for this study. The first model accounted for *closer* lags of the differenced MPI, as below:

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \boldsymbol{\Phi y_{t-1}} + \boldsymbol{\beta_1 \Delta MPI_{t-1}} + \boldsymbol{\beta_2 \Delta MPI_{t-2}} + \boldsymbol{\beta_3 \Delta MPI_{t-3}} + \boldsymbol{\varepsilon_t} \qquad \text{with } \boldsymbol{\varepsilon_t} \overset{iid}{\sim} N(0, \boldsymbol{\Sigma}) \quad \text{(A.1)}$$

Since the estimated parameters of the autoregressive parts of the model did not display substantial differences from the adopted VARX model, the output for such matrices will be purposely omitted, only focusing on the coefficients of the exogenous variable.

The results are reported in Table A.1.

The other attempt concerned the same configuration however with more *distant* past lags of the

Table A.1: VARX(1,3) Output with Close MPI Lags as Exogenous Variable

Parameter	Estimated Value	Standard Error	Test Statistic	*p-value*
β_1	0.0218	0.0699	0.3125	0.7546
β_2	0.1995	0.1545	1.2870	0.1981
β_3	-0.1321	0.2929	-0.4510	0.6520
β_4	0.0013	0.0727	0.0183	0.9854
β_5	0.0489	0.1612	0.3035	0.7615
β_6	-0.3815	0.3047	-1.2520	0.2106
β_7	0.0589	0.07265	0.8102	0.4178
β_8	0.0160	0.1611	0.0993	0.9209
β_9	-0.3419	0.3044	-1.1230	0.2614

differenced MPI, such as $t-10$, $t-11$, and $t-12$, as for the growth in bank credit.
The regression would have then looked like the following:

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \boldsymbol{\Phi y_{t-1}} + \boldsymbol{\beta_1 \Delta MPI_{t-10}} + \boldsymbol{\beta_2 \Delta MPI_{t-11}} + \boldsymbol{\beta_3 \Delta MPI_{t-12}} + \boldsymbol{\varepsilon_t} \qquad \text{with } \boldsymbol{\varepsilon_t} \overset{iid}{\sim} N(0, \boldsymbol{\Sigma}) \tag{A.2}$$

. . . whose corresponding output is presented in Table .

Table A.2: VARX(1,3) Output with Distant MPI Lags as Exogenous Variable

Parameter	Estimated Value	Standard Error	Test Statistic	*p-value*
β_1	0.0655	0.0881	0.7434	0.4572
β_2	-0.1542	0.1945	-0.7929	0.4278
β_3	-0.0002	0.3765	-0.0006	0.9996
β_4	-0.0858	0.0947	-0.9053	0.3653
β_5	-0.0359	0.2093	-0.1716	0.8638
β_6	-0.0812	0.4051	-0.2005	0.8411
β_7	0.0237	0.0913	0.2599	0.7949
β_8	-0.1314	0.2017	-0.6515	0.5147
β_9	-0.0961	0.3905	-0.2460	0.8057

