



The causal structure of bond yields

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ABSTRACT

This paper implements an emerging data-driven method of directed acyclic graphs to study the contemporaneous causal structure among the federal funds rate and U.S. Treasury bond yields of various maturities. Using high frequency daily data from 1994 to 2009, we find that innovations in the two-year Treasury bond yield play a central role. They contemporaneously cause most other bond yields. Therefore, monetary policy makers would benefit from closely monitoring the two-year yield in setting the interest rate target, a result echoing the policy rule suggested by Piazzesi (Journal of Political Economy, 2005). Both Fed and investors should also watch the seven-year bond yield because it explains significant portions of variability in many other yields.

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1. Introduction

Both macroeconomists and financial economists have intensively studied bond yields (prices), because the term structure of interest rates is a rich source of economic and financial information. The majority of bond-yield curve models employ a structure that consists of a small number of factors and the associated factor loadings that relate yields of different maturities to those factors (Diebold, Piazzesi, & Rudebusch, 2005; Rudebusch & Wu, 2008). In latent factor models which are popular in finance literature, the factors (or unobservable state variables) are typically backed out from yield data. These estimated factors are oftentimes given further economic interpretations. However, as evident in numerous empirical studies, economic and financial information is difficult to extract from the term structure of interest rates because of its dependence on monetary policy and the existence of time-varying term premia (Palomino, 2010).

In this paper, we complement existing literature by studying bond yields from a different perspective. Specifically, we are interested in the contemporaneous causal structure of shocks (unanticipated changes or innovations) to bond yields of various

maturities. Rather than estimating a few factors each as a function of all yields, here we assess the relative importance of shocks to each yield by identifying the contemporaneous causal relationship between each pair of shocks that drive the yields.¹ As our later empirical results show, not all shocks are “created” equal in that the market reaction to a shock to short-term bonds is unlikely to be the same as that to long-term bonds. Some shocks cause changes in other yields immediately. Others are local in the sense that they are less likely to transmit to other yields in the contemporaneous time, although they probably also affect other yields over time. Clearly, this type of causal information can provide guidance on which bond yields the Fed Reserve and other market participants should watch more carefully.²

It is well known that inferring contemporaneous causality from observational data is by no means a simple task. In this paper we apply a data-driven method to search for the causal structure of

¹ In this paper we focus on the dynamics of shocks. We do not seek to link the shocks to economic fundamentals. By contrast, as discussed in the first paragraph, existing literature look for fundamentals-proxying factors that drive the dynamics of the yield curve. Clearly, interest rates are causally determined by more fundamental factors, both measured and unmeasured. In this sense, our focus on interest rates is *conditioned* on these short- and long-term factors.

² According to Meyer (1998), the Federal Open Market Committee (FOMC) does react to *current* yield data because each FOMC meeting starts with a review of the “financial outlook.”

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the innovations in bond yields. The suggested method of directed graphs is the graph-theoretic analysis of causality (Pearl, 2000; Spirtes, Glymour, & Scheines, 2000). The study and application of the directed graph method is in line with the growing interest from applied researchers in automated model discovery (more on this in the Methodology section).

Innovations or shocks are unexpected components of bond yields and, by definition, are unobservable. The standard strategy, also applied in this paper, is to estimate them as the residuals of a vector autoregression-type (VAR) model (e.g., a vector error correction (VEC) model with cointegration). In determining which variables to include in the VAR model, we follow a growing literature and model the term structure in combination with monetary policy.³ Namely, we include in the VAR both U.S. bond yields of maturities running from one to 20 years and a monetary policy variable. We study the U.S. data because, compared to yields on other sovereign debt, the U.S. Treasury yields are probably most investigated in the international markets, arguably due to the U.S. market size and liquidity. We use the federal funds rate as the indicator of the Fed’s monetary policy stance. This is because over much of the past decades the Fed has implemented policy changes through changes in the federal funds rate (Bernanke & Blinder, 1992).

Our most interesting finding is that unexpected changes in the two-year Treasury constant maturity rate contemporaneously cause unexpected changes in most other Treasury bond interest rates. Therefore, monetary policy makers should closely monitor the two-year yield in setting the interest rate target, a result echoing the policy rule suggested by Piazzesi (2005) based on a much more complicated parametric model.⁴ To capture the full dynamics of bond yields, we also conduct standard forecast error variance decomposition within the vector autoregressions (VARs) framework. Rather than using a restrictive recursive structure, we orthogonalize the reduced-form VAR residuals according to the identified contemporaneous causal structure (DAG). Results from this part of the analysis also suggest the importance of both two- and seven-year bonds in driving the dynamics of the bond market.

