

A tractable framework for analyzing a class of nonstationary Markov models

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We consider a class of infinite-horizon dynamic Markov economic models in which the parameters of utility function, production function, and transition equations change over time. In such models, the optimal value and decision functions are time-inhomogeneous: they depend not only on state but also on time. We propose a quantitative framework, called *extended function path* (EFP), for calibrating, solving, simulating, and estimating such nonstationary Markov models. The EFP framework relies on the turnpike theorem which implies that the finite-horizon solutions asymptotically converge to the infinite-horizon solutions if the time horizon is sufficiently large. The EFP applications include unbalanced stochastic growth models, the entry into and exit from a monetary union, information news, anticipated policy regime switches, deterministic seasonals, among others. Examples of MATLAB code are provided.

KEYWORDS. Turnpike theorem, time-inhomogeneous models, nonstationary models, semi-Markov models, unbalanced growth, time-varying parameters, trends, anticipated shock, parameter shift, parameter drift, regime switches, stochastic volatility, technological progress, seasonal adjustments, Fair and Taylor method, extended path.

JEL CLASSIFICATION. C61, C63, C68, E31, E52.

1. INTRODUCTION

Dynamic stochastic infinite-horizon models are normally built on the assumption of a stationary (time-homogeneous) environment, namely, it is assumed that the econ-

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omy's fundamentals such as preferences, technologies, and laws of motions for exogenous variables do not change over time. In such models, optimal value and decision functions are also stationary, that is, they depend only on the economy's state but not on time.

However, actual economies evolve over time, experiencing population growth, technological progress, trends in tastes and habits, policy regime changes, evolution of social and political institutions, etc. Modeling time-dependent features requires the assumption that the parameters of economic models systematically change over time. The resulting models are generally nonstationary (time-inhomogeneous) in the sense that the optimal value and decision functions depend on both state and time. To characterize a solution in such models, we need to construct not just one optimal value and decision functions but an infinitely long sequence (path) of such functions, that is, a separate set of functions for each period of time.¹ Generally, this is a difficult task!

The literature distinguished a number of special cases in which nonstationary dynamic economic models can be reformulated as stationary ones. Labor augmenting technological progress is a well-known example of a deterministic trend that leads to balanced growth and stationarity in the neoclassical growth model; see King, Plosser, and Rebelo (1988).² Time-homogeneous Markov processes are also consistent with stationarity, for example, Markov regime switching models (e.g., Davig and Leeper (2007, 2009), Farmer, Waggoner, and Zha (2011), and Foerster, Rubio-Ramírez, Waggoner, and Zha (2016)) and stochastic volatility models (e.g., Bloom (2009), Fernández-Villaverde and Rubio-Ramírez (2010), and Fernández-Villaverde, Guerrón-Quintana, and Schorfheide (2016)). Finally, anticipated shocks of fixed horizon and periodicity are also consistent with stationarity, including deterministic seasonals (e.g., Barsky and Miron (1989), Christiano and Todd (2002), Hansen and Sargent (1993, 2013)) and news shocks (Schmitt-Grohé and Uribe (2012)).

However, many interesting nonstationary models do not admit stationary representations. In particular, deterministic trends typically lead to unbalanced growth, for example, investment-specific technical change (see Krusell, Ohanian, Ríos-Rull, and Violante (2000)); capital-augmenting technological progress (see Acemoglu (2002, 2003)); time trends in the volatility of output and labor-income shares (see Mc Connel and Pérez-Quiros (2000), and Karabarbounis and Neiman (2014), respectively), etc. Furthermore, anticipated parameter shifts also lead to time-dependent value and decision functions, for example, anticipated accessions of new members to the European Union (e.g., Garmel, Maliar, and Maliar (2008)), presidential elections with predictable outcomes, credible policy announcements, anticipated legislative changes.

In the paper, we focus on these and other generically nonstationary Markov models.³ We propose a quantitative framework, called *extended function path* (EFP), which

¹We can also think of these models as ones that contain “time” as an additional state variable.

²There are examples of balanced-growth models that do not satisfy the restrictions in King, Plosser, and Rebelo (1988) but they are limited; see Maliar and Maliar (2004, 2011), Boppart and Krusell (2016), and Grossman, Helpman, Oberfield, and Sampson (2017).

³A Markov model can be nonstationary (i.e., have no stationary unconditional distribution) even if all the parameters are time-invariant, for example, the unit root and explosive processes. We do not explicitly study these kinds of nonstationarities but focus on time-inhomogeneity of the economic environment.

makes it possible to construct a sequence of time-varying decision and value functions for time-inhomogeneous Markov models. The condition that lies in the basis of our construction is the so-called *turnpike theorem*. This condition ensures that a solution to the finite-horizon model provides an arbitrarily close approximation to the infinite-horizon solution if the time horizon is sufficiently large.

The EFP framework has three steps. First, we assume that, in some remote period, the economy becomes stationary and construct the usual stationary Markov solution. Second, given the constructed terminal condition, we solve backward the Bellman or Euler equations to construct a sequence of value and decision functions. Finally, we verify that the turnpike property holds. Although our numerical examples are limited to problems with few state variables, we implement EFP in a way that makes it tractable in large-scale applications. Examples of the MATLAB code are provided.

For a simple optimal growth model, we can characterize the properties of the EFP solution analytically, including its existence, uniqueness, and time-inhomogeneous Markov structure. Moreover, we can prove a turnpike theorem that shows uniform convergence of the truncated finite-horizon economy to the corresponding infinite-horizon economy. But for more complex models, analytical characterizations are generally infeasible. In the paper, we advocate a numerical approach to turnpike analysis, namely, we check that during a given number of periods, the constructed finite-horizon numerical approximation is insensitive to the specific terminal condition and terminal date assumed. Such a “numerical” way of verifying the turnpike theorem enlarges greatly a class of tractable nonstationary applications.

We illustrate the EFP methodology in the context of three examples.⁴ Our first example is a stylized neoclassical growth model with labor-augmenting technological progress. Such a model can be converted into a stationary one by detrending and solved by any conventional solution method, but EFP makes it possible to solve the model without detrending. Our second example is an unbalanced growth model with capital-augmenting technological progress which cannot be analyzed by conventional solution methods but which can be easily solved by EFP. Our last example is a version of the new Keynesian model that features the forward guidance puzzle, namely, future events have a nonvanishing impact on today’s economy no matter how distant these events are. This example shows the limitations of the EFP analysis: Even though the finite-horizon solution can be constructed, it is not a valid approximation to the infinite-horizon solution if the turnpike theorem does not hold.

The idea of approximating infinite-horizon solutions with finite-horizon solutions is not new to the literature but was introduced and developed in several contexts. First, the turnpike analysis dates back to Dorfman, Samuelson, and Solow (1958), Brock (1971), and McKenzie (1976); see also Nermuth (1978) for a summary of the earlier literature and for generalizations of Brock’s (1971) original results. In particular, there are turnpike theorems for models with time-dependent preferences and technologies; see, for example, Majumdar and Zilcha (1987), and Mitra and Nyarko (1991). However, the turnpike

⁴A working paper version of Maliar, Maliar, Taylor, and Tsener (2015) presented a collection of further examples and applications, including growth models with news shocks, regime switches, stochastic volatility, deterministic trend in labor shares and depreciation rates, seasonal fluctuations.

literature in economics has focused exclusively on the existence results and has never attempted to construct time-dependent solutions in practice.⁵ The main novelty of our analysis is that we show how to effectively combine the turnpike analysis with numerical techniques to analyze a challenging class of time-inhomogeneous Markov equilibrium problems that are either not studied in the literature yet or studied under simplifying assumptions.