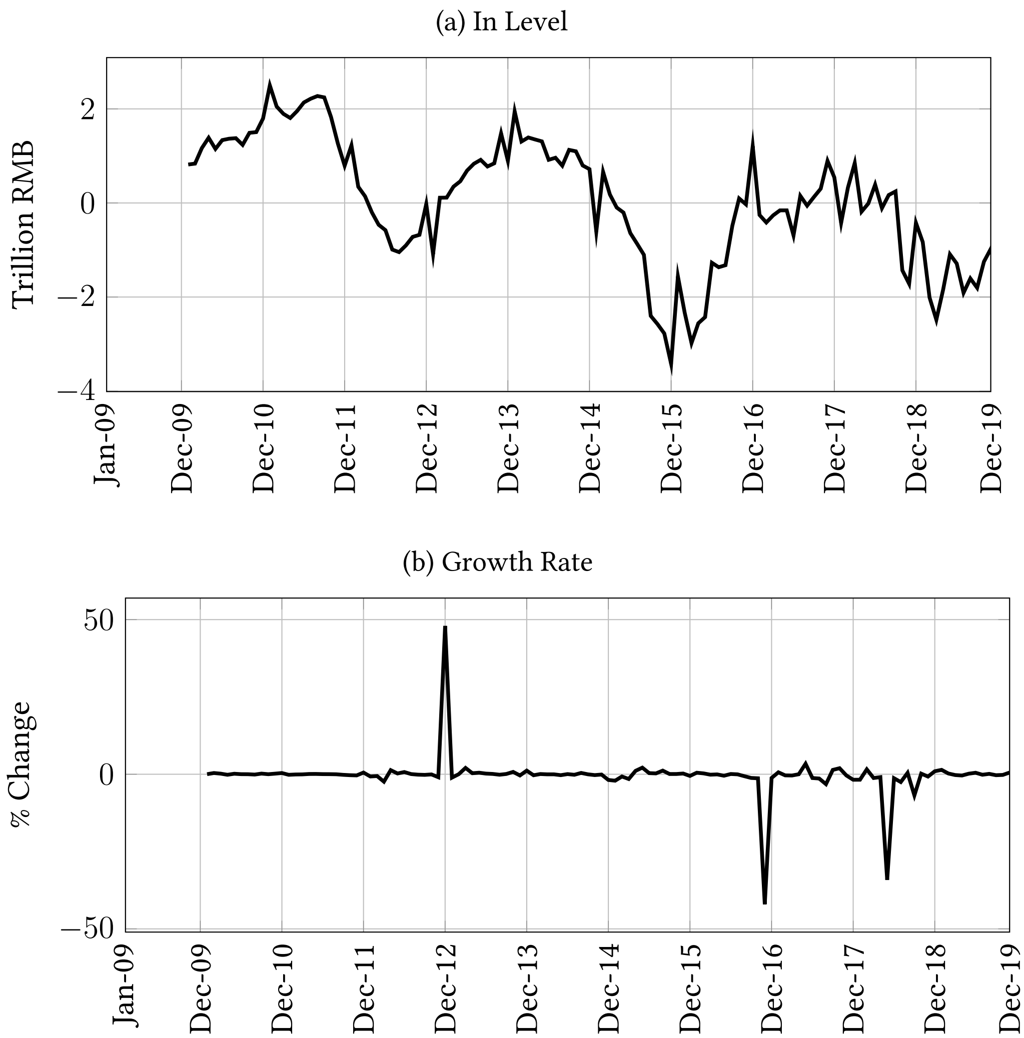
As shown, the new MPI is unfortunately not significant for this sample and hence required a new proxy to be adopted.
Neither for closer lags of the (differenced) MPI nor for further ones the instrument is able to have a significant effect on the Nelson-Siegel parameters defining the corporate bond term structure, as understandable from the high magnitude *p-values* of every regression coefficient.

Finally, one last attempt was conducted during the quest for a proper proxy for Chinese monetary policy, which consisted in delegating such a role to (the growth of) PBoC's total assets.
PBoC's assets reflect monetary interventions like OMOs and hence were used in the literature as

a proxy for such a policy.

Figure A.5 presents the detrended, seasonally adjusted variable in A.5a and its growth rate in A.5b.

Figure A.5: Detrended, Seasonally-Adjusted PBoC's Total Assets (in Trillion RMB) and its Growth Rate



The lack of usability of the growth rate of PBoC's total assets mainly arises because of the peaks in percentage change found in correspondence to some dates, such as December 2012, November 2016, and May 2018, reaching a magnitude of nearly 50%.

The same procedure applied to the fused MPI has been repeated, hence two regressions were run accounting for a set closer and of further lags of the exogenous variable in order to properly assess whether the growth in PBoC's assets was capable of statistically influencing the yields.

The first regression coincided with the below equation:

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \boldsymbol{\Phi y_{t-1}} + \beta_1 \textbf{\%PBoC Assets}_{t-1} + \beta_2 \textbf{\%PBoC Assets}_{t-2} + \beta_3 \textbf{\%PBoC Assets}_{t-3} + \boldsymbol{\varepsilon_t} \qquad \text{with } \boldsymbol{\varepsilon_t} \overset{iid}{\sim} N(0, \boldsymbol{\Sigma}) \tag{A.3}$$

... whose results are presented the results in Table A.3.

