

Duration Effects in Macro-Finance Models of the Term Structure

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Abstract

This paper studies a class of optimizing, no-arbitrage models in which the term structure of interest rates depends on the maturity structure of assets held by investors. The key assumption is that the stochastic discount factor is a function of the return on wealth. Portfolio choice matters for asset prices because it affects the distribution of this return. Such models are inherently nonlinear, and I propose a numerical algorithm for solving them. As an illustration, I solve and estimate a model in which investors price inflation and consumption risk in addition to wealth risk. The equilibrium duration of investors' portfolio is treated as an unobserved factor. This factor is largely responsible for the nominal term premium and is correlated with the quantity of Treasury debt held by the public. Shocks to the factor that are roughly equivalent to the Federal Reserve's large-scale asset purchases reduce the ten-year nominal yield by about 50 basis points on impact. However, the model suggests that the macroeconomic effects of such shocks are modest.

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1 Introduction

Over the last decade, economists have made considerable progress in reconciling the behavior of the yield curve with standard consumption- and production-based asset pricing.¹ In these models, the term structure of interest rates is explained by investors' attitudes toward inflation and consumption risk, and by the rule that monetary policymakers use to determine the short-term interest rate.

At the same time that these models have been developed, several central banks have tried to shift the yield curve through purchases of long-term debt. Recent empirical work has been nearly universal in concluding that those purchases and other fluctuations in the structure of government liabilities have significant effects on the term structure of interest rates and, most likely, on other asset prices.² Perhaps the most commonly cited explanation for these results is that a reduction in the quantity of longer-term bonds that investors must hold leads them to require less compensation for bearing the remaining interest-rate risk in their portfolios; consequently, expected returns, term premiums, and yields on bonds fall. This phenomenon is sometimes known as the “duration channel” of government debt.

This type of mechanism is completely absent from the structural, consumption-based term-structure literature. In that literature, a shift in the quantity and distribution of government debt is either neutral or undefined. Indeed, partly on these grounds, several authors argue that the empirical evidence on the effects of asset purchases may reflect some other mechanism. A common refrain is that, in frictionless markets, asset quantities should be irrelevant for asset prices, a critique exemplified by Eggertsson and Woodford's (2003) proof that, in a particular class of general-equilibrium models, the structure of government debt available to the public makes no difference for either asset prices or macroeconomic outcomes.

Meanwhile, advocates of the duration channel frequently point to models such as Vayanos and Vila (2009) and Greenwood and Vayanos (2014) (collectively, “GVV”) for theoretical support. In those models, shifts in the supply of long-term assets available to investors change their equilibrium exposures to interest-rate risk, causing fluctuations

¹Among others, see Wachter (2006), Piazzesi and Schneider (2007), Van Binsbergen et al. (2012), and Rudebusch and Swanson (2012).

²See Bernanke et al. (2004), Kuttner (2006), Gagnon et al. (2010), Greenwood and Vayanos (2010, 2014), Krishnamurthy and Vissing-Jorgensen (2011, 2013), Meaning and Zhu (2011), Swanson (2011), D'Amico et al., (2012), Hamilton and Wu (2012), Joyce et al. (2011), Li and Wei (2012), Cahill et al. (2013), D'Amico and King (2013), Bauer and Rudebusch (2014), and Rogers et al. (2014), among others.

in term premia.³ Although these models clearly contain elements that are appealing for those seeking to formalize and explore the link between bond supply and bond pricing, a number of difficulties have prevented their use for policy analysis or their incorporation into broader asset-pricing and macroeconomic models. In the GVV model, investors only hold Treasury bonds, inflation and consumption risk are not priced, and policy actions by the government are not explicitly modeled. And, despite these simplifications, the models are only analytically tractable in certain special cases. These limitations make it difficult to assess the economic importance of their central mechanism and to reconcile it with other macro-finance literature, including Eggertsson and Woodford’s neutrality proposition.

This paper attempts to make some progress in reconciling the duration channel with standard macro-finance approaches to the term structure. First, I point out that the essential effect captured by the GVV model can be present in *any* no-arbitrage model in which the stochastic discount factor depends on the return on wealth. In such models, changes in the relative quantities of assets that are held by investors affect the distribution of the wealth return and therefore affect all asset prices. Preferences that result in pricing kernels that depend on the return on wealth have long been common in the finance literature, and, since Epstein-Zin-Weil utility has this property, are increasingly used in macroeconomic models as well. (The Eggertsson-Woodford model does not have it, which is why there are no such effects there.) The equilibrium duration channel that is possible under this specification is descended from the “portfolio balance” effects developed in papers such as Tobin (1968) and Frankel (1985), but, unlike those papers, the models considered here are arbitrage free, obey rational expectations, and do not require anything special about money or short-term debt.

Second, I provide a numerical method for solving such models in a wide variety of cases, iterating on a version of Tauchen and Hussey (1991). The solution is a nontrivial computational task because, even under simplifying assumptions about functional forms, equilibrium asset prices involve a nonlinear recursion in multidimensional function space. (This is why Vayanos-Vila can only be solved analytically in limiting cases.) One advantage of the approach I propose is that it allows for arbitrary nonlinearities in the state vector and in the pricing kernel. A key nonlinearity is introduced by allowing investors to have relative, rather than absolute, risk aversion. Another is introduced

³These models have been extended and applied in various ways by Hamilton and Wu (2012), Altavilla et al. (2015), Greenwood et al. (2015), King (2015), Haddad and Sraer (2015), Malkhozov et al. (2016), and King (forthcoming), among others.

by imposing an effective lower bound (ELB) on the nominal short rate.

Finally, I apply the approach to a model with three observable macro factors and one unobservable factor that governs the maturity structure of investors' assets. The nominal pricing kernel depends on the return on wealth, inflation, and consumption growth, with a functional form that nests Epstein-Zin. Because the SDF explicitly accounts for inflation, the model allows for the pricing of real as well as nominal bonds. The nominal short rate in the model is bounded by zero using a "shadow rate" specification.⁴

I estimate the model on data since 1971 using nonlinear Bayesian filtering methods. The model fits the nominal yield data well—far better than a comparable model that ignores the return on wealth—and it also matches data on inflation-protected yields since 2003, which are not used in the estimation. It generates a decomposition of the yield curve that is broadly in line with other models, including a downward drift since the early 1980s in expected inflation, the expected real short rate, and the nominal term premium. Although the price of inflation risk and the volatility of inflation are constant, the model exhibits a time-varying inflation risk premium through the nonlinear interaction of inflation with wealth. This premium broadly has the properties of other estimates of the inflation-risk premium in the literature, being high during the 1970s and then gradually declining. However, it is considerably larger on average, ranging between 2 and 4 percent.

I estimate significant time variation in the effective duration of investors' exposures. In particular, the estimated duration factor rises sharply around 1980 and then drifts downward over the next two decades. Its level is correlated with measures of Treasury supply and duration. The estimates suggest that a one-year increase in duration (about a one-standard-deviation shock, on an annual basis) results in a contemporaneous increase of about 30 basis points in long-term nominal yields and about 20 basis points in long-term real yields. In addition, such shocks lead to modest decreases in consumption growth over the subsequent five years. All of these effects are smaller near the ELB. Finally, I find that conventional monetary-policy shocks (unexpected increases in the short rate) cause small but significant increases in the duration factor and thus lead to modest increases in term premia. This is consistent, for example, with the presence of yield-oriented investors, as in Hanson and Stein (2015).

⁴See Kim and Singleton (2012), Krippner (2012), and Wu and Xia (2013). Bauer Rudebusch (2014) argue that the shadow-rate specification does a good job of capturing yield-curve dynamics near the ELB, greatly outperforming traditional affine models.

Section 2 of the paper sets up the basic class of models considered here and discusses how they relate to those used in the previous literature. Section 3 describes the solution algorithm. Section 4 illustrates with some simple examples in the case where the short rate is the only stochastic factor. Section 5 discusses the development and estimation of the four-factor macro-finance model. Section 6 presents the results of that model. Section 7 concludes the paper.

2 Asset Portfolios and Returns under No Arbitrage

I consider investors who, at each time t , have claims to a series of certainty-equivalent payments over each of the following N periods. Each claim pays one unit of the consumption good at maturity. I collect the quantities of the claims at each maturity in the vector $\mathbf{X}_t = (X_t^{(1)}, \dots, X_t^{(N)})$. The time- t (real) prices of the claims are denoted by $\mathbf{p}_t = (p_t^{(1)}, \dots, p_t^{(N)})$. It is assumed that the prices and quantities of these claims are determined in equilibrium in each period to clear all asset markets. In cases in which the optimization problem faced by agents is specified, the demand and supply functions that give rise to this equilibrium can be solved explicitly. Some such cases are discussed later. Here, I simply assume that the equilibrium quantities \mathbf{X}_t follow a known reduced-form process, which may be a function of other variables in the economy.

