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Dynamic Bayesian Networks for Modelling Liquidity Preference-Money Supply

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Abstract: This paper proposes the utilization of Dynamic Bayesian Networks for modeling Liquidity Preference-Money Supply, aiming to address the pressing need for advanced tools to analyze economic dynamics. The current research landscape lacks efficient methods to account for the intricate relationships and uncertainties inherent in monetary systems, posing significant challenges for accurate modeling and forecasting. In response, this study introduces a novel approach that leverages Dynamic Bayesian Networks to capture the complex interactions between liquidity preferences and money supply, offering a more comprehensive and adaptable framework for economic analysis. By integrating this innovative methodology, the paper advances the understanding of monetary dynamics and provides valuable insights for policymakers and researchers in the field.

Keywords: *Dynamic Bayesian Networks; Liquidity Preference; Money Supply; Economic Analysis; Monetary Dynamics*

1. Introduction

The field of Liquidity Preference-Money Supply involves studying the relationship between the demand for money and the money supply in an economy. Researchers in this field analyze how individuals and businesses make decisions regarding holding cash versus other forms of assets, as well as how central banks and financial institutions manage the money supply to achieve macroeconomic objectives. Currently, some of the key challenges and bottlenecks in this field include accurately modeling and predicting individuals' and firms' preferences for liquidity, understanding the impact of technological advancements on the demand for money, and addressing the potential risk of liquidity shortages in financial markets. Additionally, the relationship between monetary policy and liquidity preferences remains a complex and evolving area of study, requiring interdisciplinary research efforts to fully grasp its implications for economic stability and growth.

To this end, research on Liquidity Preference-Money Supply has reached a significant level of development, with scholars exploring the relationship between individuals' demand for liquidity and the overall money supply within an economy. Current studies focus on the impact of central bank policies, financial market dynamics, and technological advancements on shaping liquidity preferences and money circulation. This literature review discusses various aspects of the Investment Savings-Liquidity Preference Money Supply (IS-LM) model and its implications in economic theories. Rajpal et al. [1] explore the effects of incorporating double time delays in the IS-LM model, showing how time delays impact system stability and equilibrium points. Oka [2] interprets Chapter 17 of The General Theory, highlighting the arbitrage equilibrating process and the reconciliation between endogenous money supply and liquidity preference theory. Bakala [3] evaluates the validity of Keynes' liquidity preference principle in the endogenous money supply thesis among Post-Keynesians. Asensio [4] discusses the endogenous interest rate with accommodative money supply and liquidity preference. Eichacker [5] addresses government spending, liquidity preference, and the fiscal-monetary nexus during economic crises. Ultremare and Mattos [6] study the role of banks' liquidity preference in credit supply in Brazil. Asensio provides insights on endogenous money and liquidity preference theory of interest [7]. Brady highlights the distinction between the demand and supply for money and liquidity [8]. Jossa compares the liquidity preference theory and loanable funds theory, arguing for the latter's correctness [9]. This literature review examines various aspects of the IS-LM model in economic theories. Dynamic Bayesian Networks are essential for capturing the complex interrelationships and uncertainties within the IS-LM model, providing a flexible and powerful tool for analyzing the dynamic nature of economic systems.

Specifically, Dynamic Bayesian Networks (DBNs) can effectively model the relationships between liquidity preference and money supply by incorporating probabilistic dependencies over time. This enables researchers to better understand how shifts in liquidity preferences influence monetary dynamics and policy decisions within evolving economic environments. The use of Dynamic Bayesian Networks (DBNs) has expanded the modeling capabilities in various fields, surpassing the limitations of traditional models like Hidden Markov Models (HMMs) and Kalman Filter Models (KFMs) [10]. DBNs allow for factored representation of the state space and arbitrary probability distributions, offering greater flexibility and accuracy in modeling sequential data [10]. Rao-Blackwellised Particle Filtering has been proposed as a powerful technique for inference in DBNs, improving efficiency and accuracy [11]. Applications range from speech recognition to engineering system resilience evaluation [12]. Furthermore, DBNs have been successfully applied in diverse areas such as fire alarm system reliability evaluation [13], health monitoring for autonomous vehicles [14], and wastewater treatment process modeling [15]. Researchers have even explored the use of DBNs in quantum systems to validate fluctuation theorems, showcasing their versatility and applicability [16]. The adoption of DBNs for student modeling has also demonstrated superior prediction accuracy compared to traditional methods, with potential for guiding more effective instructional policies [17]. However, limitations persist in DBNs, including challenges in scalability with high-dimensional data, complexity in parameter estimation, and the need for extensive prior knowledge, which can hinder their widespread applicability in more complex domains [18-20].