Table A.3: Regression of Total PBoC's Assets Used as Proxy for Chinese Monetary Policy

Parameter	Estimated Value	Standard Error	Test Statistic	*p-value*
β_1	0.0020	0.0022	0.9012	0.3675
β_2	0.0096	0.0048	1.0176	0.1436
β_3	-0.0127	0.0092	-1.3910	0.1642
β_4	-0.0008	0.0021	-0.3630	0.7166
β_5	0.0015	0.0047	0.3152	0.7526
β_6	-0.0080	0.0091	-0.8842	0.3766
β_7	0.0005	0.0021	0.2247	0.8223
β_8	-0.0006	0.0046	-0.1326	0.8945
β_9	-0.0060	0.0089	-0.6706	0.5025

The second regression on the other hand was again based on the principle of late responsiveness of the term structure to monetary interventions, and as a consequence, the canonical $t-10$, $t-11$, and $t-12$ lags were included, as shown below:

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \boldsymbol{\Phi y_{t-1}} + \beta_1 \textbf{\%PBoC Assets}_{t-10} + \beta_2 \textbf{\%PBoC Assets}_{t-11} + \beta_3 \textbf{\%PBoC Assets}_{t-12} + \boldsymbol{\varepsilon_t} \qquad \text{with } \boldsymbol{\varepsilon_t} \overset{iid}{\sim} N(0, \boldsymbol{\Sigma}) \tag{A.4}$$

Once again the output is presented in Table A.4

Table A.4: Regression of Total PBoC's Assets Used as Proxy for Chinese Monetary Policy

Parameter	Estimated Value	Standard Error	Test Statistic	*p-value*
β_1	-0.0003	0.0022	-0.1337	0.8937
β_2	0.0053	0.0047	1.1291	0.2588
β_3	-0.0024	0.0086	-0.2755	0.7830
β_4	-0.0023	0.0022	-1.0630	0.2878
β_5	0.0000	0.0047	-0.0037	0.9971
β_6	0.0021	0.0086	0.2483	0.8039
β_7	0.0000	0.0022	-0.0348	0.9722
β_8	-0.0046	0.0047	-0.9869	0.3237
β_9	-0.0014	0.0086	-0.1619	0.8714

Similarly to the new MPI created by fusing Girardin's *et al.* and Pauwels' ones, the growth in PBoC's total assets is not capable of influencing the variables of interest, making the choice of another proxy of monetary policy necessary.

A.3 VARX Model with Lower Lags

This dissertation adopted a VARX(1,3) model to explain the effect of the differenced Chinese bank credit on Nelson-Siegel parameters defining the country's corporate bond term structure, however as anticipated in the closing of Section 3.2, the monetary policy proxy lacks a timely effect on yields hence distant past lags had to be chosen in order to have a noticeable influence. The final configuration included lagged differenced bank credit at $t-10$, $t-11$, and $t-12$.
Other model specifications were tried with unsuccessful results.
The first one consisted in again a VARX(1,3) but with closer ΔBC lags, expressed by the equality below:

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \boldsymbol{\Phi y_{t-1}} + \boldsymbol{\beta_1 \Delta BC_{t-1}} + \boldsymbol{\beta_2 \Delta BC_{t-2}} + \boldsymbol{\beta_3 \Delta BC_{t-3}} + \boldsymbol{\varepsilon_t} \qquad \text{with } \boldsymbol{\varepsilon_t} \overset{iid}{\sim} N(0, \boldsymbol{\Sigma}) \tag{A.5}$$

The results in Table A.5 outline that the same cross-parameter effects of the chosen model are still

Table A.5: Alternative VARX(1,3) Output

Parameter	Estimated Value	Standard Error	Test Statistic	*p-value*
μ_1	-0.0064	0.0142	-0.4505	0.6524
μ_2	0.0092	0.0321	0.2869	0.7742
μ_3	-0.0075	0.0619	-0.1207	0.9040
$\phi_{1,1}$	0.1749	0.0876	1.9965	$0.0459^{(**)}$
$\phi_{2,1}$	-0.1137	0.1986	-0.5728	0.5668
$\phi_{3,1}$	-0.2305	0.3830	-0.6019	0.5473
$\phi_{1,2}$	0.1023	0.0453	2.2585	$0.0239^{(**)}$
$\phi_{2,2}$	0.1548	0.1026	1.5079	0.1316
$\phi_{3,2}$	-0.1057	0.1980	-0.5337	0.5935
$\phi_{1,3}$	0.0901	0.0235	3.8297	$0.0001^{(***)}$
$\phi_{2,3}$	0.0000	0.0533	0.0009	0.9993
$\phi_{3,3}$	-0.1586	0.1029	-1.5422	0.1230
β_1	0.0250	0.1252	1.5077	0.1457
β_2	0.0242	0.0284	0.8531	0.3936
β_3	-0.0177	0.0548	-0.3226	0.7470
β_4	0.0110	0.0124	0.8915	0.3726
β_5	-0.0076	0.0280	-0.2693	0.7877
β_6	0.0153	0.0542	0.2825	0.7775
β_7	0.0070	0.0092	0.7572	0.4489
β_8	-0.0222	0.0209	-1.0642	0.2872
β_9	-0.0052	0.0402	-0.1283	0.8979