The main message from our empirical results is that both the short-term and the long-term states of the economy are important determinants of interest rates. And they appear well proxied by the two-year and the seven-year rates, respectively. By pinpointing the prominent influence of the two interest rates behind the bond market, our results complement existing latent factor models which typically explain the term structure by one or two linear combinations of interest rates of all maturities. For example, Cochrane and Piazzesi (2005) show that a single linear combination of forward rates predicts excess returns on 1–5-year maturity bonds, where the largest effect comes from the three-year bond.

The remainder of the paper is structured as follows. Section 2 presents econometric methodology. Section 3 describes the data. Section 4 presents major empirical results, and Section 5 discusses the results and concludes the paper.

2. Econometric methodology

In this section, we first briefly describe the intuition of the directed acyclic graph (DAG) analysis and the search algorithm

³ A partial list of these studies includes McCallum (1994), Cochrane and Piazzesi (2002), Diebold et al. (2005), Gallmeyer, Hollifield, and Zin (2005), Piazzesi (2005), Rudebusch and Wu (2008), and Palomino (2010).

⁴ This is a normative statement (“should do”). Our results cannot tell whether, in reality, the Fed and other market participants are acting this way, which is a positive matter (“actually do”).

we use to implement the emerging method. We then show how the uncovered contemporaneous causal structure based on the reduced-form residuals of a vector autoregression can be used to identify the system and to estimate dynamic effects in the bond market.

2.1. Causality and directed acyclic graph

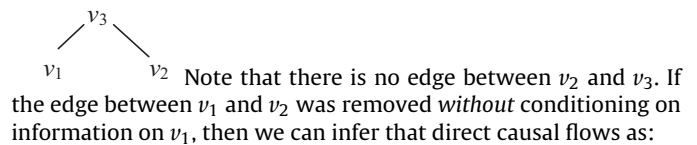
The directed acyclic graph analysis, a method for learning causal relationships from non-experimental data, has been developed by mathematically connecting probabilistic dependency patterns to graph theory, a branch of mathematics concerned with networks of points connected by lines. While easy to apply, an accurate and complete review of the method involves knowledge from various areas and is beyond the scope of this paper. Here we offer a minimal non-technical description. Haigh and Bessler (2004), Awokuse (2006), Wang, Yang, and Li (2007), Demiralp, Hoover, and Perez (2008), Moneta (2008) are a few sources for additional introduction of the method. More interested readers can refer to Pearl (2000) and Spirtes et al. (2000) for theoretical development.

It is well known that correlation does not imply causation. A directed graph can be understood as an assignment of the contemporaneous causal flow (or lack thereof) among a set of variables based on their observed correlations. As shown later, (conditional) independence plays an essential role in the DAG analysis. Denote $p(v_1, v_2, \dots, v_n)$ as the joint probability of variables v_1, v_2, \dots, v_n . Mathematically, we have the following recursive product decomposition:

$$p(v_1, v_2, \dots, v_n) = \prod_{i=1}^n p(v_i|V_i), \tag{1}$$

where V_i refers to the realization of some subset of the variables that precede (come before in a causal sense) v_i in order ($i = 1, 2, \dots, n$), and \prod is the product (multiplication) operator. In practice, to make prediction possible, we are often interested in calculating the distribution of, say, v_2 , conditional on v_1 takes a certain value (say, m) from the above joint distribution (Scheines, Spirtes, Glymour, & Meek, 1994, p. 1). However, calculating the conditional distribution $p(v_2|v_1 = m)$ is not the same as calculating the distribution of v_2 after v_1 is forced to equal m , unless the underlying causal structure is such that does v_1 cause v_2 .

The contribution of the directed graphs analysis is to provide graphical characterization of conditional independence as implied by Eq. (1) with explicit causal interpretations for all estimated connections between variables. The basic intuition behind DAG may be derived from the following simplified example. Suppose we are left with the following structure among three variables (the technical term is node) after removing any link (edge) between two variables which are unconditionally or conditionally uncorrelated (obviously, there is no causal relationship between two variables if they are unconditionally or conditionally uncorrelated):



This is because, if the edge between v_1 and v_2 were removed conditional on information on v_1 , (hence v_1 and v_2 are unconditionally correlated but conditionally uncorrelated), then logically it must be true that v_3 causes v_1 and v_2 , namely,

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