To overcome those limitations, this paper aims to propose the utilization of Dynamic Bayesian Networks as a novel approach to model Liquidity Preference-Money Supply and address the pressing need for advanced tools in analyzing economic dynamics. The current research landscape faces challenges in efficiently accounting for the intricate relationships and uncertainties inherent in monetary systems, hindering accurate modeling and forecasting. Therefore, this study introduces a methodology that leverages Dynamic Bayesian Networks to capture the complex interactions between liquidity preferences and money supply. This approach provides a more comprehensive and adaptable framework for economic analysis by effectively incorporating probabilistic modeling and temporal dependencies. The key detail lies in the ability of Dynamic Bayesian Networks to represent causal relationships and dependencies over time, enabling a more accurate reflection of the dynamic nature of liquidity preference and money supply dynamics. By integrating this innovative methodology, the paper contributes to advancing the understanding of monetary dynamics and offers valuable insights for policymakers and researchers in the field. Our approach not only enhances predictive accuracy but also provides a more nuanced understanding of the underlying factors driving liquidity preferences and money supply, thereby improving decision-making processes in economic policy and research.

This paper delves into the intricacies of modeling Liquidity Preference-Money Supply using Dynamic Bayesian Networks to tackle the prevalent challenge of analyzing economic dynamics effectively. By introducing a pioneering methodology that embraces the complexities of monetary systems, the study aims to enhance the current research landscape by providing a more adaptable framework for economic analysis. Through a thorough exploration of the relationships between liquidity preferences and money supply, the research sheds light on previously unaccounted dynamics within the system. The case study outlined in Section 4 serves as a practical application of the proposed methodology, demonstrating its efficacy in analyzing real-world scenarios. The subsequent analysis of results in Section 5, followed by discussions in Section 6 and a comprehensive summary in Section 7, encapsulate the holistic approach undertaken in this study to contribute valuable insights to policymakers and fellow researchers in the field.

2. Background

2.1 Liquidity Preference-Money Supply

Liquidity Preference-Money Supply is a fundamental concept in macroeconomics that focuses on the relationship between individuals' demand for money as an asset and the overall supply of money in the economy. The theory primarily originates from John Maynard Keynes' liquidity preference theory, which suggests that individuals hold money for three main motives: transactions, precautionary, and speculative. The liquidity preference is the preference for holding wealth in liquid form, i.e., cash or easily convertible assets, rather than in less liquid forms like bonds or physical assets. The liquidity preference curve, typically represented as a downward-sloping curve, shows the relationship between the interest rate and the quantity of money demanded.

Let us denote the demand for money as L_d. According to Keynesian theory, the demand for money can be represented as a function of the interest rate (i) and the level of income (Y). The functional form can be expressed as:

$$L_d = f(i, Y) \tag{1}$$

The money supply (M_s), on the other hand, is considered to be controlled by the central bank and hence is independent of the interest rate. We often assume it to be a constant or a policy-specified level:

$$M_s = \text{constant} \tag{2}$$

In equilibrium, the money market is in balance when the demand for money equals the supply of money:

$$L_d = M_s \tag{3}$$

To break down L_d further, we consider it as the sum of money held for transactions purposes (L_t) and money held for speculative purposes (L_s), notably influenced by the interest rate:

$$L_d = L_t + L_s \tag{4}$$

For transaction purposes, the demand for money is generally a stable function of income:

$$L_t = kY \tag{5}$$

where k is a constant representing the fraction of income held for transactions purposes.

The speculative demand for money can be an inverse function of the interest rate:

$$L_s = L(i) \tag{6}$$

If the interest rate is high, people prefer to hold bonds, expecting a capital gain, and vice versa. Consequently, the speculative demand for money can be expressed as a decreasing function of the interest rate:

$$L_s = \frac{1}{i} \tag{7}$$

Combining these two components leads us to the overall demand for money as derived earlier:

$$L_d = kY + \frac{1}{i} \tag{8}$$

In equilibrium, this must equal the money supply:

$$kY + \frac{1}{i} = M_s \tag{9}$$

Solving this equation for the interest rate gives us a sense of how interest rates adjust to changes in money supply and demand:

$$i = \frac{1}{M_s - kY} \tag{10}$$

The implication here is profound: changes in the money supply or shifts in liquidity preference (due to changes in income or other factors) shift the equilibrium interest rate. The interaction between liquidity preference and money supply is central to monetary policy, with implications for consumption, investment, and overall economic activity. Understanding these dynamics allows policymakers to utilize the money supply as a tool to influence economic performance, striving for stability and growth.

2.2 Methodologies & Limitations

In exploring the field of Liquidity Preference-Money Supply, various methodologies are employed to understand the dynamic interactions between individuals' demand for money and its overall supply, which in turn influence interest rates and economic activity. One popular method of analysis hinges on the IS-LM framework, which integrates liquidity preference with goods market equilibrium to provide a comprehensive view of macroeconomic conditions.