present and significant, as a matter of fact, the level L_t is influenced by its previous lag and by the lagged slope S_t and curvature C_t. However, as far as the effect of the monetary policy proxy is concerned, lagged bank credit has no significant effect on any parameter for the sample analyzed. This phenomenon favors the assumption of late responsiveness of the term structure and also supports the choice of a VARX model with far more distant lags, as the one adopted for this study.

A.4 Decomposing Bank Credit into Other Monetary Policy Components

It has been shown that the differenced bank credit has a mainly negative effect on the Chinese corporate bond term structure at far past lags, precisely the yields need from 10 to 12 months to properly react to shocks to the variable.

Bank credit has been chosen as the proxy for monetary policy since it is a continuous variable and is also able to capture the latent presence of window guidance.

Since bank credit is a well-rounded measure controlled by the Chinese government, one could be interested in assessing if it could have some meaningful links with other monetary policy tools at the disposal of the PBoC.

In order to address such a concern, one could rely on an approach similar to the one used by M. Petreski and B. Jovanovic (2013)[22], and by P.G. Egan and A.J. Leddin (2016)[5], who investigated the relationship between the Chinese monetary base (M2) by regressing it on other monetary instruments and various macroeconomic variables.

Their procedure's main purpose consisted of the identification of the unquantifiable window guidance via Kalman filtering, however, offered interesting insights into the overall approach.

By adopting a similar framework, one could regress the (differenced, detrended, seasonally-adjusted) bank credit on the set of (differenced) monetary policy tools controlled by the Chinese government and on the fused MPI, as below:

$$\Delta \text{BC}_t = \alpha + \beta_1 \Delta \text{Lending Rate}_t + \beta_2 \Delta \text{RRR}_t + \beta_3 \Delta \text{OMO}_t + \beta_4 \Delta \text{MPI}_t + \varepsilon_t \tag{A.6}$$

The deposit rate has been excluded from the regression because it is almost perfectly collinear with the lending rate.

The regression output is reported in Table A.6.

The very high *p-values* can be traced back to the high multicollinearity present in the data since many policy tools react simultaneously and in the same direction to the Chinese government solicitations, hence making the overall regression not significant.

On further inspection, again following the procedure of Petreski and B. Jovanovic, and by P.G. Egan and A.J. Leddin, one could extract the unobservable window guidance by adding a regression variable governed by an autoregressive process and perform a signal extraction regression via

Table A.6: Bank Credit Growth Regressed on Other PBoC's Tools

Parameter	Estimated Value	Standard Error	Test Statistic	*p-value*
α	-0.0736	0.1521	-0.4840	0.6293
β_1	-0.5318	1.7920	-0.2968	0.7672
β_2	0.3182	0.5486	0.5800	0.5631
β_3	0.0001	0.0004	0.3258	0.7451
β_4	0.2002	0.7931	0.2525	0.8012

Kalman filtering.