Furthermore, other solution methods in the literature construct finite-horizon approximations to infinite-horizon problems by (implicitly) relying on the turnpike property, in particular, an extended path (EP) method of Fair and Taylor (1983).⁶ The key difference between EP and EFP is that the former constructs a path for variables under one specific realization of shocks (by using certainty equivalence approximation), whereas the latter constructs a path for value or decision functions (by using accurate numerical integration methods). As a result, EFP can accurately solve those models in which the EP's certainty equivalence approach is insufficiently accurate. Furthermore, a simulation of the EFP solutions is cheap, unlike the simulation of the EP solutions which requires recomputing the optimal path under each new sequence of shocks.

Finally, there is a literature that studies a transition between two aggregate steady states in heterogeneous-agent economies by constructing a deterministic transition path for aggregate quantities and prices; see, for example, Conesa and Krueger (1999) and Krueger and Ludwig (2007). The EFP analysis includes but is not equivalent to modeling transition from one steady state to another; in particular, some of our applications do not have steady states (e.g., models with deterministic trends and anticipated shocks do not generally have steady states).

The rest of the paper is as follows. In Section 2, we show analytically the turnpike theorem for a nonstationary growth model. In Section 3, we introduce EFP and show how to verify the turnpike theorem numerically. In Section 4, we assess the performance of EFP in a nonstationary test model with a balanced-growth path. In Section 5, we use EFP for analyzing an unbalanced growth model with capital-augmenting technological progress. In Section 6, we discuss the limitations of the EFP framework in the context of the stylized new Keynesian model. Finally, in Section 7, we conclude.

2. VERIFYING THE TURNPIKE THEOREM ANALYTICALLY

We analyze a time-inhomogeneous stochastic growth model in which the parameters can change over time. We show that such a model satisfies the *turnpike theorem*; specif-

⁵In the optimal control theory, the turnpike analysis was used for numerical analysis of some applications; see Anderson and Kokotovic (1987), Trélat and Zuazua (2015), as well as Zaslavski (2019) for a recent comprehensive reference.

⁶Other related path-solving methods are shooting methods, for example, Lipton, Poterba, Sachs, and Summers (1980), Atolia and Buffie (2009a, 2009b); a continuous-time analysis of Chen (1999); a parametric path method of Judd (2002); an EP method built on Newton-style solver of Heer and Maußner (2010); a framework for analyzing time-dependent linear rational expectation models of Cagliarini and Kulish (2013); a nonlinear predictive control method for value function iteration of Grüne, Semmler, and Stieler (2015); refinements of the EP method, for example, Adjemian and Juillard (2013), Krusell and Smith (2015), and Ajevskis (2017).

ically, the trajectory of the finite-horizon economy converges to that of the infinite-horizon economy as the time horizon increases.

2.1 Growth model with time-varying parameters

We consider a stylized stochastic growth model but allow for the case when preferences, technology, and laws of motion for exogenous variables change over time,

$$\max_{\{c_t, k_{t+1}\}_{t=0}^T} E_0 \left[\sum_{t=0}^T \beta^t u_t(c_t) \right] \tag{1}$$

$$\text{s.t. } c_t + k_{t+1} = (1 - \delta)k_t + f_t(k_t, z_t), \tag{2}$$

$$z_{t+1} = \varphi_t(z_t, \epsilon_{t+1}), \tag{3}$$

where $c_t \geq 0$ and $k_{t+1} \geq 0$ denote consumption and capital, respectively; initial condition (k_0, z_0) is given; $u_t : \mathbb{R}_+ \rightarrow \mathbb{R}$, $f_t : \mathbb{R}_+^2 \rightarrow \mathbb{R}_+$, and $\varphi_t : \mathbb{R}^2 \rightarrow \mathbb{R}$ are time-inhomogeneous utility function, production function, and Markov process for exogenous variable z_t , respectively; ϵ_{t+1} is an i.i.d. random variable; $\beta \in (0, 1)$ is a discount factor; $\delta \in (0, 1]$ is a depreciation rate; $E_t[\cdot]$ is an operator of expectation, conditional on a t -period information set; and T can be either finite or infinite.

Exogenous variables In the usual time-homogeneous (stationary) model, the functions $u_t \equiv u$, $f_t \equiv f$, and $\varphi_t \equiv \varphi$ are fixed, time invariant, and known to the agent at $t = 0$. For example, if $f(k_t, z_t) = Az_t k_t^\alpha$, the agent knows A and α . To construct a time-inhomogeneous model in a parallel manner, we need to fix the sequence of u_t , f_t , and φ_t and assume that it is known to the agent at $t = 0$. That is, if $f_t(k_t, z_t) = A_t z_t k_t^{\alpha_t}$, we assume that the agent knows $\{A_t, \alpha_t\}_{t=0}^\infty$.

The time-inhomogeneous Markov framework allows us to model a variety of interesting time-dependent scenarios. As an example, consider the technology level A_t . We can assume that A_t can gradually change over time (drifts) or make sudden jumps (shifts). These changes can be either anticipated or not. In particular, we can have (i) technological progress $A_t = A_0 \gamma^t$, where $A_0 > 0$ and γ is the technology growth rate; (ii) seasonal fluctuations $A_t = \{\underline{A}, \bar{A}, \underline{A}, \bar{A}, \dots\}$, where \underline{A}, \bar{A} are technology levels in the high and low seasons; (iii) news shocks about future levels of A_t ; etc.

We can also consider time-dependent scenarios for the parameters of stochastic processes. For example, consider the following process for z_t in (3):

$$\ln z_{t+1} = \rho_t \ln z_t + \sigma_t \epsilon_{t+1}, \tag{4}$$

where $\sigma_t > 0$, $|\rho_t| \leq 1$, and $\epsilon_{t+1} \sim \mathcal{N}(0, 1)$. The process (4) is Markov since the probability distribution $\ln z_{t+1} \sim N(\ln A_t + \rho_t \ln z_t, \sigma_t^2)$ depends only on the current state but not on the history. However, if either the mean $\ln A_t + \rho_t \ln z_t$ or the variance σ_t^2 change over time, then the transition probabilities of $\ln z_{t+1}$ also change over time, that is, the Markov

process is time-inhomogeneous; see Appendix A.1 of the Supplemental Material (Maliar, Maliar, Taylor, and Tsener (2020)) for formal definitions.⁷ We can analyze similar time-dependent scenarios for other parameters of the model, including the time-dependent policies.

Endogenous variables and the optimal program A feasible program is a pair of adapted processes $\{c_t, k_{t+1}\}_{t=0}^T$ such that, given initial condition (k_0, z_0) and any history $h_T = (\epsilon_0, \dots, \epsilon_T)$, it reaches a given terminal condition k_{T+1} at T and satisfies $c_t \geq 0$, $k_{t+1} \geq 0$, (2), and (3) for $t = 1, \dots, T$. “Adapted” means that the agent does not know future stochastic shocks ϵ ’s (although she does know the deterministic changes in u_t , f_t , and φ_t for all $t \geq 0$).

A feasible program is called *optimal* if it gives higher expected lifetime utility (1) than any other feasible program.