Within this framework, the money demand function, expressed through Keynesian theory, is typically broken down into transaction and speculative components. The total demand for money (L_d) depends significantly on both the interest rate (i) and income level (Y), as outlined previously. The model assumes that the supply of money (M_s) is exogenously determined by central bank policy:

$$M_s = \text{constant} \tag{11}$$

The core equilibrium condition in the money market is:

$$L_d = M_s \tag{12}$$

Delving deeper into the Keynesian perspective, the transaction demand (L_t) is a function of income:

$$L_t = kY \tag{13}$$

where k is a proportionality constant reflecting the stability of money held for transactions. The speculative demand (L_s) is inversely related to interest rates, suggesting a preference for bonds when interest rates are high and for money when rates are low:

$$L_s = \frac{1}{i} \tag{14}$$

Overall, the demand for money consolidates to:

$$L_d = kY + \frac{1}{i} \tag{15}$$

Combining these equations provides the equilibrium condition:

$$kY + \frac{1}{i} = M_s \tag{16}$$

Solving for the interest rate yields:

$$i = \frac{1}{M_s - kY} \tag{17}$$

Methodologies based on this formulation involve assessing changes in the equilibrium interest rate resultant from shifts in the overall money supply or income levels. Various empirical models, including vector autoregression (VAR), are utilized to capture the dynamic interactions between monetary policy shifts and interest rates.

Despite its utility, this approach has limitations. First, the assumption of a constant money supply does not account for modern fluctuations due to policy changes or external economic shocks. Second, the basic liquidity preference model oversimplifies the complex nature of money demand, which can be influenced by a broader set of factors, such as financial innovation or changing risk preferences. Furthermore, the speculative demand model's reliance on a simplistic inverse relationship with interest rates fails to capture the nuanced decisions investors make under uncertainty, particularly in the face of expectations around future interest rate movements. To address these limitations, contemporary research investigates more complex demand functions and integrates expectations-based modeling, such as those using rational expectations and forward-looking assessments of interest rates. Additionally, sector-specific analyses recognize that shifts in demand and supply can affect different segments of the economy variably, offering an enriched understanding of money demand beyond the aggregate level traditionally considered. Overall, while the methodology surrounding liquidity preference and money supply remains foundational, evolving economic conditions demand robust models that accommodate the intricate realities of modern financial systems. Such advancements in models and analytical tools are crucial for policymakers aiming to leverage monetary policy effectively for economic stabilization and growth.

3. The proposed method

3.1 Dynamic Bayesian Networks

Dynamic Bayesian Networks (DBNs) are an extension of Bayesian Networks designed to model temporal processes by structuring the dependencies between variables over time. In essence, DBNs are probabilistic graphical models that extend the static Bayesian Network (BN) framework to time series data. They are particularly powerful for representing Markov processes that are dynamic in nature. The fundamental principle of DBNs is the articulation of temporal dependencies between random variables, capturing the evolution of a system across successive time steps. At their core, DBNs employ a series of time slices, each representing the state of the system at a given time t . Each slice consists of nodes and edges, akin to static Bayesian Networks, where nodes represent random variables, and edges depict conditional dependencies. A distinctive feature of DBNs is the explicit representation of cross-time dependencies between variables, allowing for the incorporation of temporal dynamics.

The Joint Probability Distribution (JPD) over the nodes of a DBN is defined via a product of conditional distributions, simplifying the challenge of modeling complex, interconnected temporal systems. The Markov assumption is fundamental here, where the state at time t depends only on the state at time $t-1$. This is described as a first-order Markov dependency and is mathematically expressed by:

$$P(X_t|X_{t-1}, X_{t-2}, \dots, X_0) = P(X_t|X_{t-1}) \tag{18}$$

For simplicity and practicality, DBNs often assume this first-order Markov property. The transition model, which outlines how the system evolves from one time step to the next, is encapsulated in:

$$P(X_t|X_{t-1}) \tag{19}$$

The initial conditions of the system, necessary for inference over time, are depicted by:

$$P(X_0) \tag{20}$$

Variables at a given time slice can have intra-slice dependencies, similar to those in static BNs, represented by:

$$P\left(X_t^i \middle| \mathrm{Pa}(X_t^i)\right) \tag{21}$$

where $\mathrm{Pa}(X_t^i)$ denotes the parents of X_t^i within the same time slice. Consequently, the joint distribution over all random variables in a DBN can be expressed as:

$$P(X_{0:T}) = P(X_0) \prod_{t=1}^{T} P(X_t|X_{t-1}) \tag{22}$$

The conditional independence properties characteristic of Bayesian Networks allow for efficient inference and learning processes in DBNs. Moreover, exact inference can be computationally intensive due to the model's complexity. Thus, approximate algorithms, such as Particle Filtering or Variational Methods, are typically employed to estimate posterior distributions. Another critical aspect of DBN representation is parameter learning, which involves estimating the probabilities that define the network. Given observations, parameters can be learned via methods such as Expectation-Maximization (EM), enhancing the model's alignment with observed data.