The absence of equilibrium arbitrage opportunities is equivalent to the existence of a stochastic discount factor (SDF) $M_{t,t+n}$ that prices all assets in the economy. In particular, the real price of an arbitrary asset at time t is given by

$$p_t = E_t [M_{t,t+n} q_{t+n}] \quad (1)$$

where q_{t+n} is the asset's payoff n periods hence, and E_t indicates the expectation conditioned on information at time t . This condition must hold for all horizons $n > 0$. The following standard relationships follow immediately:

$$p_t^{(n)} = E_t [M_{t,t+n}] \quad (2)$$

$$M_{t,t+n} = \prod_{i=1}^n M_{t,t+i} \quad (3)$$

Define the n -period zero-coupon real bond yields in the usual way, as

$$y_t^{(n)} = -\frac{1}{n} \log p_t^{(n)} \quad (4)$$

and define the real short rate $r_t \equiv y_t^{(0)}$. Equations (2) and (4) imply

$$r_t = -\log E_t [M_{t,t+1}] \quad (5)$$

Given a real SDF, $M_{t,t+n}$, the nominal SDF is defined as

$$M_{t,t+n}^{\$} \equiv \Pi_{t+n} M_{t,t+n} \quad (6)$$

where Π_{t+n} is the gross rate of inflation between periods t and $t+n$. Nominal bond prices and yields, denoted $p_t^{\$(n)}$ and $y_t^{\$(n)}$, are given analogously to equations (2) and (4). The nominal short-term interest rate is denoted $i_t = y_t^{\$(0)}$.

I consider models in which the one-period stochastic discount factor takes the form

$$M_{t,t+1} = M(\mathbf{s}_{t+1}, \mathbf{s}_t, R_{t+1}) \quad (7)$$

where R_{t+1} is the one-period gross return on investors' wealth, $M(\cdot)$ is a known function, and the vector \mathbf{s}_t summarizes the time- t state of the economy. I assume that \mathbf{s}_t follows a first-order Markov process on the support \mathbf{S} with transition density $\tau(\mathbf{s}_{t+1}|\mathbf{s}_t)$. I restrict attention to cases in which investors do not care about the quantities of the particular securities that they hold *per se*. This rules out, for example, models with convenience yields, monetary services, or other special benefits that might attach to certain assets beyond their pecuniary returns. Formally, I assume $X_t^{(n)} \notin \mathbf{s}_t \forall n$.

The return on wealth is defined as follows:

$$R_{t+1} \equiv \frac{\mathbf{X}_t' \mathbf{q}_{t+1}}{\mathbf{X}_t' \mathbf{p}_t} \quad (8)$$

where the payoff vector $\mathbf{q}_{t+s} = (1 \ p_{t+1}^{(1)} \ \dots \ p_{t+1}^{(N-1)})$. It is through (7) and (8) that asset quantities are related to asset prices. Fluctuations in the state of the economy that change the value of \mathbf{X}_t will change \mathbf{p}_t because expected returns—and therefore current prices—must adjust to make investors willing to hold the outstanding net positions at each point in time. For convenience, define $\mathbf{x}_t = (x_t^{(1)} \ \dots \ x_t^{(N)})$ as the vector of

par value asset shares, i.e., $x_t^{(n)} \equiv X_t^{(n)} / \sum_{m=1}^N X_t^{(m)}$. Since the same vector \mathbf{X}_t appears in both the numerator and denominator of (8), the dollar values of assets outstanding will not themselves be relevant for pricing in the class of models considered here, only their relative quantities will be. In particular, note that $R_{t+1} = \mathbf{x}'_t \mathbf{q}_{t+1} / \mathbf{x}'_t \mathbf{p}_t$.

Define the log real return on an n -maturity asset as

$$\rho_{t+1}^{(n)} = \log \frac{q_{t+1}^{(n-1)}}{p_t^{(n)}} \quad (9)$$

If one were willing to assume that $M(\cdot)$ was exponentially affine and that \mathbf{s}_t and R_t were jointly Gaussian, then expected returns could be written as

$$\mathbb{E}_t \left[\rho_{t+1}^{(n)} \right] = r_t + \text{cov}[\boldsymbol{\lambda}' \mathbf{s}_{t+1}, \rho_{t+1}^{(n)}] + \lambda^R \text{cov}[\log R_{t+1}, \rho_{t+1}^{(n)}] + J^{(n)} \quad (10)$$

where $J^{(n)}$ is a term reflecting Jensen's inequality. However, while equation (10) is linear in $\log R_t$, it is not linear in the quantities \mathbf{X}_t . This means that it will generally not be possible to provide closed-form solutions for expected returns (or prices) as functions of portfolio quantities.

The GVV models mentioned in the introduction achieve an analytical solution by instead assuming *absolute* risk aversion. In particular, the expected log return on an n -maturity bond in those models (using the notation of this paper) is

$$\mathbb{E}_t \left[\rho_{t+1}^{(n)} \right] = r_t + \lambda^R \text{cov}_t \left[\mathbf{X}'_t \mathbf{q}_{t+1}, X_t^{(n)} q_{t+1}^{(n-1)} \right] + J_t^{(n)} \quad (11)$$

Thus, if \mathbf{X}_t has an affine factor structure (as GVV assume), then so do bond returns. This linearity allows the model to be solved analytically, at least in cases where the conditional covariances can be calculated in closed form.

As the only model to incorporate supply effects into an affine representation of the term structure, GVV has been highly influential in the way that economists have designed and interpreted recent empirical studies.⁵ However, the unusual assumption of absolute risk aversion that is needed to solve it has uncomfortable asset-pricing implications. For example, the model implies that term premia should generally trend upward with wealth, which runs counter to historical evidence. Moreover, it is not obvious how to incorporate additional features, such as inflation or the ELB, into the

⁵See, for example, Hamilton and Wu (2011), and Li and Wei (2012).

model while retaining tractability. The method proposed here, by solving the models numerically, overcomes these problems.

3 Solution Method

The central difficulty in solving models like the above—in which $M(\cdot)$ is a function of R_{t+1} and R_{t+1} is determined endogenously—is that the solution for asset prices involves the moments of future prices, and, under rational expectations, the future prices themselves depend on the same fundamental process. While it is common in asset-pricing models for today's asset prices to depend on the distribution of tomorrow's asset prices, the particular difficulty here is that the SDF itself depends upon both of these objects.

I propose to solve these models numerically for the time- t vector of asset prices \mathbf{p}_t using an iterative, discrete-state approximation method. This approach has the added advantage that it places very few constraints on either the functional form of the pricing kernel or the dynamics of the state vector. Consequently, it is straightforward to consider models with potentially important nonlinearities, such as the ELB.

I first make explicit that prices and quantities depend on the state of the economy. Namely, let $X^{(n)}(\mathbf{s}_t)$ be the function that maps the state vector into the quantity of asset n , and let $\Pi(\mathbf{s}_t)$ be the function that maps the state vector into gross inflation. It is assumed that the form of the SDF in equation (7), the laws of motion for the states, and the dependence of quantities on the states are known—that is, we (and investors) have knowledge of the functions $\tau(\mathbf{s}_{t+1}|\mathbf{s}_t)$, $M(\mathbf{s}_t, \mathbf{s}_{t+1}, R_{t,t+1})$, $M^{\$}(\mathbf{s}_t, \mathbf{s}_{t+1}, R_{t,t+1})$, and $X^{(n)}(\mathbf{s}_t)$. We seek vector-valued functions $\mathbf{p}(\mathbf{s}_t) = (p^1(\mathbf{s}_t) \dots p^N(\mathbf{s}_t))$ and $\mathbf{p}^{\$}(\mathbf{s}_t) = (p^{\$(1)}(\mathbf{s}_t) \dots p^{\$(N)}(\mathbf{s}_t))$ that describe how all asset prices depend on \mathbf{s}_t and \mathbf{X}_t .

With this notation, the nominal price of asset n is given by

$$p^{\$(n)}(\mathbf{s}_t) = \int_{\mathbf{s}} \tau(\mathbf{s}'|\mathbf{s}_t) M^{\$}(\mathbf{s}_t, \mathbf{s}', R_{t,t+1}) q^{\$(n)}(\mathbf{s}') d\mathbf{s}' \quad (12)$$

where the integral is taken over all dimensions of the state and $\mathbf{q}^{\$}(\mathbf{s}_t) = (1 \ p^{\$(1)}(\mathbf{s}_t) \dots p^{\$(N-1)}(\mathbf{s}_t))$ is the vector of functions determining nominal asset payoffs in state \mathbf{s}_t . An analogous relationship holds for real prices $\mathbf{p}(\mathbf{s}_t)$ with respect to the real SDF $M(\mathbf{s}_t, \mathbf{s}_{t+1}, R_{t,t+1})$ and real payoffs $\mathbf{q}(\mathbf{s}_t)$.

Given a distribution for the market return, R_{t+1} , (12) is a system of linear Fred-

holm equations of the first kind, which in principle can be discretized and solved by quadrature in one step (see Tauchen and Hussey, 1991). However, the fact that R_{t+1} is defined as in (8) requires us to iterate by, first, solving (12) using a given distribution of R_{t+1} , and, second, given the resulting pricing functions finding the updated distribution of R_{t+1} . These steps can be repeated to convergence.

Specifically, let $\mathbf{p}_d^{\$,k}(\mathbf{s}_t)$ be a proposal for the nominal pricing function on a discretization of the state space $\mathbf{D} = (\mathbf{d}_1, \dots, \mathbf{d}_G) \in \mathbf{S}^G$, where G is the number of nodes and $k = 0, \dots, K$ indexes iterations, and let $\mathbf{q}_d^{\$,k}$ be the corresponding discretization of $\mathbf{q}^{\$,k}(\mathbf{s}_t)$. Suppose that the nodes are uniformly distributed over the state space, so that the conditional transition probability from node j to node h can be approximated by⁶

$$\hat{\tau}(\mathbf{d}_h|\mathbf{d}_j) \equiv \tau(\mathbf{d}_h|\mathbf{d}_j) \left[\sum_{g=1}^G \tau(\mathbf{d}_g|\mathbf{d}_j) \right]^{-1} \quad (13)$$

The solution algorithm proceeds as follows.