We make standard (strong) assumptions that u_t and f_t are twice continuously differentiable, strictly increasing, strictly quasi-concave, and satisfy the Inada conditions for all t . Moreover, we assume that lifetime utility (1) is bounded; see Appendix A.2 of the Supplemental Material for a formal description of our assumptions.

The optimal program in the economy (1)–(3) can be characterized by Bellman equations,

$$V_t(k_t, z_t) = \max_{c_t, k_{t+1}} \{u_t(c_t) + \beta E_t[V_{t+1}(k_{t+1}, z_{t+1})]\}, \quad t = 0, 1, \dots, T. \quad (5)$$

Also, the interior optimal program satisfies the Euler equations,

$$u'_t(c_t) = \beta E_t[u'_{t+1}(c_{t+1})(1 - \delta + f'_{t+1}(k_{t+1}, z_{t+1}))], \quad t = 0, 1, \dots, T. \quad (6)$$

In our assumptions, we follow Majumdar and Zilcha (1987) and Mitra and Nyarko (1991), except that we assume strict quasi-concavity of the utility and production functions that lead to unique solutions.

2.2 Finite-horizon economy

We first consider a finite-horizon model, $T < \infty$. We know that finite-horizon models are solvable by backward induction from a given terminal condition. To solve such models, we do not need stationarity: the models’ parameters (e.g., discount factor, depreciation rate, persistence and volatilities of shocks) can change in every period but backward iteration still works.

THEOREM 1 (Existence and uniqueness of time-inhomogeneous Markov solution). *Fix a partial history $h_T = (\epsilon_0, \dots, \epsilon_T)$, initial condition (k_0, z_0) , and a terminal condition given by a Markov process $K_T(k_T, z_T)$ such that the set of feasible programs is not empty. Then, the optimal program $\{c_t, k_{t+1}\}_{t=0}^T$ exists, is unique, and is given by a time-inhomogeneous Markov process.*

⁷Mitra and Nyarko (1991) referred to a class of time-inhomogeneous Markov processes as semi-Markov processes because of their similarity to Lévy’s (1954) generalization of the Markov renewal process for the case of random arrival times; see Jansen and Manca (2006) for a review of applications of semi-Markov processes in statistics and operation research.

PROOF. The existence of the optimal program $\{c_t, k_{t+1}\}_{t=0}^T$ under our assumptions is well known; see, for example, Theorem 3.1 of [Mitra and Nyarko \(1991\)](#). The uniqueness follows by strict quasi-concavity of the utility and production functions. We are left to check the time-inhomogeneity of the Markov process for the decision functions. We outline the proof by using the Euler equation (6), but a parallel proof can be given via Bellman equation (5); see [Majumdar and Zilcha \(1987, Theorem 1\)](#) for related analysis. Our proof is constructive and follows by backward induction.

Given a T -period (terminal) capital function K_T , we define the capital functions K_{T-1}, \dots, K_0 in previous periods to satisfy the sequence of the Euler equations. As a first step, we write the Euler equation for period $T - 1$,

$$u'_{T-1}(c_{T-1}) = \beta E_{T-1} [u'_T(c_T)(1 - \delta + f'_T(k_T, z_T))], \tag{7}$$

where c_{T-1} and c_T are related to k_T and k_{T+1} in periods T and $T - 1$ by

$$c_{T-1} = (1 - \delta)k_{T-1} + f_{T-1}(k_{T-1}, z_{T-1}) - k_T, \tag{8}$$

$$c_T = (1 - \delta)k_T + f_T(k_T, z_T) - k_{T+1}. \tag{9}$$

By our assumptions, $z_T = \varphi_T(z_{T-1}, \epsilon)$ and $k_{T+1} = K_T(k_T, z_T)$ are Markov processes. Combining these assumptions with (7)–(9), we obtain a functional equation that defines k_T for each possible state (k_{T-1}, z_{T-1}) , that is, we obtain an implicitly defined function $k_T = K_{T-1}(k_{T-1}, z_{T-1})$. By proceeding iteratively backward, we construct a sequence of Markov time-dependent capital functions $K_{T-1}(k_{T-1}, z_{T-1}), \dots, K_0(k_0, z_0)$ that satisfy (7)–(9) for $t = 0, \dots, T - 1$ and that match the terminal function $K_T(k_T, z_T)$. The resulting solution is a time-inhomogeneous Markov process by construction. \square

2.3 Infinite-horizon economy: Stationary case

Let us now turn to the infinite-horizon model with $T = \infty$. The literature extensively focuses on the stationary version of (1)–(3) in which preferences, technology, and laws of motion for exogenous variables are time homogeneous $u_t = u$, $f_t = f$, and $\varphi_t = \varphi$ for all t . This model has a stationary Markov solution in which value function $V(k_t, z_t)$ and decision functions $k_{t+1} = K(k_t, z_t)$, $c_t = C(k_t, z_t)$ are time invariant and Markov functions that satisfy the stationary versions of the Bellman equation (5) and Euler equation (6), respectively, are

$$V(k_t, z_t) = \max_{c_t, k_{t+1}} \{u(c_t) + \beta E_t [V(k_{t+1}, z_{t+1})]\}, \tag{10}$$

$$u'(c_t) = \beta E_t [u'(c_{t+1})(1 - \delta + f'(k_{t+1}, z_{t+1}))]. \tag{11}$$

The numerical algorithms solve stationary infinite-horizon models by finding fixed point for the value function V and policy function K such that if we substitute them in the right-hand side of the Bellman equation (10) and the Euler equation (11), respectively, we obtain the same functions in the left-hand side of these equations.

However, this solution procedure is not applicable to a time-inhomogeneous version of the model (1)–(3). In such a model, we have different optimal Markov functions $V_t, K_t,$

and C_t in each period, and no fixed point exists for such functions or such fixed points are not optimal.

2.4 *Infinite-horizon economy: Nonstationary case*

An alternative we explore in the paper is to approximate an infinite-horizon solution with the corresponding finite-horizon solution. Our analysis is related to the literature on *turnpike theorems*.

2.4.1 *Illustration of the turnpike theorem for a model with closed-form solution* Let us first illustrate the turnpike property for a version of the model (1)–(3) that admits a closed-form solution. We specifically assume Cobb–Douglas utility and production functions,

$$u_t(c) = \frac{c^{1-\eta} - 1}{1 - \eta} \quad \text{and} \quad f_t(k, z) = zk^\alpha A_t^{1-\alpha}, \tag{12}$$

where A_t and z_t represent labor-augmenting technological progress and stochastic shock given, respectively, by

$$A_t = A_0 \gamma_A^t \quad \text{and} \quad \ln z_{t+1} = \rho \ln z_t + \sigma \epsilon_{t+1}, \tag{13}$$

where $\gamma_A \geq 1$, $\epsilon_{t+1} \sim \mathcal{N}(0, 1)$, $\rho \in (-1, 1)$, and $\sigma \in (0, \infty)$.