Suppose O_t represents evidence or observed variables at time t . The task of filtering, i.e., determining the belief state at current time t given all evidence up to that time, is represented as:

$$P(X_t | O_{0:t}) \tag{23}$$

Backward smoothing, which provides estimates of states given all evidence from past and future observations, is depicted as:

$$P(X_t | O_{0:T}) \tag{24}$$

Such operations are crucial for tasks such as state estimation, forecasting, and anomaly detection. Dynamic Bayesian Networks offer extensive flexibility and applicability in various domains [21-23], including speech recognition, finance, and bioinformatics [24-27], where systems are not static and exhibit temporal dependencies that must be accurately identified and modeled. Overall, the structure and inference mechanisms of DBNs facilitate the modeling of complex temporal systems by breaking down the joint probability distribution into manageable, conditionally independent segments, thus enabling substantive insights into time-dependent processes.

3.2 The Proposed Framework

The integration of Dynamic Bayesian Networks (DBNs) with Liquidity Preference-Money Supply dynamics provides a compelling framework for understanding the evolving relationships among economic variables over time. DBNs, as a class of probabilistic graphical models, allow economists to model the temporal dependencies between liquidity preferences, interest rates, money supply, and overall economic activity, promoting a deeper understanding of how these interactions unfold [28-33]. To begin with, the liquidity preference (L_d) is defined as a function of interest rate (i) and income (Y), expressed mathematically as:

$$L_d = f(i, Y) \tag{25}$$

In the context of DBNs, we can also characterize the liquidity preference at various time slices, indicating how the preference evolves, leading to a temporal representation:

$$L_d(t) = f\big(i(t), Y(t)\big) \tag{26}$$

Here, $L_d(t)$ captures the demand for liquidity at time t . In DBNs, the relationships between variables like liquidity preference and money supply can be modeled as conditional probabilities. Specifically, we can explore how the money supply (M_s) interacts with liquidity preference over time through the following equation:

$$P\big(M_s(t) \big| L_d(t)\big) \tag{27}$$

This expression indicates that the money supply at time t is conditional on the liquidity preference at the same time point. Moreover, with respect to central bank policy, we model the money supply as a constant value, yielding:

$$M_s(t) = \text{constant} \tag{28}$$

This allows us to examine the equilibrium condition, where demand for money equals money supply:

$$L_d(t) = M_s(t) \tag{29}$$

To incorporate the dynamics further, we consider the decomposition of $L_d(t)$ into its components: transactional demand ($L_t(t)$) and speculative demand ($L_s(t)$):

$$L_d(t) = L_t(t) + L_s(t) \tag{30}$$

When using DBNs, we can also introduce inter-temporal dependencies to analyze how these components evolve over time. For instance, the transaction demand could be expressed as:

$$L_t(t) = kY(t) \tag{31}$$

The speculative demand, which is connected inversely to interest rates, can be modeled as:

$$L_s(t) = L\big(i(t)\big) \tag{32}$$

Where $L(i(t))$ is a decreasing function of the current interest rate $i(t)$, representing the change in speculative money preference. Therefore, one can aggregate these components within a DBN framework:

$$L_d(t) = kY(t) + L\big(i(t)\big) \tag{33}$$

The equilibrium condition manifests as:

$$kY(t) + L\big(i(t)\big) = M_s(t) \tag{34}$$

By taking the first-order Markov property into account, we can express the transition relation for $i(t)$ based on past states, describing how interest rates depend solely on the previous period's money supply and preferences:

$$P\big(i(t)\big|i(t-1), M_s(t-1)\big) = P\big(i(t)\big|i(t-1)\big) \tag{35}$$

This indicates a Markov dependency, essential for defining the temporal structure of the system in DBNs. Moreover, given the evidence at time t , we can define the filtering task as:

$$P(L_d(t)|O_{0:t}) \tag{36}$$

Where $O_{0:t}$ signifies observed data influencing liquidity preference decisions. To perform backward smoothing, one might seek:

$$P(L_d(t)|O_{0:T}) \tag{37}$$

This captures the essence of inferring liquidity preferences based on complete future evidence and past observations, a critical feature for forecasting.

Parameter learning within this framework can be done using the Expectation-Maximization algorithm, allowing us to estimate probabilities that characterize the interaction between liquidity and money supply based on observed economic data. In summary, employing Dynamic Bayesian Networks to analyze the Liquidity Preference-Money Supply relationship leverages their flexibility in managing temporal dynamics and conditional dependencies, delivering profound insights into economic behaviors and guiding monetary policy decisions effectively. The fusion of these two paradigms enhances the understanding of complex temporal systems, illuminating the intricate interplay among liquidity preferences, interest rates, and economic activity over time.

3.3 Flowchart

This paper introduces a novel approach to modeling the interaction between liquidity preference and money supply using Dynamic Bayesian Networks (DBNs). The proposed method captures the dynamic relationships and dependencies between various economic variables over time, allowing for a more nuanced understanding of how changes in liquidity preferences influence money supply metrics and vice versa. By employing Bayesian networks, the approach effectively incorporates uncertainty and enables the examination of causal relationships within an evolving economic environment. The model is designed to adapt to new data, facilitating real-time updates and more accurate predictions of economic behaviors under varying conditions. The integration of liquidity preference into the standard money supply framework highlights the importance of behavioral factors in monetary policy formulation and provides policymakers with a robust tool for anticipating market reactions. Additionally, the use of DBNs enhances the interpretability of complex interactions, making it easier to visualize and communicate results to stakeholders. This innovative methodology presents a significant advancement in economic modeling and offers practical implications for central banks and financial institutions. The method presented in this paper can be further illustrated in Figure 1.