Set the iterator $k = 0$.

1. Guess a function $\mathbf{p}^{\$,k}(\cdot)$ such that $\mathbf{p}_t^{\$} = \mathbf{p}^{\$,k}(\mathbf{s}_t)$ on a discretization of \mathbf{S} . Find the corresponding values of $\mathbf{p}_d^k(\mathbf{d}_t)$ at each node in \mathbf{D} .
2. Based on this function, compute the real return on wealth between each pair of nodes (j, g) as

$$R^k(d_j, d_g) = \frac{\mathbf{x}(\mathbf{d}_j)' \mathbf{q}_d^{\$,k}(\mathbf{d}_g)}{\mathbf{x}(\mathbf{d}_j)' \mathbf{p}_d^{\$,k}(\mathbf{d}_j)} - \Pi(\mathbf{d}_g) \quad (14)$$

3. Compute the updated nominal pricing function for the vector $\mathbf{p}_d^{\$,k+1}(\mathbf{d}_j)$ at each node $j = 1, \dots, G$ by setting

$$p_{\mathbf{d}_j}^{\$(0),k+1}(\mathbf{d}_j) = \exp[i(-\mathbf{d}_j)] \quad (15)$$

and

$$p_d^{\$(n),k+1}(\mathbf{d}_j) = \sum_{g=1}^G \hat{\tau}(\mathbf{d}_g|\mathbf{d}_j) M^{\$}(\mathbf{d}_j, \mathbf{d}_g, R(d_j, d_g)) p_d^{\$(n-1),k+1}(\mathbf{d}_g) \quad (16)$$

for $n = 1, \dots, N$. Set $\mathbf{q}_d^{\$,k+1}(\mathbf{d}_g) = (1 \quad p_d^{\$(1),k+1}(\mathbf{d}_g) \quad \dots \quad p_d^{\$(N-1),k+1}(\mathbf{d}_g))$.

⁶The uniform discretization is only for expositional ease and is not essential. Indeed, standard quadrature methods are likely to be more efficient.

4. Set $k = k + 1$ and return to step 2.

This procedure constitutes a contraction mapping on \mathbf{D} so long as the moments of the pricing kernel are well behaved. The Banach Theorem then guarantees for any given discretization \mathbf{D} , $\mathbf{p}_d^{\$,k}(\mathbf{d}_j) \rightarrow \mathbf{p}_d^{\$}(\mathbf{d}_j) \forall \mathbf{d}_j \in \mathbf{D}$, where $\mathbf{p}_d^{\$}$ is the (unique) nominal pricing function that obtains if $\hat{\tau}$ is the data-generating process. But continuity of τ ensures that, for any node j ,

$$\lim_{G \rightarrow \infty} p_d^{\$(n)}(\mathbf{d}_j) = E_t \left[p^{\$(n-1)}(\mathbf{s}_{t+1}) M^{\$} \left(\mathbf{d}_j, \mathbf{s}_{t+1}, \frac{\mathbf{x}(\mathbf{d}_j)' \mathbf{q}_d^{\$,k}(\mathbf{s}_{t+1})}{\mathbf{x}(\mathbf{d}_j)' \mathbf{p}_d^{\$,k}(\mathbf{d}_j)} - \Pi_{t+1} \right) \right] \quad (17)$$

i.e., in the limit, the pricing function solves the no-arbitrage condition (2). Since Π_t is a known function of the state, this argument also guarantees that the algorithm finds the unique real SDF.

Finally, by construction, if the algorithm converges, any point of convergence is a rational-expectations equilibrium. This follows immediately, since convergence is *defined as* the fixed point at which the joint distribution of $\mathbf{p}_{t+1}^{\$}$ and $M_{t+1}^{\$}$ is consistent with the vector $\mathbf{p}_t^{\$}$, for each point in the state space.

It is important to note that, although the algorithm only solves for the vector of prices at G points in the state space, once these solutions are in hand it is straightforward to calculate equilibrium prices at *any* point through the Nystrom extension. In particular, take an arbitrary state value \mathbf{s}_t . For G large enough, we have

$$p^{\$(n)}(\mathbf{s}_t) \approx \left[\sum_{g=1}^G \tau(\mathbf{d}_g | \mathbf{s}_t) M^{\$} \left(\mathbf{s}_t, \mathbf{d}_g, \frac{\mathbf{x}(\mathbf{s}_t)' \mathbf{q}_d^{\$,k}(\mathbf{d}_g)}{\mathbf{x}(\mathbf{s}_t)' \mathbf{p}_d^{\$,k}(\mathbf{s}_t)} - \Pi(\mathbf{d}_g) \right) p_{n-1}^{\$}(\mathbf{d}_g) \right] \left[\sum_{g=1}^G \tau(\mathbf{d}_g | \mathbf{s}_t) \right]^{-1} \quad (18)$$

and similarly for real prices. Once the algorithm has converged, the quantities on the right-hand side are all known. Thus, real and nominal claims can be priced in at any point in \mathbf{S} .

Figure 1 displays some results on the convergence of the solution algorithm for the one-factor model discussed in the next section. The only state variable in that model is the “shadow” short rate i_t^* . The top panel shows the computed 2-, 5-, 10-, and 15-year yields, shown for i_t^* at its average value of 5.2%, across the first 30 iterations ($k = 1, \dots, 30$). The algorithm is initialized at a price vector $\mathbf{p}_d^0(\mathbf{d}_j) = (0.95, \dots, 0.95)$ for all values of \mathbf{d}_j and uses $G = 8$ nodes distributed uniformly across the range $i^* = (-0.05, 0.15)$. It is evident from this figure that, for each maturity n , the solution

converges very quickly once $k > n$.

The middle panel shows convergence in the number of gridpoints by displaying the computed yield curve (after $k = 30$ iterations), again using $i_t^* = 0.052$ for illustration. Yield curves are shown for $G = 2, 4, 8$, and 16 , in each case spaced equally across possible values of the state variable. While 4 nodes is clearly too few to achieve convergence, the solutions using 8 or more nodes are indistinguishable from each other.

For brevity, these results were shown for the average value of the shadow short rate. Similar convergence results obtain for other points in the state space, although solutions will not be accurate near the bounds if the underlying state process itself is not actually bounded. For example, in the above case, we would not expect the procedure to generate correct solutions near $i_t = 0.15$. However, so long as the bound on the state space is imposed far enough away from the values of the states that are actually realized in practice, this limitation has a negligible effect on the results. The bottom panel of the figure illustrates this claim by comparing the yield curve computed above with the yield curve computed when the grid for i_t^* is extended over ranges of 30 and 40 percentage points, rather than the 20-point range used above.

4 One-factor examples

To illustrate some of the properties of these models, I consider a series of cases in which the nominal short rate i_t is the only source of stochastic variation. I take periods to be one year in length and suppose that assets have maturities of up to $N = 15$ periods.

I impose that the short rate is bounded below by adopting a “shadow-rate” process. (See Kim and Singleton, 2012, and Wu and Xia, 2016, among others.) In particular, suppose that the shadow short rate i_t^* follows the linear process

$$i_t^* = \phi_0 + \phi_1 i_{t-1}^* + \varepsilon_t \quad (19)$$

where ε_t has variance σ^2 . The short rate i_t is given by

$$i_t = \max[i_t^*, b] \quad (20)$$

where the parameter b defines the ELB. I assume zero inflation, so $i_t = r_t$ at all t .

For the purposes of these examples, assume that the relative supply of assets is fixed over time, $\mathbf{x}_t = \mathbf{x}$. For parsimony, I approximate the maturity structure of assets

with a normal distribution:

$$x^{(n)} \propto \exp \left[-\frac{(x^{(n)} - z)^2}{2\theta^2} \right] \quad (21)$$

where the parameter z is the average maturity outstanding, and θ is a scale parameter.

Finally, let the SDF be given by

$$M_{t,t+1} = \delta_t R_{t+1}^{\lambda^R} \quad (22)$$

where λ^R is a risk-aversion parameter. The variable δ_t is immediately determined as

$$\delta_t = \frac{\exp[-i_t]}{E_t [R_{t+1}^{\lambda^R}]} \quad (23)$$

where the denominator can be calculated from (13) and (14).

For the purposes of illustration, I set $\phi_0 = 0.0052$, $\phi_1 = 0.9$, $\sigma = 0.01$, $b = 0.002$, and $\lambda^R = -8$. These values are calibrated roughly to match the dynamics of the short-rate and the average value of the 10-year yield in the data.