We consider $\eta = 1$, which leads to a logarithmic utility function, $u_t(c) = \ln c$, and full depreciation of capital, $\delta = 1$. The Bellman equation (5) becomes

$$V_t(k_t) = \max_{k_{t+1}} \{ \ln(z_t k_t^\alpha A_t^{1-\alpha} - k_{t+1}) + \beta E_t[V_{t+1}(k_{t+1})] \}, \quad t = 1, \dots, T, \tag{14}$$

where we assume $V_{T+1}(k_{T+1}) = 0$ and hence, $k_{T+1} = 0$. It is well known that (14) admits a closed-form solution,

$$k_T = \frac{\alpha\beta}{1 + \alpha\beta} z_{T-1} k_{T-1}^\alpha A_{T-1}^{1-\alpha}, \quad k_{T-1} = \frac{\alpha\beta(1 + \alpha\beta)}{1 + \alpha\beta(1 + \alpha\beta)} z_{T-2} k_{T-2}^\alpha A_{T-2}^{1-\alpha}, \quad \text{etc.} \tag{15}$$

In Figure 1, we plot capital trajectories of the economies with finite horizons of $T = 15$ and $T = 25$, as well as of the economy with infinite horizon $T = \infty$. We set the remaining parameters at $\beta = 0.99$, $\alpha = 0.36$, $\rho = 0.95$, $\sigma = 0.01$, and $\gamma_A = 1.01$.

As we can see, if all three economies start with the same initial capital, they follow a virtually identical path for a long time and diverge only in a close proximity to the terminal date. Therefore, if we are interested in the behavior of infinite-horizon nonstationary economy during some initial number of periods τ , we can accurately approximate the infinite-horizon solution by solving the finite-horizon model. This is precisely what turnpike theorem means.

Figure 1 also helps us understand why this convergence result is called *turnpike theorem*. Turnpike (highway) is often the fastest route between two points even if it is not the shortest one. Specifically, if one drives to some remote destination (e.g., a small town), one typically tries to get on the turnpike as soon as possible, stays on the turnpike

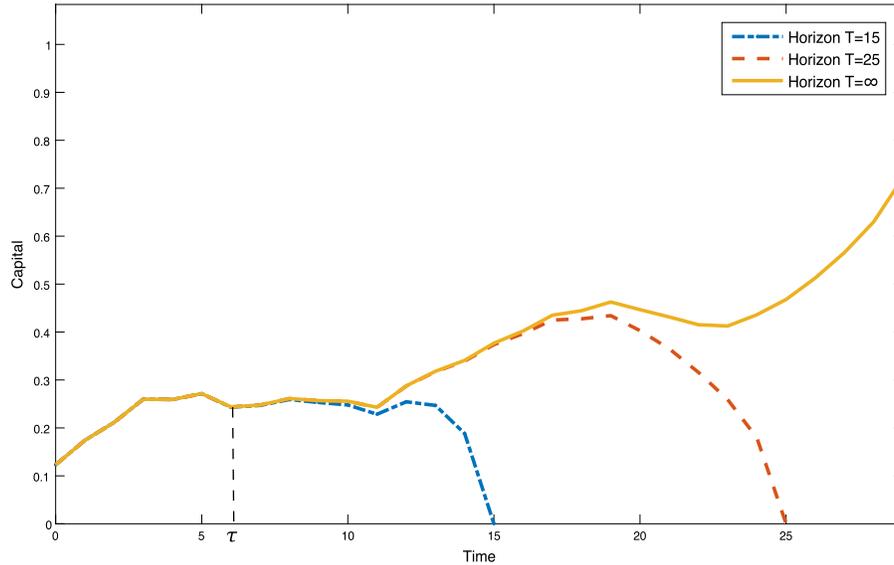


FIGURE 1. Finite- and infinite-horizon solutions in the growth model.

for as long as possible, and gets off the turnpike as close as possible to the final destination. In the figure, we see the same behavior for the model if we interpret the infinite- and finite-horizon economies as an infinite turnpike and our actual finite destination, respectively.⁸

2.4.2 A formal proof of the turnpike theorem for a general growth model The turnpike property is not limited to our example with closed-form solution but holds for the growth model (1)–(3) under general utility and production functions. Specifically, we can show that if the time horizon T is sufficiently large, then the finite-horizon solution (k_0^T, \dots, k_T^T) will be within an ε range of the infinite-horizon solution $(k_0^\infty, \dots, k_T^\infty)$ during the initial τ periods.

THEOREM 2 (Turnpike theorem). *For any real number $\varepsilon > 0$, any natural number τ , and any Markov T -period terminal condition $K_T(k_T, z_T)$, there exists a threshold terminal date $T^*(\varepsilon, \tau, K_T)$ such that, for any $T \geq T^*(\varepsilon, \tau, K_T)$, we have*

$$|k_t^\infty - k_t^T| < \varepsilon \quad \text{for all } t \leq \tau, \quad (16)$$

where $k_{t+1}^\infty = K_t^\infty(k_t^\infty, z_t)$ and $k_{t+1}^T = K_t(k_t^T, z_t)$ are the trajectories in the infinite- and finite-horizon economies, respectively, under given initial condition (k_0, z_0) and partial history $h_T = (\varepsilon_0, \dots, \varepsilon_T)$.

⁸We restrict attention to the so-called *early turnpike theorem* which shows that the initial-period decisions functions are insensitive to specific terminal conditions used. There are also medium and late turnpike theorems that focus respectively on the role of the initial and terminal conditions in the properties of the solution; see McKenzie (1976) and Joshi (1997) for a discussion. We do not analyze other turnpike theorems since they are not directly related to the proposed EFP solution framework.

PROOF. The proof is shown in Appendix A.6 of the Supplemental Material, and it relies on three lemmas presented in Appendices A.3–A.5. First, we construct a limit program of a finite-horizon economy with a terminal condition $k_{T+1} = 0$. Second, we prove the convergence of the optimal program of the T -period stationary economy with an arbitrary terminal capital stock $k_{T+1} = K_T(k_T, z_T)$ to the limiting program of the finite-horizon economy with a zero terminal condition $k_{T+1} = 0$. Finally, we show that the limit program of the finite-horizon economy with zero terminal condition $k_{T+1} = 0$ is also an optimal program for the infinite-horizon nonstationary economy (1)–(3). \square

REMARK 1. The above theorem is shown for a fixed history and can be viewed as a sensitivity result. But our analysis can be extended to hold for any history using “almost sure” convergence notion; see, for example, Majumdar and Zilcha (1987) for such a generalization. The resulting turnpike theorem will state that for all $T \geq T^*(\varepsilon, \tau, K_T)$, the constructed Markov time-inhomogeneous approximation $\{k_{t+1}^T\}$ is guaranteed to be within a given ε -accuracy range of the true solution $\{k_{t+1}^\infty\}$ almost surely during the initial τ periods for any history of shocks $h_\infty = (\varepsilon_0, \varepsilon_1, \dots)$.

The first turnpike result dates back to Dorfman, Samuelson, and Solow (1958) who studied the efficient programs in the von Neumann model of capital accumulation. Their analysis shows that for a long time period and for any initial and terminal conditions, the optimal solution to the model would get into the phase of maximal von Neumann growth, that is, the turnpike. However, the proof of the argument they provided was only valid in a neighborhood of the steady state. The subsequent economic literature provided more general global turnpike theorems; see Brock (1971), McKenzie (1976), Nermuth (1978), Majumdar and Zilcha (1987), and Mitra and Nyarko (1991).⁹

However, the turnpike literature in economics has focused exclusively on the existence results and has never attempted to construct time-dependent solutions in practice. The main novelty of our analysis is that we show how to effectively combine the turnpike analysis with numerical techniques to analyze a challenging class of time-inhomogeneous Markov models that are either not studied yet in the literature or studied under simplifying assumptions.