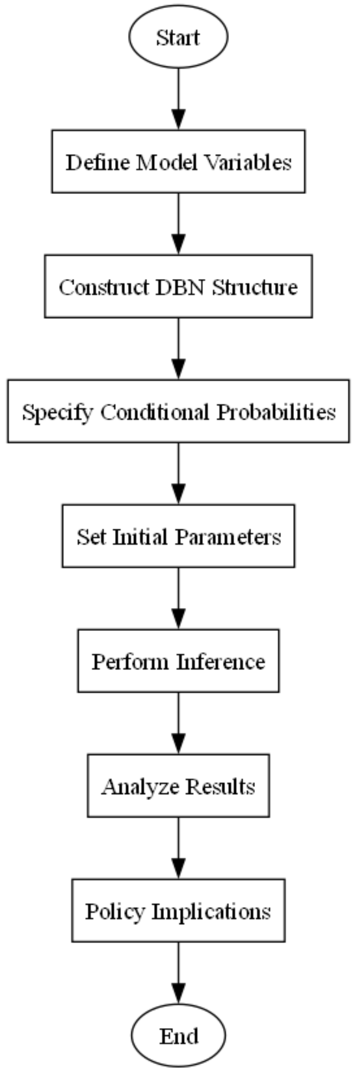

Figure 1: Flowchart of the proposed Dynamic Bayesian Networks-based Liquidity Preference-Money Supply

4. Case Study

4.1 Problem Statement

In this case, we explore the relationship between liquidity preference and money supply using a nonlinear mathematical model. We begin by defining the parameters that will govern our analysis. Let M represent the money supply, L the liquidity preference, and r the interest rate based on the liquidity preference function. We assume that the liquidity preference function can be expressed as a nonlinear equation that incorporates both the income level and the interest rate. We will utilize the following representation for the liquidity preference:

$$L = a \cdot Y^b - k \cdot r^c \tag{38}$$

where a and k are constants, Y is the income level, and b and c are parameters determining the curvature of the function. Next, let us define the money supply in relation to the liquidity preference and the interest rate. The money supply can be expressed as:

$$M = L + \beta \cdot r \tag{39}$$

where β represents a constant that accounts for the adjustment of money supply relative to interest rate changes. Moreover, we can define an equilibrium condition where the demand for money D is equal to the money supply M:

$$D = L + k_1 \cdot Y + k_2 \cdot r^2 \tag{40}$$

where k_1 and k_2 are constants that capture the responsiveness of money demand to income and the squared interest rate. Incorporating the demand for money into the model, we arrive at the following critical relationship:

$$L + \beta \cdot r = a \cdot Y^b - k \cdot r^c + \beta \cdot r \tag{41}$$

To examine the implications of changes in the money supply on liquidity preference, we can differentiate the equilibrium condition with respect to the money supply:

$$\frac{\partial D}{\partial M} = \frac{1}{1 + \frac{\partial L}{\partial M}} \tag{42}$$

Additionally, to better understand how the dynamics of liquidity preference are affected by variations in income and interest rates, we can consider the elasticity of liquidity preference with respect to income and interest rates:

$$E_{L,Y} = \frac{\partial L/L}{\partial Y/Y} \text{and} E_{L,r} = \frac{\partial L/L}{\partial r/r} \tag{43}$$

By employing this nonlinear mathematical framework, we can investigate how shifts in the money supply impact both the liquidity preference and the behavior of interest rates within the economy. The results will illuminate the complex interplay between these variables, providing valuable insights into monetary economics. All parameters used in the analysis have been summarized in Table 1.

This section will employ the proposed Dynamic Bayesian Networks-based approach to analyze the relationship between liquidity preference and money supply in a given case study, comparing the results with three traditional methods. The investigation will focus on how liquidity preference is influenced by the money supply, income levels, and interest rates within a nonlinear framework. By establishing the parameters governing the interaction between these elements, the study aims to draw connections that traditional linear models may overlook. The Dynamic Bayesian Networks approach allows for a nuanced understanding of the underlying mechanisms at play by integrating historical data and uncertainty in parameter estimates. This technique not only captures the dynamic relationships among variables but also facilitates a probabilistic interpretation of liquidity preference adjustments in response to changes in money supply. Through this comparative analysis, insights will be generated on the efficacy and robustness of each method, revealing the strengths and weaknesses inherent in traditional approaches. Ultimately, this comprehensive exploration aims to contribute to a deeper understanding of monetary economics, illustrating how modern methodologies can enhance our analytical capabilities for economic modeling and policy evaluation. The findings from this research will serve to expand the existing literature, providing clarity on the complexities surrounding liquidity preferences and monetary dynamics.