A.5 Testing for Structural Breaks in the VARX Model

In order to confirm the robustness of the model, and since it is inherently based on an OLS regression, one must study the stability of the estimated coefficients.
Structural breaks in the parameters can be caused by significant shifts or changes in the underlying relationship between variables over time. Such breaks occur when there are alterations in the fundamental structure of the economic system or the data-generating process.
Since the sample spans from January 2009 to December 2019, the two major crises of the last twenty years have been purposely excluded, however, one important occurrence dealing with China's monetary policy instruments must be accounted for. Standing Lending Facilities (SLF) have been introduced in mid-2013 enhancing the portfolio of tools at PBoC's disposal to intervene in the country's monetary policy, and hence one might be tempted to test for parameter consistency over time by splitting the overall sample into two sub-samples, with break-point coinciding with May 2013.
The results have been reported in Table A.7 for the first sub-sample and Table A.8 for second subsample.
One can notice that despite the addition of the SLF, there have not been any parameter breaks since the estimated coefficients maintain the same sign, and almost equal magnitude and significance, in favor of the robustness and adequacy of the model.
In spite of these promising results, one has to be aware of the fact that such output tables carry an inherent problem linked to the degrees of freedom since the number of coefficients is not far from the length of the sub-samples.

Table A.7: VARX Model From Jan-2009 to May-2013

Parameter	Estimated Value	Standard Error	Test Statistic	*p-value*
μ_1	-0.0005	0.0237	-0.0217	0.9827
μ_2	0.0673	0.0752	0.8944	0.3711
μ_3	-0.1565	0.1259	-1.2430	0.2139
$\phi_{1,1}$	0.4253	0.1824	2.3315	$0.0197^{(***)}$
$\phi_{2,1}$	-0.2074	0.5799	-0.3577	0.7206
$\phi_{3,1}$	0.1778	0.9709	0.1831	0.8547
$\phi_{1,2}$	0.1195	0.0064	1.8672	$0.0871^{(*)}$
$\phi_{2,2}$	0.3632	0.2333	1.5567	0.15038
$\phi_{3,2}$	0.2918	0.3905	0.7472	0.4549
$\phi_{1,3}$	0.0834	0.0422	1.9765	$0.0543^{(*)}$
$\phi_{2,3}$	-0.2578	0.1341	-1.9221	$0.0550^{(*)}$
$\phi_{3,3}$	0.0711	0.2244	0.3169	0.7513
β_1	-0.0752	0.0406	-1.8519	$0.0640^{(*)}$
β_2	0.0164	0.0128	1.2813	0.2001
β_3	0.0104	0.0680	0.1533	0.8782
β_4	-0.0099	0.0084	-1.1715	0.2414
β_5	-0.0732	0.0306	-2.3922	$0.0001^{(***)}$
β_6	0.0461	0.0449	1.0274	0.3042
β_7	-0.0090	0.0087	-1.0345	0.3009
β_8	-0.0252	0.0136	1.8529	$0.0623^{(*)}$
β_9	0.0371	0.0464	0.7987	0.4245

Table A.8: VARX Model From Jun-2013 to Dec-2019

Parameter	Estimated Value	Standard Error	Test Statistic	*p-value*
μ_1	-0.0183	0.0199	-0.9199	0.3576
μ_2	-0.0047	0.0330	-0.1436	0.8858
μ_3	0.0005	0.0648	0.0071	0.9944
$\phi_{1,1}$	0.1982	0.1125	1.7197	$0.0981^{(*)}$
$\phi_{2,1}$	-0.3354	0.1868	-1.7950	0.0727
$\phi_{3,1}$	-0.2731	0.3673	-0.7436	0.4571
$\phi_{1,2}$	0.1380	0.0757	1.8220	$0.0685^{(*)}$
$\phi_{2,2}$	0.0952	0.1258	0.7565	0.4493
$\phi_{3,2}$	-0.4008	0.2473	-1.6208	0.1035
$\phi_{1,3}$	0.1200	0.0363	3.3063	$0.0009^{(***)}$
$\phi_{2,3}$	-0.0267	0.0603	-0.4424	0.6582
$\phi_{3,3}$	-0.3773	0.1185	-3.1853	$0.0014^{(***)}$
β_1	-0.0518	0.0268	-1.9322	$0.0575^{(*)}$
β_2	0.0193	0.0446	0.4326	0.6653
β_3	-0.1415	0.0876	-1.6153	0.1195
β_4	-0.0046	0.0292	-0.1583	0.8743
β_5	-0.0947	0.0486	-1.9476	$0.0511^{(*)}$
β_6	-0.0583	0.0954	-0.6105	0.5415
β_7	-0.0444	0.0440	-1.0112	0.3119
β_8	-0.0483	0.0265	-1.8226	$0.0718^{(*)}$
β_9	-0.0340	0.0864	-0.3940	0.6936

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