3. VERIFYING THE TURNPIKE THEOREM NUMERICALLY: EFP FRAMEWORK

For a simple optimal growth model, it was possible to prove the turnpike theorem analytically. But such analytical proofs are infeasible for more complex and realistic models that are used for applied work. An alternative we offer is to verify the turnpike theorem numerically; namely, we introduce an extended function path (EFP) framework

⁹Additionally, the turnpike results are available in the literature that studies optimal control problems. Anderson and Kokotovic (1987) showed that a solution to a finite-time optimal control problem can be obtained by piecing together solutions to infinite-time problems. Trélat and Zuazua (2015) provided general turnpike results that do not rely on any specific assumption on the dynamics of the problem. The recent work of Zaslavski (2019) provides necessary and sufficient conditions for the turnpike property for a broad class of discrete-time optimal control problems for continuous-time infinite-dimensional optimal control problems.

that makes it possible to construct time-inhomogeneous finite-horizon solutions and to verify that such solutions converge to the infinite-horizon solutions as time horizon increases.

3.1 Markov models with time-varying fundamentals

We analyze two broad classes of nonstationary problems, namely, the optimal control problems and the equilibrium problems. An optimal control time-inhomogeneous Markov problem is characterized by the Bellman equation with a time-dependent value function,

$$V_t(x_t, z_t) = \max_{x_{t+1}, y_t} \{R_t(y_t, x_t, z_t) + \beta E_t[V_{t+1}(x_{t+1}, z_{t+1})]\}, \quad t = 0, 1, \dots, T, \quad (17)$$

where T can be either infinite or finite; $z_t \in H_t^z \subseteq \mathbb{R}^{d_z}$, $x_t \in H_t^x \subseteq \mathbb{R}^{d_x}$, and $y_t \in H_t^y \subseteq \mathbb{R}^{d_y}$ are vectors of exogenous state variables and endogenous state and control variables, respectively; a return function $R_t : H_t^y \times H_t^x \times H_t^z \rightarrow \mathbb{R}$ is twice continuously differentiable, strictly increasing, strictly concave, bounded, and satisfies the Inada conditions.

An equilibrium time-inhomogeneous Markov problem is characterized by a system of time-dependent Euler and other model's equations,

$$E_t[Q_t(x_t, z_t, y_t, x_{t+1}, z_{t+1}, y_{t+1})] = 0, \quad t = 0, 1, \dots, T, \quad (18)$$

where $Q_t : H_t^x \times H_t^z \times H_t^y \times H_{t+1}^x \times H_{t+1}^z \times H_{t+1}^y \rightarrow H_t^Q \subseteq \mathbb{R}^{d_Q}$ is a vector-valued function. In both (17) and (18), a solution satisfies a set of possibly time-dependent constraints:

$$G_t(x_t, z_t, y_t, x_{t+1}) = 0, \quad t = 0, 1, \dots, T, \quad (19)$$

where $G_t : H_t^x \times H_t^z \times H_t^y \times H_{t+1}^x \rightarrow \mathbb{R}^G$ is a vector-valued function that is continuously differentiable in x_t, y_t, x_{t+1} ; the set $\{(x_t, x_{t+1}) : G_t(x_t, z_t, y_t, x_{t+1}) = 0\}$ is convex and compact. The law of motion for exogenous state variables is given by time-inhomogeneous Markov process $z_{t+1} = Z_t(z_t, \epsilon_{t+1})$, where $Z_t : H_t^z \times H_t^\epsilon \rightarrow H_{t+1}^z$ and $\epsilon_t \in H_t^\epsilon \subseteq \mathbb{R}^{d_\epsilon}$ is a vector of independently and identically distributed disturbances. The set of constraints (19) can be generalized to include inequality constraints and the corresponding Karush–Kuhn–Tucker conditions. Some optimal control problems of type (17) can be represented in the form of equilibrium problems of type (18) and vice versa, but it is not always the case.

3.2 Turnpike property

We assume that the studied classes of economies satisfy the turnpike property, which we postulate by generalizing the turnpike theorem.

TURNPIKE PROPERTY. For any real number $\varepsilon > 0$, any natural number τ , and any Markov T -period terminal condition $X_T(x_T, z_T)$, there exists a threshold terminal date $T^*(\varepsilon, \tau, X_T)$ such that for any $T \geq T^*(\varepsilon, \tau, X_T)$, we have

$$|x_t^\infty - x_t^T| < \varepsilon \quad \text{for all } t \leq \tau, \quad (20)$$

where $x_{t+1}^\infty = X_t^\infty(k_t^\infty, z_t)$ and $x_{t+1}^T = X_t(k_t^T, z_t)$ are time-inhomogeneous Markov trajectories of the infinite- and finite-horizon economies, respectively, under given initial condition (x_0, z_0) and partial history $h_T = (\epsilon_0, \dots, \epsilon_T)$.

3.3 EFP framework

EFP aims to accurately approximate a sequence of time-dependent value and decision functions during a given number of periods τ by truncating the infinite-horizon economy. Since EFP in effect solves a finite-horizon model, it makes no difference for the solution procedure whether the parameters are constant or change in every period of time.

ALGORITHM 1 (Extended function path (EFP)).

Step 1: Terminal condition. Choose $T \gg \tau$ and construct time-invariant Markov decision functions $X_T(x, z) \equiv X(x, z)$.

Step 2: Backward iteration. Given the terminal condition $X_T \equiv X$, iterate backward on the Bellman or Euler equations to construct a path of time-inhomogeneous Markov decision functions (X_{T-1}, \dots, X_0) .

Step 3: Turnpike property. Verify that the initial τ functions (X_0, \dots, X_τ) are not sensitive to the choice of time horizon X_T and terminal condition T by analyzing different X_T and T .

Use (X_0, \dots, X_τ) as an approximate solution and discard the remaining $T - \tau$ functions $(X_{\tau+1}, \dots, X_T)$.

What determines the accuracy of the EFP approximation? Let us denote the EFP finite-horizon solution by $(\hat{x}_0, \dots, \hat{x}_\tau)$. Then, by a triangle inequality, the supnorm error bound on the EFP approximation is given by

$$|x_t^\infty - \hat{x}_t^T| \leq |x_t^\infty - x_t^T| + |x_t^T - \hat{x}_t^T| \quad \text{for all } t \leq \tau, \quad (21)$$

where $x_t^\infty = X_t(x_t^\infty, z_t)$, $x_t^T = X_t(x_t^T, z_t)$, and $\hat{x}_t^T = \hat{X}_t(\hat{x}_t^T, z_t)$ are the trajectories corresponding to the infinite- and finite-horizon solutions and the EFP approximation, respectively. That is, the EFP approximation error has two components: one is the error $|x_t^\infty - x_t^T|$ that results from replacing the infinite-horizon problem with the finite-horizon problem, and the other is the error $|\hat{x}_t^T - x_t^T|$ that arises because the finite-horizon solution itself is approximated numerically. The former error depends on the choice of time horizon and terminal condition, and it can be made arbitrarily small by extending the time horizon T , provided that the turnpike property is satisfied. The latter error depends on the accuracy of numerical techniques used by EFP, such as interpolation, integration, solvers, etc. Since EFP relies on the same techniques as do conventional global solution methods, the standard convergence results apply. For example, Smolyak grids used in our analysis can approximate smooth functions with an arbitrary degree of precision when the approximation level increases; see Judd, Maliar, Maliar, and Valero (2014). Below, we discuss how specific implementation of Steps 1–3 affects the accuracy and computational expense of the EFP method.