Panel A of the figure illustrates the insensitivity of the results to the shape of the asset-maturity distribution, which, in this case, is governed by the parameter θ . The left-hand graph shows the distribution with $z = 8$ and $\theta = 0.1$ (blue) or $\theta = 2$ (orange). The right-hand graph shows the corresponding yield curves, in both cases taking the short rate to be $i_t = 5.2\%$. The curves are nearly identical. This should not be surprising because the individual asset share $x_t^{(n)}$ does not matter for the individual asset price $p_t^{(n)}$. Only the weighted sums of asset shares shown in equation (8) matters, and they affect all prices in the same way through $M(\cdot)$. Consequently, this model cannot produce local-supply effects from large quantity gluts or shortages in particular sectors of the market.⁷

Panel B shows how a shift in the average duration in investors' portfolio translates into yields. Again taking the short rate to be 5.2%, I consider duration values of $z = 5$ years (blue) and $z = 10$ years (orange). In both cases, θ is set to 1, so that, as illustrated on the left, this is just a uniform transposition of the distribution of assets to higher maturities. As shown on the right, the yield curve shifts upward in response—by 72 basis points at the ten-year maturity. Because the expected path of short rates is the same in both cases, the entire difference is attributable to a change in the (real) term

⁷Malkhozov et al. (2016) make a similar point.

premium.

Since risk prices are themselves a function of the quantity of risk held by investors, heteroskedasticity can cause risk prices—and therefore term premiums—to differ significantly across states of the world. A particularly important case of this is the lower bound on the nominal short rate. The presence of this bound, all else equal, implies that there is less uncertainty about short-term interest rates in the near future when the current value of those rates is near zero. The reduction in the volatility of short-term interest rates induced by the ELB will dampen duration effects.

Panel C illustrates this effect by conducting the same comparative-statics exercise on duration that was depicted in panel B, but this time with a shadow-rate value of $i_t^* = -3\%$. (This is close to the average value of the shadow rate in the empirical estimates of Krippner (2012).) Yield curves in this region of the space have an “S” shape, due to the expectation for the short rate to remain at zero for some time. Again, the shift from a portfolio duration of 5 years to 10 years causes an increase in longer-term yields, but it is smaller than we obtained away from the ELB. In particular, in this case, the increase in the 10-year yield is only 61 basis points.⁸

Finally, Panel D shows the effect of different values of the price of wealth risk, λ^R , for $i_t = 5.2\%$, $z = 8$ years, and $\theta = 1$. A reduction in this parameter, from -8 to -4 in this case, acts much like a reduction in duration, causing the yield curve to fall at longer maturities. Again, this entire decline—77 basis points on the ten-year yield—is due to term premia.

5 A Macro-Finance Model with Portfolio Effects

I now turn to a fully specified four-factor macro-finance model in which the duration channel is operative, and I take that model to the data. I consider a three-dimensional state vector, $\mathbf{s}_t = (\pi_t, g_t, i_t^*)$, where π_t is inflation, g_t is the growth rate of real consumption, i_t^* is the shadow nominal short-term risk-free rate. Let Π_t and G_t denote the corresponding gross rates of inflation and growth, $\exp[\pi_t]$ and $\exp[g_t]$, respectively.

I assume that the two macroeconomic variables depend on their own lags and on short- and long-term interest rates, as follows. Define the vector $\tilde{\mathbf{s}}_t = (\pi_t, g_t, i_t, y_t^{\$(10)})$. Then let

$$\pi_t = \phi_0^\pi + \phi_1^\pi \tilde{\mathbf{s}}_{t-1} + e_t^\pi \tag{24}$$

⁸King (forthcoming) explores the effect of the ELB in similar models in detail.

$$g_t = \phi_0^g + \phi_1^g \tilde{s}_{t-1} + e_t^g \quad (25)$$

where e_t^π and e_t^g are error terms.

There are two unobserved state variables, the shadow short rate i_t^* and the duration factor z_t , both of which interact nonlinearly with yields and the macro variables. (Note that the reduced-form dynamics of the economic variables above do not depend on the unobserved states, but only on the observed i_t and $y_t^{\$(10)}$.) The unobserved states have laws of motion:

$$i_t^* = \phi_0^{i^*} + \phi_1^{i^*} \tilde{s}_{t-1} + \phi_2^{i^*} i_{t-1}^* + e_t^{i^*} \quad (26)$$

$$z_t = \phi_0^z + \phi_1^z \tilde{s}_{t-1} + \phi_2^z z_{t-1}^* + e_t^z \quad (27)$$

The short-term nominal rate is given by equation (20), where I calibrate the value of b to 20 basis points. Meanwhile, the unobserved factor z_t determines equilibrium asset quantities as in equation (21), with $\theta = 1$. As noted in the previous section, the value of θ is likely to make very little difference. The magnitude of the factor has the interpretation as the average duration of the investors' equilibrium portfolio. The reduced-form error vector $\mathbf{e}_t = (e_t^\pi \ e_t^g \ e_t^{i^*} \ e_t^z)$ has covariance matrix Σ . Finally, I collect all of the ϕ parameters in equations (24) through (27) in the vector Φ for ease of notation.

I suppose that investor preferences are such that the nominal SDF is

$$M_{t,t+1}^{\$} = \delta_t \Pi_{t+1} G_{t+1}^{\lambda_1} R_{t+1}^{\lambda_2} \quad (28)$$

where, as above, R_{t+1} is the gross return on wealth, given by equation (8). Epstein-Zin preferences are nested in this specification. As in the previous section, the random variable δ_t can be calculated exactly, given the other time- t model objects, as

$$\delta_t = \exp[-i_t] E_t [\Pi_{t+1} G_{t+1}^{\lambda_1} R_{t+1}^{\lambda_2}]^{-1} \quad (29)$$

In the special case of Epstein-Zin preferences, δ_t is proportional to the rate of time preference.

I estimate the above model on annual data from 1971 through 2017. There are two reasons for using annual data. First, from a practical standpoint, having both fewer observations and fewer points on the yield curve greatly increases computational efficiency. Second, it is important to capture lower-frequency properties of the macro data to fit bond yields. (See, e.g., Piazzesi and Schneider, 2007.) Using annual data

allows for this, while still maintaining a relatively parsimonious first-order dynamic process.

I fit the model to PCE inflation rates, growth of nondurables and services from the NIPA data, and 1-, 5-, 10-, and 15-year nominal Treasury yields. All yields are Gurkaynak et al. (2007) zero-coupon yields and are averaged to produce annual values. I denote by Ω the 3×3 covariance matrix of the error terms on the long-term nominal yields produced by the model.

Because Treasury yields depend on the duration factor and the shadow rate in a nonlinear way without a closed-form solution, I estimate the series $\{z_t\}$ by means of a particle filter (see Doucet et al., 2001). The fixed parameters Φ , Σ , Ω , λ_1 , and λ_2 are estimated by a Gibbs sampling procedure. Specifically, estimation proceeds as follows.

Set the iterator $j = 1$. Draw Φ_j , Σ_j , and Ω_j from the prior distribution.

1. Calculate the nominal SDF $M_j^\$$ based on Φ_j and Σ_j , using the procedure described in Section 3.
2. Using Φ_j and Σ_j for the state dynamics, run the particle filter. Set $t = 1971$ (corresponding to the first annual observation). Then,
 - (a) Draw values of $z_{t,k} \sim p(z_t | \Phi_j, \Sigma_j, \mathbf{s}_{t-1})$, for $k = 1$ to 10,000.
 - (b) If $2009 < t < 2015$, take i_t to be constrained by the ELB and draw values of $i_{t,k}^* \sim p(i_t^* | z_{t,k}, \Phi_j, \Sigma_j, \mathbf{s}_{t-1})$, for $k = 1$ to 10,000. Reject any draw for which $i_t^* > b$.
 - (c) For each draw $z_{t,k}$, use the pricing kernel $M_j^\$$ to construct model implied nominal yields.
 - (d) Evaluate the weights $w_{k,t} \propto \Pr(y_t^{(5)}, y_t^{(10)}, y_t^{(15)} | z_t, \pi_t, g_t, i_t, \Phi_j, \Sigma_j, \Omega_j)$ based on the yield data.
 - (e) Resample 10,000 draws from the distribution of $\{z_t\}_{1971}^t$, using the weights $w_{k,t}$.
 - (f) $t = t + 1$.

Note that, in running the particle filter, I keep the whole history of each re-sampled particle. The resulting distribution of paths is a random sample from the posterior distribution $p(\{z_t\}_{1971}^{2017} | \Phi_j, \Sigma_j, \Omega_j, \{\pi_t, g_t, i_t, y_t^{(5)}, y_t^{(10)}, y_t^{(15)}\}_{1971}^{2017})$. That is, it is a smoothed, rather than a filtered, estimate.

3. Sample one history $\{z_t\}_{1971}^{2017}$ from the distribution j . Estimate the reduced-form dynamics (24) - (27) based on this draw and the observed data.
4. Set $j = j + 1$.

I repeat these steps 10,000 times, dropping the first 1,000 draws to allow for burn-in.

6 Results

6.1 Yield curve fit and decomposition

Table 1 reports the parameter estimates. The coefficients λ^G and λ^R , reflecting the market prices of consumption risk and wealth risk, respectively, are -70 and -25. It is interesting to note that Epstein-Zin would generally imply that these two parameters should have opposite signs, so in this sense the data reject that special case of the model.

The left-hand column of Figure 3 shows the 5-, 10-, and 15-year nominal yields used in the estimation (in red), together with the posterior medians and 10% - 90% credibility intervals of the model-implied yields. As shown in Table 1, the estimated standard deviations of the error terms, evaluated at the posterior median, range from 25 to 30 basis points. The right-hand column compares model-implied real 5- and 10-year yields to yields on Treasury inflation-protected securities (TIPS), for which the data begin in 2003. These data were not used in the estimation and so provide an out-of-sample test. (The n -period real yields in the model are calculated as the expectation of the real SDF, $E_t[M_{t,t+n}]$, conditional on the time- t state vector.). The model does reasonably well in tracking TIPS yields; indeed, those yields are always within the 80% credibility interval.