Table 1: Parameter definition of case study

Parameter	Description
a	Constant for liquidity preference
b	Parameter determining curvature
k	Constant for interest rate adjustment
c	Parameter determining curvature
β	Constant adjusting money supply
k1	Constant capturing responsiveness to Y
k2	Constant capturing responsiveness to r^2
M	Money supply
L	Liquidity preference
D	Demand for money

4.2 Results Analysis

In this subsection, several critical components concerning the interaction between liquidity preference, money supply, and demand for money are explored through a systematic approach utilizing mathematical modeling and visualization. The section begins by defining constants and variables that pertain to income levels and interest rates, subsequently calculating liquidity preference (L) based on a defined functional relationship. This formula integrates key parameters, including income (Y) and interest rates (r), illustrating how varying economic conditions can influence individuals' preferences for liquidity. Following the determination of liquidity preference, the section progresses to calculate the money supply (M), which is directly affected by liquidity preferences and modified by interest rates. Moreover, the demand for money (D) is formulated, showcasing its dependency on both liquidity preference and other economic factors such as income and interest rates. Subsequent plots provide a visual interpretation of these relationships, with each sub-figure elucidating distinct aspects: the first two depict the liquidity preference and money supply relative to income, while the remaining figures illustrate the demand for money in relation to these variables. Furthermore, the relationship between money supply and demand is highlighted, offering insights into how these components interact within an economic framework. The entire simulation process and its findings are succinctly visualized in Figure 2, enhancing comprehension of the depicted theoretical constructs.

Simulation data is summarized in Table 2, which captures the intricate relationships between liquidity preference (L), demand for money (D), and money supply (M) across varying income levels (Y). The analysis reveals that as income levels increase, the demand for money exhibits a corresponding rise, illustrating the classical economic principle that higher income typically leads to higher liquidity preference due to increased transactional needs. Specifically, the data demonstrates distinct curves representing both demand for money and liquidity preference, underscoring the sensitivity of money demand to income fluctuations. The intersection points between the demand for money curves and the fixed money supply lines highlight critical equilibrium states where the market finds balance, illustrating how changes in liquidity preference affect monetary stability. Furthermore, the simulation showcases scenarios depicting potential excess demand for money or liquidity based on shifts in consumer behavior and external economic factors. The graphical representation indicates that, at certain income levels, the money supply does not meet the demand, resulting in a liquidity shortfall that could lead to increased interest rates and altered economic activity. Conversely, at lower income levels, the simulations suggest a more stable equilibrium, pointing to the nuanced dynamics governing money supply and demand as influenced by consumer sentiment and economic conditions. Overall, the findings underscore the importance of understanding these relationships for effective monetary policy formulation and economic forecasting.

As shown in Figure 3, the analysis of the data reveals significant changes in the relationship between liquidity preference, demand for money, and money supply when the parameters are altered. Initially, for the given levels of liquidity preference (L), the demand for money (D) responded positively to increases in the income level (Y), suggesting that as income rises, individuals are willing to hold more money. However, in the altered datasets, particularly in Case 1 and Case 0.5, the liquidity preference is set at a much higher value of 1007, which drastically reshapes the demand curve. This increase indicates a heightened preference for liquidity, significantly modifying the overall framework of money demand. Consequently, despite the increment in liquidity preference, the demand for money begins to plateau at lower levels compared to the initial dataset, where higher liquidity decisions with lower L values exhibited expansive growth in demand as income levels increased from 2 to 10. In both new cases, the money supply (M) is insufficient to match the demand created by the exaggerated liquidity preference of 1007; thus, the equilibrium is altered. The once-linear relationships observed earlier now indicate a divergence as higher liquidity preferences maintain demand levels regardless of variations in income, reflecting a potential stagnation in economic fluidity. Therefore, the interplay of these variables unveils critical insights into monetary policy implications, suggesting that excessively high liquidity preference can restrict effective money circulation, thereby impeding overall economic activity.