Step 1: Terminal condition In Step 1, we can choose any attainable Markov terminal condition. In particular, we can assume that either the economy converges to a deterministic steady state of some stationary model, or that it reaches a stationary solution with time-invariant Markov value and decision functions, or that it approaches a balanced-growth path. To solve stationary or balanced-growth models, we can use any conventional projection, perturbation, and stochastic simulation methods; see Taylor and Uhlig (1990) and Judd (1998) for reviews of the earlier methods; and see Maliar and Maliar (2014) and Fernández-Villaverde, Guerrón-Quintana, and Schorfheide (2016) for reviews of more recent literature. It is even possible to use a trivial (zero) terminal condition by assuming that the life ends at T and by setting all variables to zero, so Step 1 is always implementable. Under the turnpike theorem, a specific terminal condition used has just a negligible effect on the solution in the initial periods provided that the time horizon is large enough. How large the time horizon should be for attaining some given accuracy level does depend on the specific terminal condition used. To increase accuracy and to economize on costs, we must construct a terminal condition that is as close as possible to the infinite-horizon solution at T ; in Sections 4 and 5, we explain the construction of the terminal condition in numerical examples.

Step 2: Backward iteration Conventional projection, perturbation, and stochastic simulation methods are designed for solving stationary problems and are not directly suitable for analyzing nonstationary problems. However, the techniques used by these methods can be readily employed as ingredients of EFP. In particular, to approximate value and decision functions, we can use a variety of grids, integration rules, approximation methods, iteration schemes, etc. Furthermore, to solve for a path, we can use any numerical procedure that can solve a system of nonlinear equations, including Newton-style solvers, as well as Gauss–Siedel or Gauss–Jacobi iteration methods. To make EFP tractable in large-scale models, we can use low-cost sparse, simulated, cluster, and epsilon-distinguishable-set grids; nonproduct monomial and simulation based integration methods; derivative-free solvers; see Maliar and Maliar (2014) for a survey of these techniques.

Step 2 is equivalent to conventional backward (time) iteration on the Bellman and Euler equations, as is done in case of life-cycle models; see, for example, Krueger and Kubler (2004) and Hasanhodzic and Kotlikoff (2018); see Ríos-Rull (1999) and Nishiyama and Smetters (2014) for reviews of the literature on life-cycle economies.¹⁰ Time iteration requires the existence of integrals in (17) and (18); see, for example, Chapter 7 in Stachurski (2009) for a discussion of integrability. Furthermore, optimal problem (17) must have a well-defined maximum, while the system in equilibrium problem (18) must be invertible with respect to the next-period state variables x_{t+1} . These are very mild restrictions that are satisfied in virtually any model studied in the related literature.

As a criterion of convergence, we can evaluate the decision functions on low-discrepancy grids or simulated series, as is done for stationary economies; see, for example, Maliar and Maliar (2014). The difference is that in the stationary case, we must

¹⁰Time iteration is commonly used in the context of dynamic programming methods, as well as some Euler equation methods; for example, Coleman (1991), Mirman, Morand, and Reffett (2008), Malin, Krueger, and Kubler (2011).

check the convergence of just one time-invariant decision function, while in the non-stationary case, we must check the pointwise convergence of the entire path (sequence) of such functions.

Step 3. Turnpike property If we knew or could somehow guess the exact solution X_T^∞ of the infinite-horizon model at T and use it as a terminal condition, the infinite- and finite-horizon trajectories would coincide up to T . However, the infinite-horizon solution is typically unknown in any period (as this is a solution we are trying to find), so the right terminal condition is also unknown. The turnpike property solves the problem of unknown terminal condition: no matter what terminal condition X_T we use, the finite-horizon solution (X_0, \dots, X_T) provides an accurate approximation to the infinite-horizon solution $(X_0^\infty, \dots, X_T^\infty)$ during the given number of periods τ provided that the time horizon T is sufficiently large. However, this is only true if the turnpike property holds, so Step 3 is a critical ingredient of the EFP analysis.

To test the turnpike property, we construct the EFP solution (X_0, \dots, X_T) under several different T 's and X_T 's; for each constructed solution (X_0, \dots, X_T) , we simulate the economy's trajectories (x_0^T, \dots, x_T^T) under different initial conditions (x_0, z_0) and different histories h_T ; and we evaluate the approximation errors or residuals in the model's equations. Provided that the approximation errors or residuals are small for all T 's and X_T 's, we conclude that the EFP solution converges to a unique limit, that is, $\lim_{T \rightarrow \infty} (X_0^T, \dots, X_T^T) = (X_0^*, \dots, X_T^*)$.

Does our test produce types I and II errors? The former type of errors is not possible: if a model satisfies the turnpike theorem, our test will confirm that the solution is insensitive to a specific terminal condition and time horizon used. The latter type of errors is, however, possible, that is, we can erroneously conclude that turnpike theorem holds for some models for which effectively it does not. This is because EFP relies on the assumption that the infinite-horizon solution $(x_0^\infty, \dots, x_T^\infty)$ is equivalent to the limit of the finite-horizon solution (x_0^*, \dots, x_T^*) . However, there are models in which this is not the case, in particular, dynamic games. For example, finite-horizon prisoner's dilemma has a unique stage equilibrium but the infinite-horizon game has a continuous set of equilibria (folk theorems), and a similar kind of multiplicity is observed for dynamic models with hyperbolic consumers; see Maliar and Maliar (2016) for a discussion. Our test cannot detect this problem: by constructing the EFP solution under different T 's and X_T 's, we only check that the finite-horizon solution has a well-defined unique limit $\lim_{T \rightarrow \infty} (x_0^T, \dots, x_T^T) = (x_0^*, \dots, x_T^*)$, but we have no way to check that such a limit is equivalent to infinite-horizon solution $(x_0^\infty, \dots, x_T^\infty)$.

3.4 An example: The EFP analysis of nonstationary growth model

We now use the EFP framework to revisit the optimal growth model studied in Section 2. Below, we elaborate the implementation of Algorithm 1 for that specific model.

ALGORITHM 1a (Extended function path (EFP) for the growth model).

Step 1: Terminal condition. Choose some $T \gg \tau$ and assume that for $t \geq T$, the economy becomes stationary, that is, $u_t = u$, $f_t = f$, and $\varphi_t = \varphi$ for all $t \geq T$. Con-

struct a stationary Markov capital function K satisfying: $u'(c) = \beta E[u'(c')(1 - \delta + f'(k', \varphi(z, \epsilon')))]$, $c = (1 - \delta)k + f(k, z) - k'$, $c' = (1 - \delta)k' + f(k', \varphi(z, \epsilon')) - k''$, $k' = K(k, z)$ and $k'' = K(k', \varphi(z, \epsilon'))$.

Step 2: Backward iteration. Construct a time-inhomogeneous path for capital policy functions (K_0, \dots, K_T) that matches the terminal condition $K_T \equiv K$ and that satisfies for $t = 0, \dots, T - 1$: $u'_{t-1}(c_{t-1}) = \beta E_{t-1}[u'_t(c_t)(1 - \delta + f'_t(k_t, \varphi_{t-1}(z_{t-1}, \epsilon_t)))]$, $c_{t-1} = (1 - \delta)k_{t-1} + f_{t-1}(k_{t-1}, z_{t-1}) - k_t$, $c_t = (1 - \delta)k_t + f_t(k_t, \varphi_{t-1}(z_{t-1}, \epsilon_t)) - k_{t+1}$, $k_t = K_{t-1}(k_{t-1}, z_{t-1})$ and $k_{t+1} = K_t(k_t, \varphi_{t-1}(z_{t-1}, \epsilon_t))$.