Figure 4 shows the model-implied decomposition of the 10-year yield into its four components: the expected real short rate, the expected inflation rate, the real term premium, and the inflation-risk premium. The real term premium and the inflation risk premium sum to the nominal term premium by definition. The average expected nominal rate and average expected inflation over the next ten years are computed, for each period's state vector, based on the state dynamics in equations (24) - (27). The average expected real rate is the difference between these series. The corresponding real and nominal term premia are simply the differences between the model-implied

(real or nominal) 10-year yield and its expectation component. The series are shown as posterior medians.

The model has several features that are common to less-restricted term-structure models (i.e., those with multiple latent factors and no economic interpretation of the SDF), such as Kim and Wright (2007), Adrian et al. (2017), and D’Amico et al. (2017). In particular, it implies a fairly rapid increase in the nominal term premium in the late 1970s and early 1980s, followed by a gradual downward drift. There is also a fairly sharp decline of about 1 percentage point during the period 2003 - 2005, around the time of the “conundrum” in long-term rates. The real term premium is estimated to always be small and slightly negative. Expected inflation also moved lower in the 1980s, largely following realized inflation. The ten-year expected real short rate has drifted lower by about 150 basis points between about 2000 and 2017, consistent with some other estimates of “r-star.”

The model does produce one fairly unusual result in this decomposition—the inflation-risk premium is large over the entire sample period. Indeed, although it drifts downward since the 1980s, consistent with other models, it never falls below 2 percentage points. This leads to a somewhat higher estimate of the nominal term premium, compared, for example, to the Kim-Wright estimate, which is a bit over 1% for the last few years of the sample. It is interesting to note that the model exhibits significant time variation in the inflation-risk premium, because (apart from the effects of the ELB) the variance of inflation is constant, and it enters into the SDF with a constant exponent of 1. Thus, the time variation arises solely from the covariance of inflation with the return on wealth, which is a function of the duration factor z_t .

6.2 The duration factor

Figure 5 shows the estimated path of the duration factor over time (median and 80% credibility interval). It starts the sample period low but rises sharply in the early 1980s. It then gradually trends downward over the remainder of the sample, although it spikes around the trough of every recession. Although the level of the estimated z_t is correlated with the other model objects shown in figure 4 at low frequencies, it does not bear a one-to-one correspondence with any of them.

The factor has an interpretation as the average maturity of claims to future payments held by investors. While these claims may take a number of forms—including privately issued securities, real assets, and future income streams—a case of particular

interest is that of Treasury debt. To see whether the size and structure of actual Treasury debt bears any relation to the duration factor, I regress the median estimate of z_t on the weighted-average maturity of all Treasury debt outstanding (WAM) and on the maturity-weighted debt-to-GDP ratio (MWD). Both measures are calculated using all outstanding Treasury securities available in CRSP, and I control for 1-year yields in the regressions.

Table 2 reports the results. Both measures are strongly positively correlated with the estimated factor. (In fact, coincidentally, they take almost identical coefficient values.) Of the two, WAM is more consistent with the interpretation given to the factor in the model, since it is in units of duration. According to the regression, a one-year increase in Treasury WAM is associated with a 1.36-year increase in overall portfolio duration. We cannot reject that the coefficient is equal to 1.

Figure 6 shows the estimated relationship between the duration factor and the level of the 10-year yield. In the top panel, the other three state variables are all set to their sample means. In the bottom panel, inflation and growth are set to their sample means, but the shadow rate i_t^* is set to -3%, so that the ELB is binding. In both cases, there is a positive association between duration and yields. As in the one-factor model of the previous section, this association is attenuated at the ELB.

Figure 7 shows that a significant portion of the level of and variation in the ten-year yield is driven by z_t . Specifically, I set $\lambda^R = 0$, so that the return on wealth is no longer an element of the SDF, holding all other parameters and state variables the same. The resulting counterfactual 10-year yield is shown by the blue line, while the black line is the yield implied by the baseline model. The shaded-blue region, which averages about 3 percentage points, represents the contribution of the return on wealth to long-term rates. Looked at in this way, the duration channel accounts for essentially all of the nominal term premium. This result is also shown in the second column of Table 3, which reports the model errors in the counterfactual model. (Column 1 reports the errors in the baseline model, for comparison.)

A related question is whether a model that includes only consumption and inflation in the SDF can do equally well in fitting the data. To answer this question, I re-estimated the model without including R_t in $M(\cdot)$. Note that, even in this case, the unobserved factor z_t may continue to help, to the extent that it might absorb predictable variation in nominal yields that is not accounted for by the observable variables, although it would no longer have an interpretation as reflecting portfolio du-

ration. The last column of Table 3 reports the model fit in this case. Re-optimizing the parameters of the model improves the fit substantially relative to the second column, mostly because the model is able to raise the level of yields relative to that column and eliminate the downward bias that was present in Figure 7. However, the errors in matching yields are still about twice as large as in the baseline model (even though the number of observable and unobservable factors is the same). Evidently, adding the return on wealth to the SDF and treating z_t as reflecting portfolio duration is advantageous for fitting the yield-curve data.

6.3 Impulse-response functions

I now consider the dynamic effects of shocks to the short rate and the duration factor. For this purpose, I adopt a structural decomposition of Σ using short-run ordering restrictions. Given the use of annual data, it is not realistic to impose the usual assumption that certain variables cannot respond to others for a least one period. Therefore, I estimate the shocks using higher-frequency data, as follows. First, using the Φ parameters and the estimated annual values of z_t , I interpolate the z_t series to a quarterly frequency. Then, I re-run the model using quarterly data for all four variables, including three lags of the states. I apply the Cholesky decomposition to the covariance matrix of the error terms of this higher-frequency model to obtain the short-run ordering. I order the duration factor last and the short rate second-to-last.

The responses of the real and nominal yield curves to the two shocks is shown in Figure 8. Monetary-policy shocks decay nearly monotonically, and the expectation of this behavior is reflected in the initial response of the yield curve, which is greatest at the short end. (This shape is somewhat different at the ELB, not shown.). These shocks have modest effects on inflation, so most of this behavior is passed through to real yields.

The duration shock results in a much different shape of the initial response. In response to a one-standard-deviation shock (about 1 year, at an annual frequency) short-term yields do not move at all, while nominal yields beyond about 7 years rise by about 30 basis points. About half of that effect is due to an increase in the real yield curve, although that response exhibits a slight hump shape across maturities, with the peak around the 5-year sector. The effect of duration shocks on nominal yields decays rapidly over the first few years, while the response of real yields is more gradual.

Taking a closer look at these responses, Figure 9 shows the response of the ex-

expectations and term-premium components of nominal yields across maturities, in the period when the shocks occur. Most of the effect of the monetary-policy shock is on the expectations component, but there is a modest and marginally significant effect on term premia as well. I will return to this result momentarily. The duration shock has essentially no effect on the expectations component. Almost all of the response shown in the previous figure results from a change in the term premium, as we would expect.

The shocks also have implications for the dynamic paths of the economic variables. These are shown in Figure 10. Both shocks have no significant effect on inflation but a modestly negative effect on consumption. Interestingly, the duration factor rises following a shock to the nominal short rate. This reaction is responsible for the modest increase in term premia associated with this shock, noted in the previous figure. It is consistent with investors moving into longer-term assets in response to increases in interest rate, a behavior that Hanson and Stein (2015).

Using these results, we can do a back-of-the-envelope calculation to consider the effects of the Federal Reserve’s asset purchase program. In King (forthcoming) I calculate that the Fed’s asset purchases collectively reduced the dollar duration in public hands by about 20%, relative to what it would have otherwise been at the end of the program. MWD at the end of 2014 was 5.0. Thus, QE may have been responsible for a reduction of about 1.25 in this variable. From the second column of Table 2, this would map into a value of z_t that is about 1.7 years lower. The IRFs above suggest that this would translate into about a 50 basis point decrease in long-term nominal yields and about a 25 basis point decrease in long-term real yields, with the latter effect having a half-life of about 8 years. In addition, such a shock would have raised consumption growth by about 0.25% over each of the following three to four years.

There are several caveats to this calculation. First, QE programs were implemented at the ELB, and the attenuating effects of that environment have already been noted. Second, the programs were spread over several years, rather than occurring as a single large shock. That timing difference could matter in the presence of nonlinearities. Third, the dynamics of central bank asset purchases are likely to differ from those of Treasury debt or other elements of investors’ equilibrium portfolios. Since investors’ perceptions of these dynamics matters for their response, the effect of QE on yields and economic variables might be different from the effects of other types of shocks to z_t .

7 Conclusion

This paper has presented a method for solving a broad class of models in which the maturity distribution of investors' assets matters for bond yields (and other asset prices) through the dependence of the pricing kernel on the return on wealth. These models are inherently nonlinear and analytically intractable, and I develop an algorithm for solving them. I set up and estimate one such model, which includes both inflation and real activity as observable factors. To my knowledge, this is the first attempt to integrate portfolio-balance / duration effects of the type explored in Vayanos-Vila into a structural macro-finance asset pricing model. The model allows one to examine such issues as the relative effects of short-rate and bond-supply shocks, which might be of interest for calibrating monetary policy.