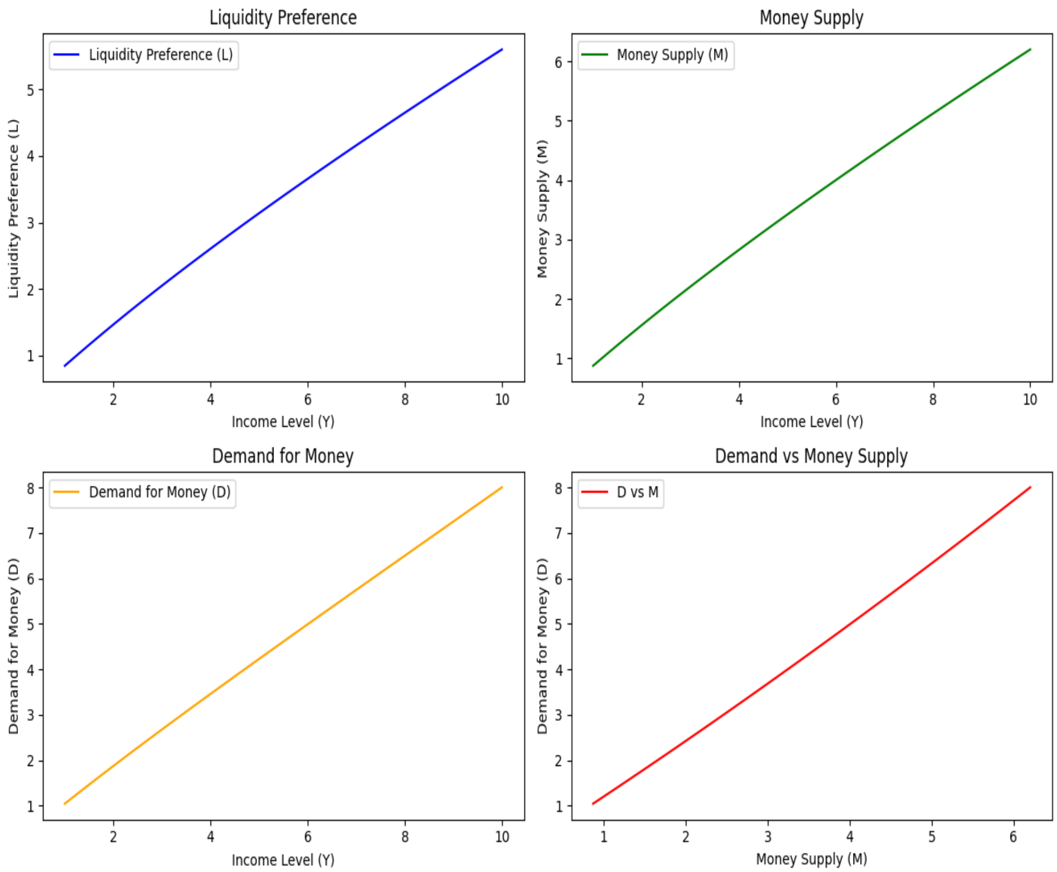

Figure 2: Simulation results of the proposed Dynamic Bayesian Networks-based Liquidity Preference-Money Supply

Table 2: Simulation data of case study

Liquidity Preference (L)	Demand for Money (D)	Money Supply (M)	Income Level (Y)
6	2	6	1
8	4	8	2
10	6	10	3