Step 3: Turnpike property. Draw a set of initial conditions (k_0, z_0) and histories $h_\tau = (\epsilon_0, \dots, \epsilon_\tau)$ and use the EFP decision functions (K_0, \dots, K_τ) to simulate the economy's trajectories (k_0^T, \dots, k_τ^T) . Check that the trajectories converge to a unique limit $\lim_{T \rightarrow \infty} (k_0^T, \dots, k_\tau^T) = (k_0^*, \dots, k_\tau^*)$ by constructing (K_0, \dots, K_T) under different T and K_T .

Use (K_0, \dots, K_τ) as an approximate solution to (17) or (18) and discard the remaining $T - \tau$ functions $(K_{\tau+1}, \dots, K_T)$.

Parameterization We consider the model (1), (2) parameterized by (13) and (12). For all experiments, we fix $\alpha = 0.36$, $\eta = 5$, $\beta = 0.99$, $\delta = 0.025$, and $\rho = 0.95$. The remaining parameters are set in the benchmark case at $\sigma_\epsilon = 0.03$, $\gamma_A = 1.01$, and $T = 200$, but we vary these parameters across experiments.

Step 1: Markov terminal condition In the studied example, nonstationarity comes from the fact that the economy experiences the economic growth $A_t = A_0 \gamma_A^t$. To implement Step 1, we assume that the economic growth stops at T and that the economy becomes stationary, that is, $A_t = A_T \equiv A$ for all $t \geq T$. To solve the resulting Markov stationary model and construct K_T , we use a conventional projection method based on Smolyak grids as in Judd et al. (2014); this method is tractable in high-dimensional applications.

Step 2: Time-inhomogeneous Markov decision functions In Step 2, we apply backward iteration: given K_T , we can use the Euler equation to compute K_{T-1} at $T - 1$; next, we use K_{T-1} to compute K_{T-2} ; we proceed until the entire path (K_T, \dots, K_0) is constructed. In Figure 2, we illustrate the resulting sequence of time-inhomogeneous Markov capital decision functions (a function path) produced by Algorithm 1a for the model (1)–(3) with exogenous labor-augmenting technological progress (13).

As an example, we plot the capital functions for periods 1, 20, and 40 by setting the productivity level equal to one $z = 1$ (i.e., $k_2 = K_1(k_1, 1)$, $k_{21} = K_{20}(k_{20}, 1)$ and $k_{41} = K_{40}(k_{40}, 1)$). In Step 1 of the algorithm, we construct the capital function K_{40} by assuming that the economy becomes stationary in period $T = 40$; in Step 2, we construct a path of the capital functions (K_0, \dots, K_{39}) that matches the corresponding terminal function K_{40} . The domain for capital and the range of the constructed capital function grow at the rate of labor-augmenting technological progress. In Appendix B of the Supplemental Material, we also provide a three-dimensional plot of the capital functions; see Figure S1.

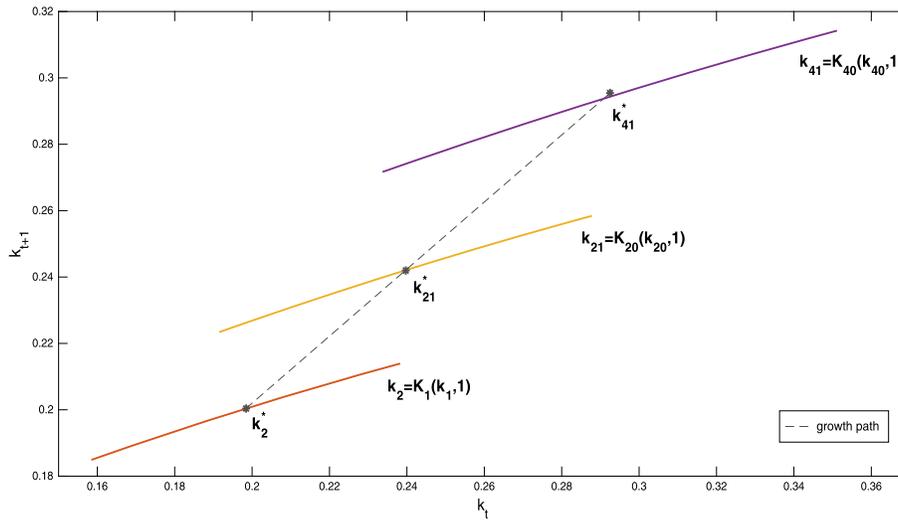


FIGURE 2. Function path, produced by EFP, for a growth model with technological progress.

Step 3: Numerical verification of the turnpike property Finally, in Step 3, we verify the turnpike property, that is, we check that the initial τ decision functions (K_0, \dots, K_τ) are not sensitive to the choice of terminal condition K_T and time horizon T . We implement the test by constructing 100 simulations under random initial conditions (k_0, z_0) and histories $h_T = (\epsilon_0, \dots, \epsilon_T)$. We consider two time horizons, $T = 200$ and $T = 400$, and two different terminal conditions, one on the balanced-growth path and the other a solution to the stationary model. The EFP solution proved to be remarkably robust and accurate during the initial periods under all time horizons and terminal conditions considered; in particular, the approximation errors during the first $\tau = 50$ periods do not exceed $10^{-6} = 0.0001\%$. In Section 4, we discuss these accuracy results in detail and we compare the EFP solution with those produced by other methods for solving time-inhomogeneous models.

Figure 3 illustrates the turnpike theorem with the graph. For a given initial condition (k_0, z_0) and history of shocks $h_T = (\epsilon_0, \dots, \epsilon_T)$, it shows that the initial τ decision functions (K_0, \dots, K_τ) are not sensitive to various terminal conditions (given by K_L , K_T , k' , k'' , and K_T^∞). The EFP numerical solution in Figure 3 looks similar to the solution in Figure 1, which we derived analytically. As predicted by the turnpike theorem, the finite-horizon solution converges to the infinite-horizon solution under all terminal conditions considered; however, the convergence is faster under terminal conditions k' and k'' , that are located relatively close to the true T -period capital of the nonstationary economy $\{k_T^\infty\}$, than under a zero terminal condition that is located farther away from the true solution. We observe that even though the choice of specific terminal condition plays no role in asymptotic convergence established in the turnpike literature, it can play a critical role in the accuracy and speed of numerical solution methods. To attain the fastest possible convergence, we need to choose the terminal condition K_T^T of the finite-horizon economy to be as close as possible to the T -period capital stock of the infinite-horizon nonstationary economy K_T^∞ .

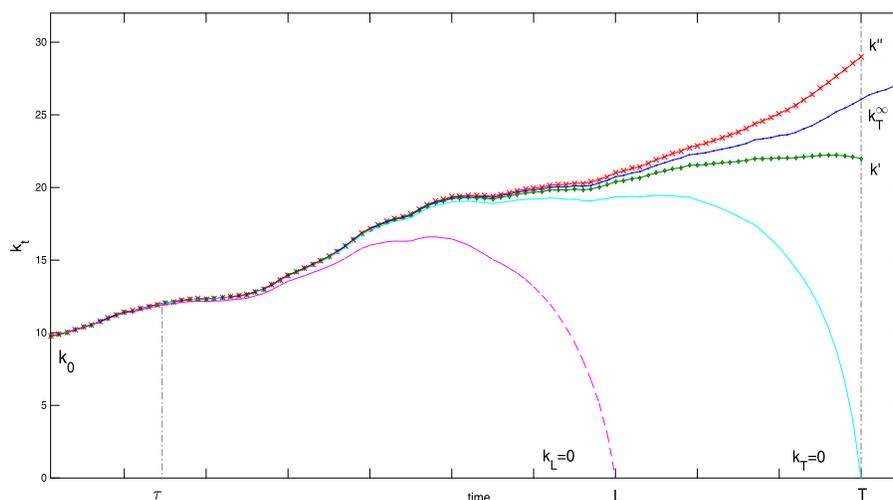


FIGURE 3. Convergence of the optimal program of T -period stationary economy.