Generally, the model suggests that the direct effects of duration shocks on term premia are fairly small. However, the *presence* of duration in the model, through the return-on-wealth term in the stochastic discount factor, is very important for explaining the behavior of yields. Put somewhat differently, fluctuations in duration are less important for the term structure than fluctuations in real asset prices, which then feed back through their affect on aggregate portfolio returns. Adding these features to more-realistic and fully specified models of the macroeconomy is an important direction for future research.

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Table 1. Parameter Estimates

λ^G	λ^R	$\omega^{(5)}$	$\omega^{(10)}$	$\omega^{(15)}$
-75	-25	0.30%	0.25%	0.27%

Table 2. Regressions of Duration Factor on U.S. Debt Metrics

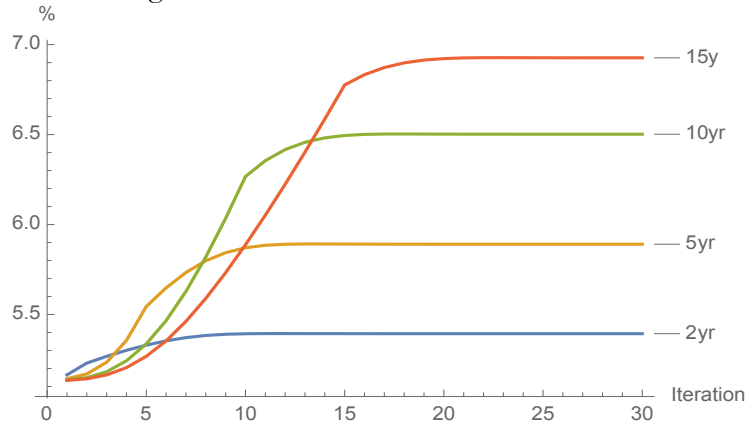
<i>Dep. var: Estimated duration factor</i>		
Intercept	-5.37** (2.10)	-2.34 (1.40)
1y yield	30.2*** (10.9)	46.2*** (12.1)
WAM	1.36*** (0.35)	
MWD/GDP		1.36*** (0.35)
Adj. R ²	0.679	0.681

Table 3. Fit Statistics

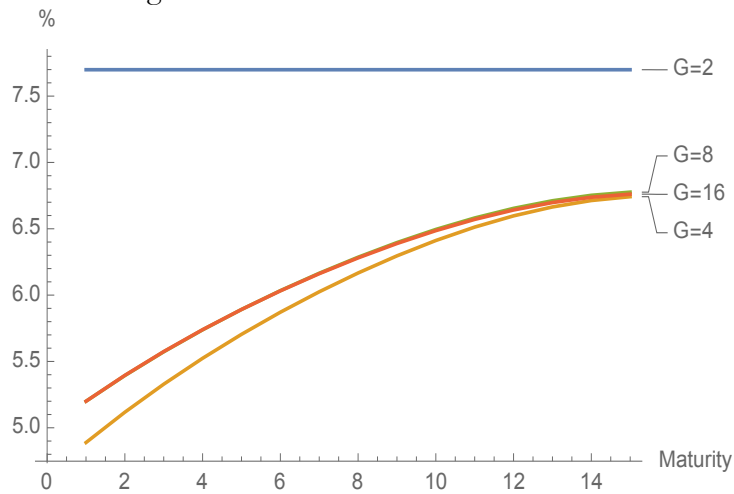
	Baseline	Baseline parameters, but $\lambda^R = 0$	Re-estimated w/o R_{t+1} in SDF
Inflation $t+1$	1.37%	1.37%	1.38%
Consumption $t+1$	1.20%	1.20%	1.20%
1y yield $t+1$	1.42%	1.42%	1.44%
5y nom. yield t	0.30%	3.51%	0.60%
10y nom. yield t	0.25%	2.98%	0.49%
15y nom. yield t	0.27%	3.28%	0.58%

Figure 1. Convergence of the Algorithm in the One-Factor Model

A. Convergence over iterations



B. Convergence over number of nodes



C. Convergence over range of nodes

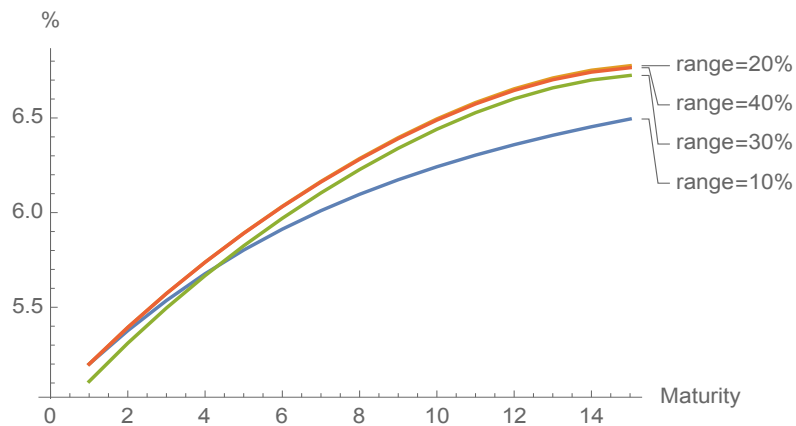
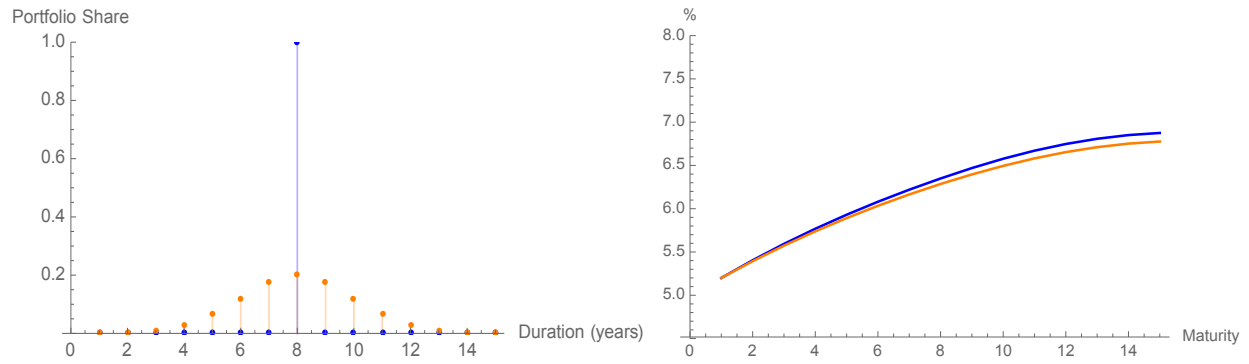
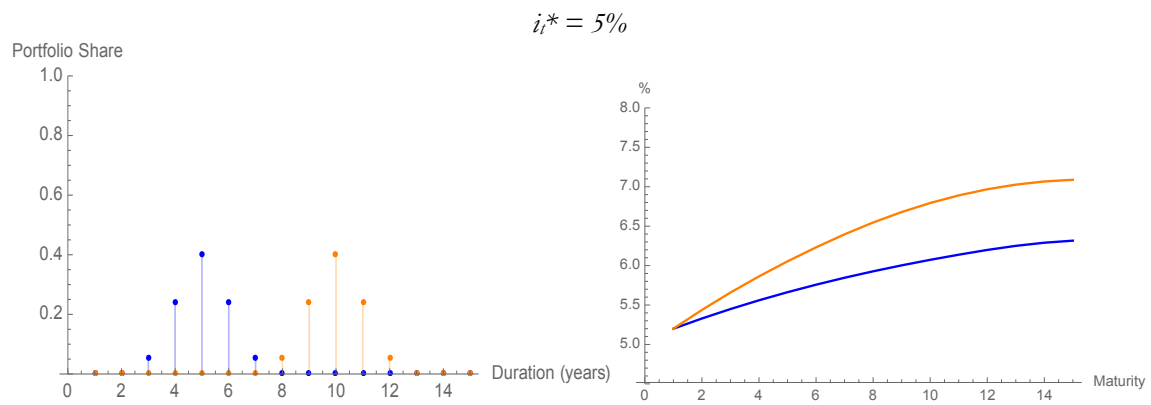


Figure 2. Duration Effects in the One-Factor Model

A. Effect of the distribution shape



B. Effect of duration



C. Effect of the ELB

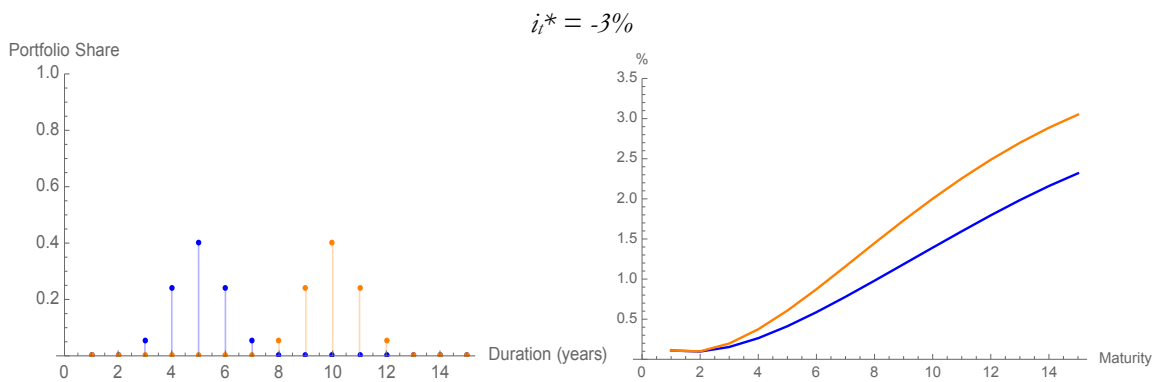


Figure 2. (continued)