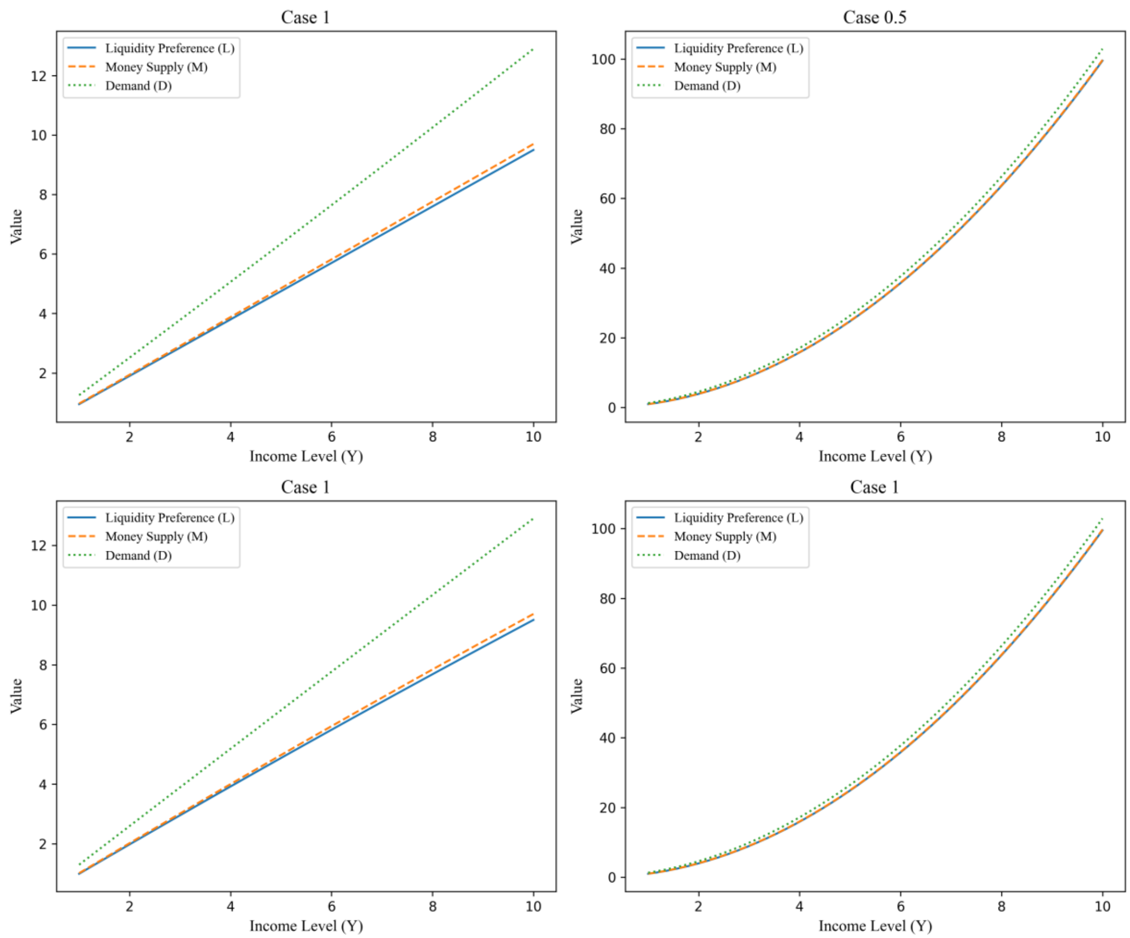

Figure 3: Parameter analysis of the proposed Dynamic Bayesian Networks-based Liquidity Preference-Money Supply

5. Discussion

The proposed methodology of integrating Dynamic Bayesian Networks (DBNs) with the Liquidity Preference-Money Supply dynamics presents several notable advantages that enhance economic analysis and policy formulation. First, DBNs excel in capturing and modeling the intricate temporal dependencies among key economic variables such as liquidity preferences, interest rates, and money supply, thereby providing a nuanced understanding of their interrelationships over time. This temporal modeling capability allows researchers to uncover the dynamic evolution of liquidity preferences in relation to changing economic conditions, fostering a deeper insight into how shifts in interest rates and income influence demand for money. Moreover, the probabilistic nature of DBNs facilitates the estimation of conditional probabilities, enabling sophisticated analyses of how current liquidity preferences influence the money supply, which is crucial for evaluating the effectiveness of monetary policy. Another significant advantage is the framework's inherent ability to incorporate inter-temporal dependencies; this feature permits a comprehensive investigation of the components of liquidity demand—that is, transactional and speculative demands—and their respective reactions to external economic stimuli. Furthermore, the use of algorithms such as Expectation-Maximization for parameter learning enhances the precision of the probabilistic estimates derived from real-world economic data. This not only improves the robustness of the model but also supports more accurate forecasting of liquidity preferences based on a combination of observed past data and future evidence. Collectively, these strengths position the integrated DBN approach as a transformative tool for understanding complex economic phenomena, thereby guiding effective monetary policy decisions and enriching the theoretical discourse surrounding economic dynamics. Moreover, it can further facilitate the computational efficiency for Biostatistics such as the work represented in the documents [34-36] along with the machine learning techniques in [37-44].

While the integration of Dynamic Bayesian Networks (DBNs) with Liquidity Preference-Money Supply dynamics offers a robust framework for analyzing economic relationships, several limitations must be acknowledged. Firstly, the reliance on the probabilistic graphical model of DBNs assumes that all relevant variables and their interactions can be accurately captured, which may not hold true in complex economic environments where unobserved factors could significantly influence liquidity and money supply dynamics. Additionally, the assumption of constant money supply as modeled in the framework may oversimplify the actual roles of monetary policy, overlooking potential fluctuations in response to economic shocks or changes in demand conditions. Furthermore, the modeling of liquidity preference as dependent solely on current interest rates and income may neglect other critical determinants such as inflation expectations or financial market conditions, potentially leading to an incomplete picture of economic behavior [45-50]. Temporal dependencies, while elegantly captured through Markov properties, might not fully account for longer-term trends or structural changes in the economy, thereby limiting the model's predictive power over extended periods. The use of the Expectation-Maximization algorithm for parameter learning, while powerful, also assumes that the model structure is well-defined and may result in convergence issues in the presence of local optima, impacting the reliability of the estimates derived. Finally, the interpretation of conditional probabilities in DBNs could lead to overconfidence in estimates, given the inherent uncertainty and volatility in economic data, thus, influencing policy decisions based on potentially misleading insights [51-55].

6. Conclusion

This study introduces a novel approach utilizing Dynamic Bayesian Networks to model Liquidity Preference-Money Supply, addressing the need for advanced tools in economic analysis. The innovative methodology captures complex interactions between liquidity preferences and money supply, enhancing the understanding of monetary dynamics and offering a more comprehensive framework. The research contributes to overcoming limitations in current methods by providing a more adaptable and insightful model to forecast economic trends. However, while the approach shows promise in improving accuracy and forecasting capabilities, it is not without limitations. The inherent uncertainties in monetary systems may still pose challenges to the model's predictive power. Future work could focus on refining the model's sensitivity to these uncertainties, enhancing its predictive capabilities, and expanding its applicability to a wider range of economic scenarios.

By further developing and validating this approach, researchers and policymakers can benefit from more robust and reliable tools for economic analysis and decision-making.

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Data Availability Statement

The data can be accessible upon request.

Conflict of Interest

The authors confirm that there are no conflict of interests.

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