D. Effect of the risk price

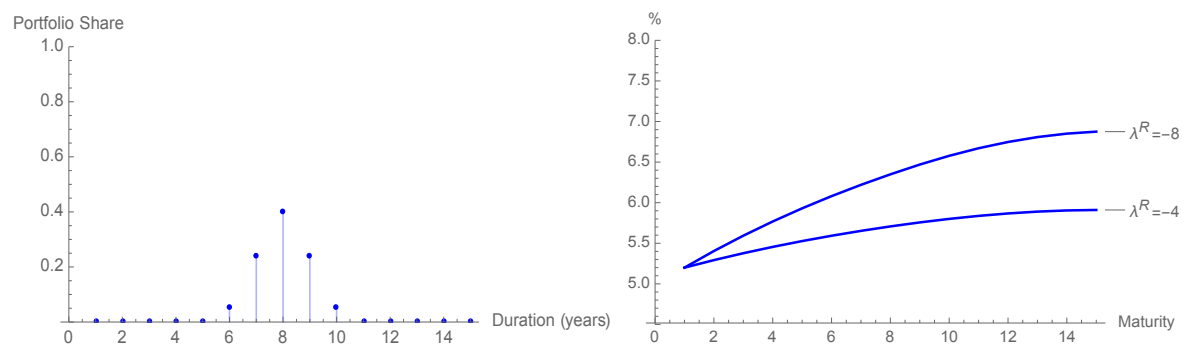
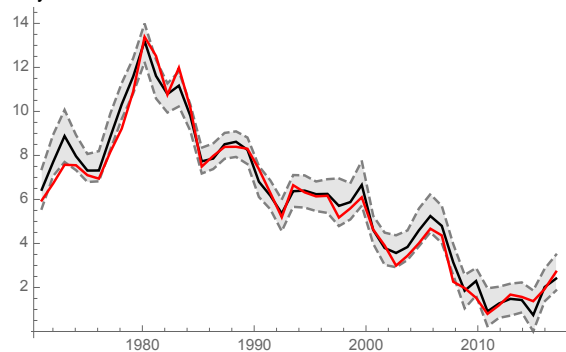
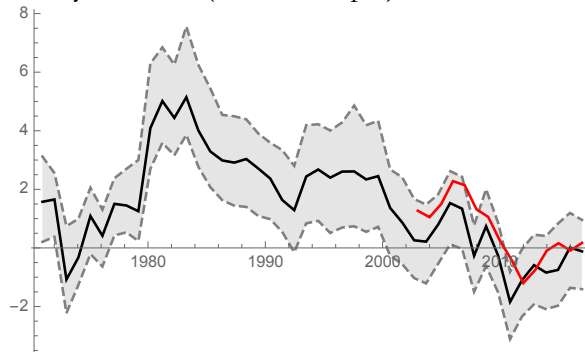


Figure 3. Four-factor model-implied yields vs. data

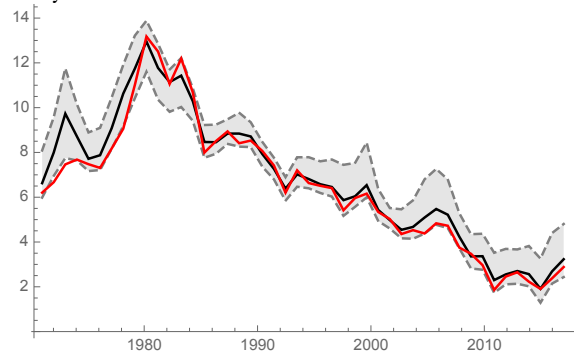
5-year nominal



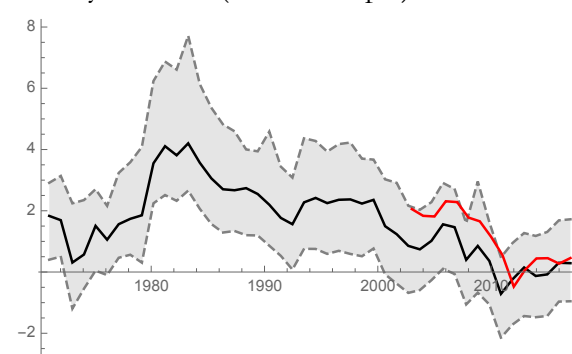
5-year TIPS (out-of-sample)



10-year nominal



10-year TIPS (out-of-sample)



15-year nominal

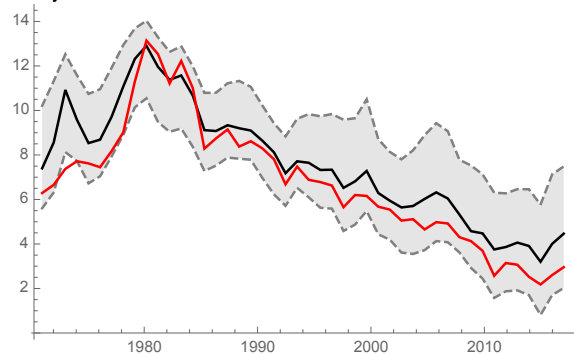
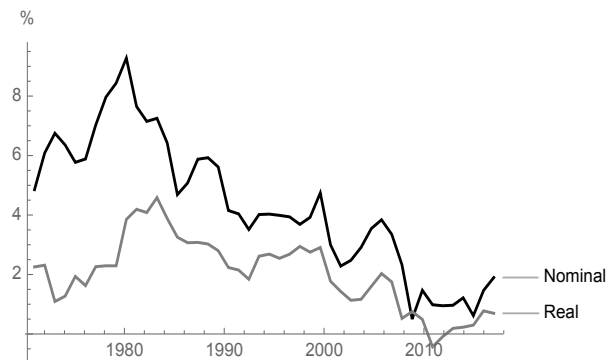
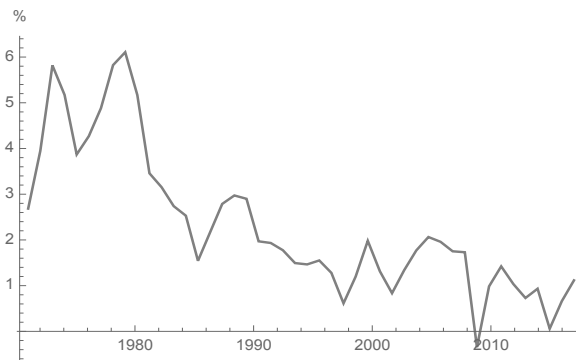


Figure 4. Decomposition of 10-year Nominal Yield

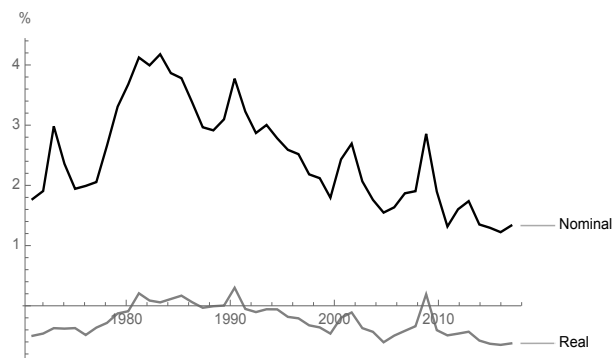
Expected short rates



Expected inflation



Term premia



Inflation-risk premium



Figure 5. Estimated duration factor

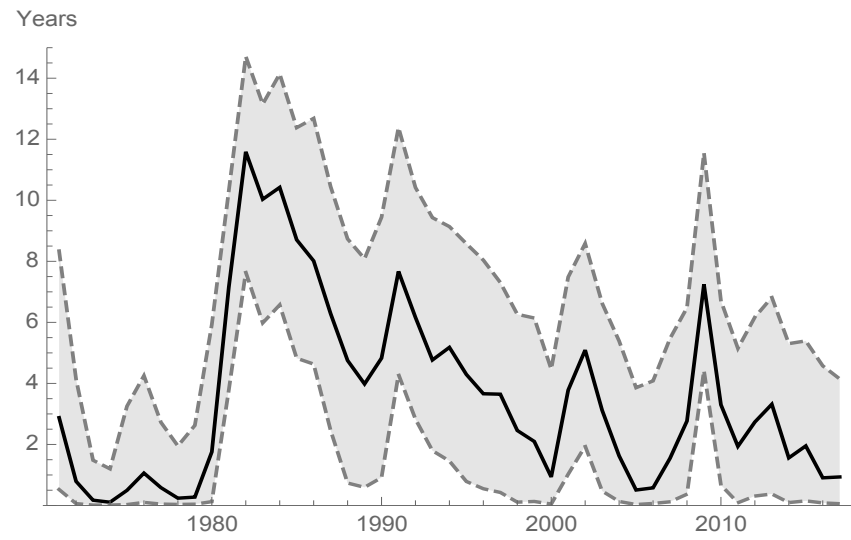
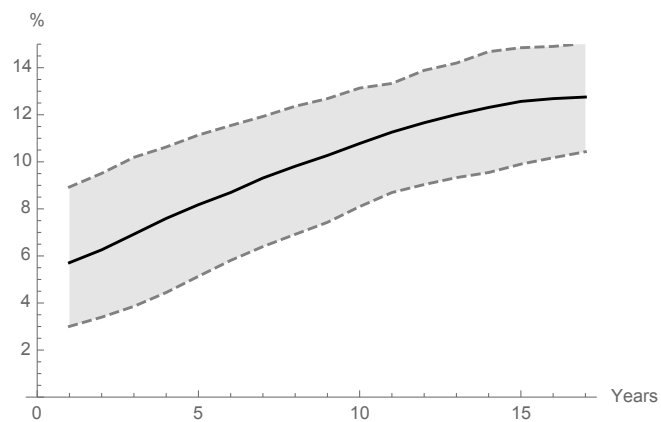


Figure 6. 10-year yield as a function of the duration factor

At average short rate



At ELB

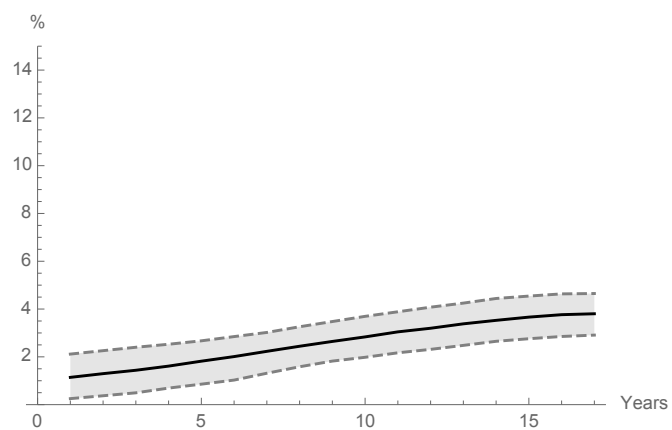


Figure 7. Contribution of duration effect to 10-year yield

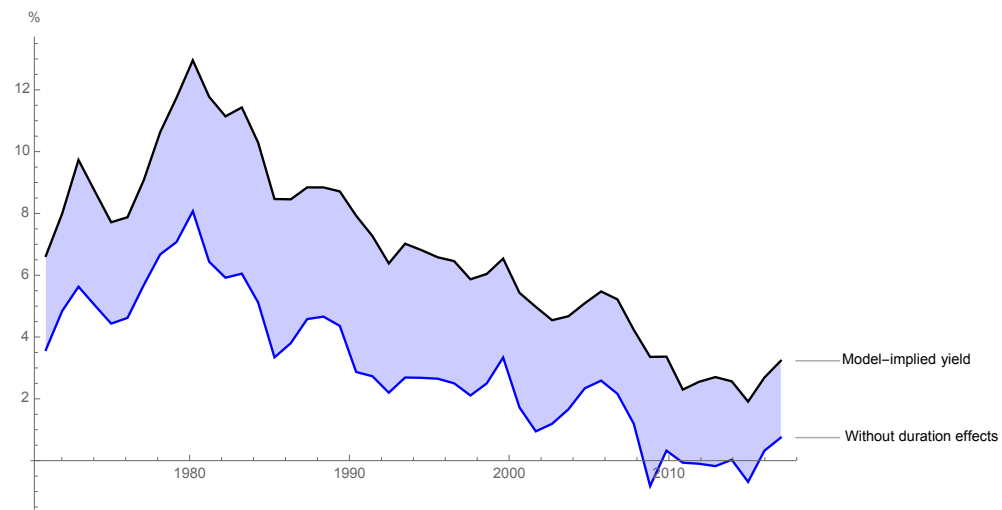


Figure 8. Impulse-response functions – Yield curve

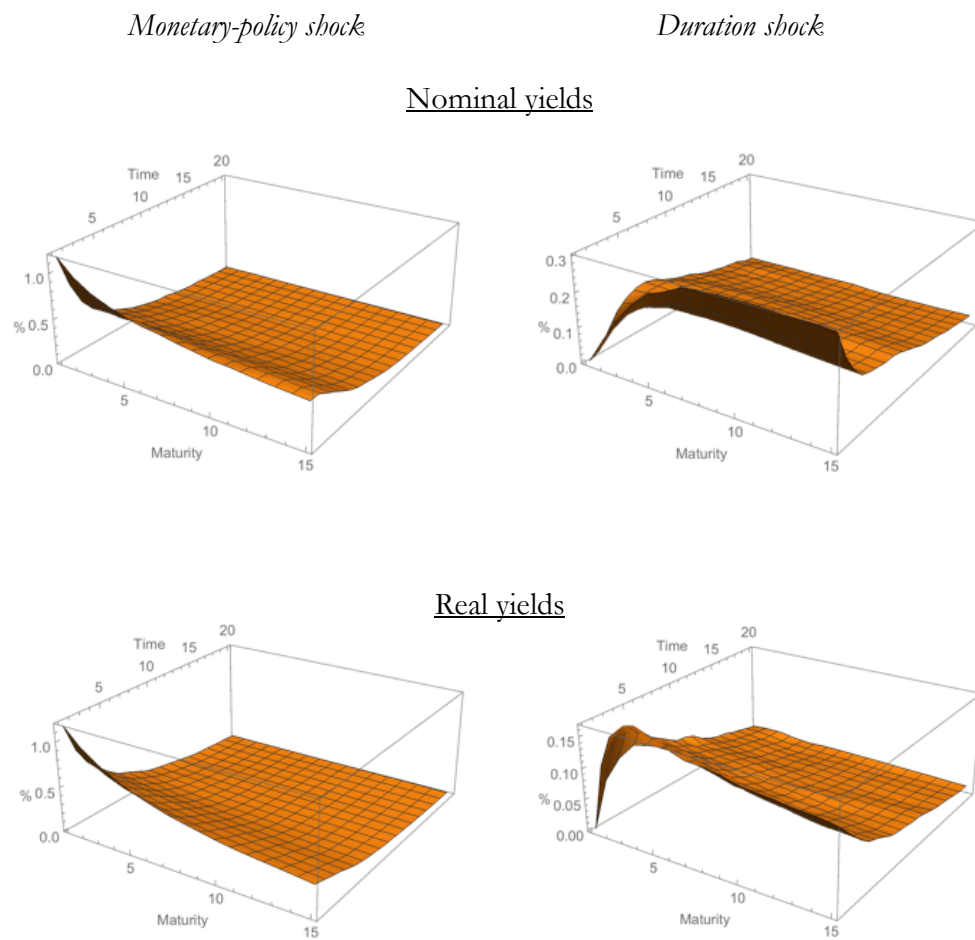


Figure 9. Immediate impact of shocks on yield curve components

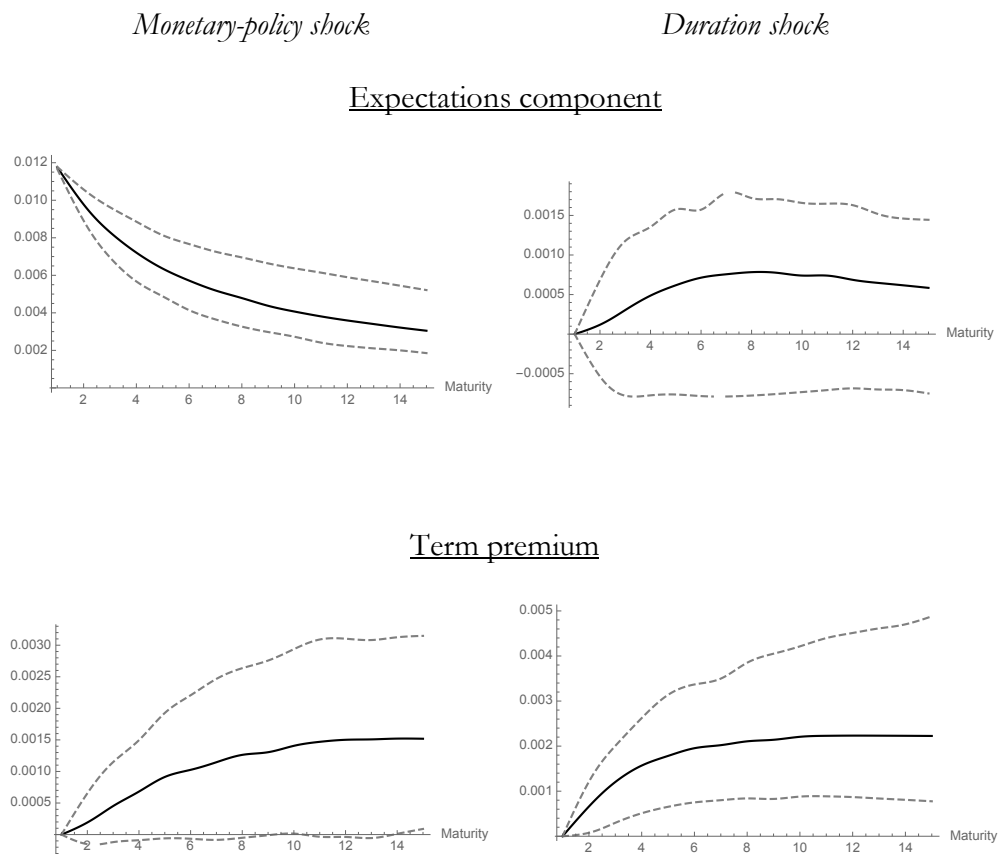


Figure 10. Impulse-response functions – state variables