4. EFP VERSUS EP AND NAIVE METHODS

In this section, we assess the quality of the EFP solutions in the optimal growth model (1)–(3) with labor-augmenting technological progress and compare it to solutions produced by other methods. We focus on the growth model that is consistent with balanced growth because in this special case, the nonstationary model can be converted into a stationary model and can be accurately solved by using conventional solution methods; this yields us a high-quality reference solution for comparison.

4.1 Four solution methods

We implement four alternative solution methods which we call *exact*, *EFP*, *Fair and Taylor*, and *naive* ones.

(i) *Exact solution method.* We first convert the nonstationarity model into a stationary one using the property of balanced growth; we then accurately solve the stationary model using a Smolyak projection method in line with Krueger and Kubler (2004) and Judd et al. (2014); and we finally recover a solution to the original nonstationary model; see Appendix D of the Supplemental Material for details. The resulting numerical solution is very accurate, namely, the unit-free maximum residuals in the model's equations are of order 10^{-6} on a stochastic simulation of 10,000 observations. We loosely refer to this numerical solution as *exact*, and we use it as a benchmark for comparison.

(ii) *EFP solution method.* EFP constructs a time-inhomogeneous Markov solution to a nonstationary model without converting it into stationary—we follow the steps outlined in Algorithm 1a; see Appendix B for implementation details.

(iii) *Fair and Taylor (1983) solution method.* Fair and Taylor's (1983) method also solves a nonstationary model directly, without converting it into stationary. It constructs a path for the model's variables (not functions!) under one given sequence of shocks by using the certainty equivalence approach for approximating the expectation functions.

The implementation of Fair and Taylor's (1983) method is described in Appendix C of the Supplemental Material; for examples of applications of such methods, see, for example, Chen, Imrohoroglu, and Imrohoroglu (2006), Bodenstein, Erceg, and Guerrieri (2009), Coibion et al. (2012), Braun and Körber (2011), and Hansen and Imrohoroglu (2016).

(iv) *Naive solution method.* A naive method replaces a nonstationary model with a sequence of stationary models and solves such models one by one, independently of one another. Similar to EFP, the naive method constructs a path of decision functions for $t = 0, \dots, T$, but it differs from EFP in that it neglects the connections between the decision functions in different time periods. A comparison of the EFP and naive solutions allows us to appreciate the importance of anticipatory effects.

The absence of steady state and the deterministic growth path The studied growing economy has no steady state. However, we can define an analogue of steady state for the growing economy as a solution to an otherwise identical deterministic economy in which the shocks are shut down. We refer to such a solution as the growth path, and we denote it by a superscript “*”. We use the growth path as a sequence of points around which the Smolyak grids are centered. In particular, in Figures 2 and 4, the growth path is shown with a dashed line. In our balanced-growth model (12), the growth path can be constructed analytically. Namely, in the detrended economy, the steady-state capital is given by $k_0^* \equiv A_0 \left(\frac{\gamma_A^\eta - \beta + \delta\beta}{\alpha\beta} \right)^{1/(\alpha-1)}$, and in the growing economy, it evolves as $k_t^* = k_0^* \gamma_A^t$ for $t = 1, \dots, T$; see Appendix D for details. Therefore, we know the exact terminal condition (i.e., the one that coincides with the infinite-horizon solution) for our economy with growth is $k_{T+1}^* = k_0^* \gamma_A^{T+1}$. To assess the role of the terminal condition, we also use another terminal condition that is constructed by assuming that at T , the economy arrives to the steady state with no growth $k_{T+1}^{ss} \equiv A_{T+1} \left(\frac{1-\beta+\delta\beta}{\alpha\beta} \right)^{1/(\alpha-1)}$.

To see how far T -period steady-state terminal condition k_{T+1}^{ss} is from the exact growing one k_{T+1}^* , we computed the ratio of the two terminal capital stocks,

$$\frac{k_{T+1}^*}{k_{T+1}^{ss}} = \left(\frac{\gamma_A^\eta - \beta + \delta\beta}{1 - \beta + \delta\beta} \right)^{1/(\alpha-1)}.$$

It turned out that this ratio is very different from one under the standard calibration; in particular, with $\eta = 1$, it is 0.67, and with $\eta = 3$, it is 0.38. Thus, by assuming that the economy arrives to the steady state at T , we can overstate the correct terminal capital stock by several times! Using so inaccurate terminal condition requires us to considerably increase the time horizon to make the EFP solutions sufficiently accurate solutions. So, instead of the steady state, we find that it is better to use a terminal condition that leads to a convergence to a nonvanishing growth path—we discuss how to construct such terminal condition in Section 5.

Software and hardware For all simulations, we use the same initial condition and the same sequence of productivity shocks for all methods considered. Our code is written in MATLAB 2018, and we use a desktop computer with Intel(R) Core(TM) i7-2600 CPU (3.40 GHz) with RAM 12 GB.

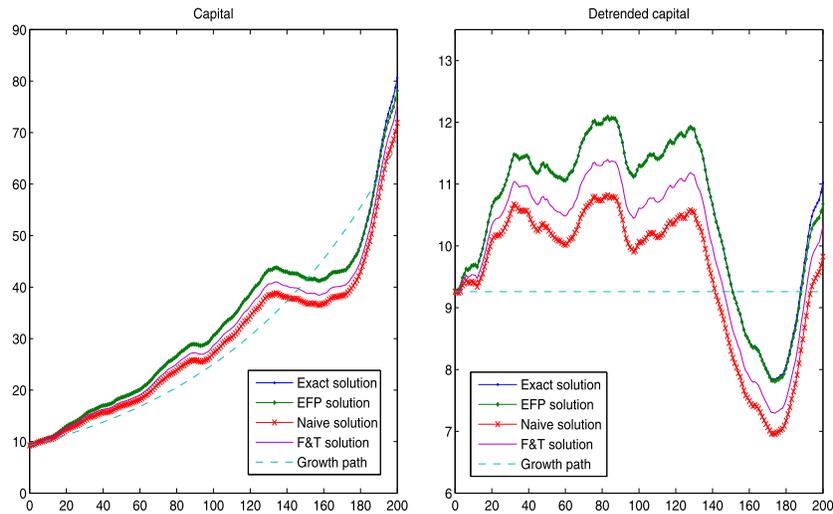


FIGURE 4. Comparison of the solution methods for the test model with balanced growth.

Comparison results In the left panel of Figure 4, we plot the growing time-series solutions for the four solution methods, as well as the (steady-state) growth path for capital under one specific realization of shocks. In the right panel, we display the time-series solutions after detrending the growth path.

As is evident from both panels, the EFP and exact solutions are visually indistinguishable except for a small difference at the end of time horizon—the last 10–15 periods. This difference is due to the use of different terminal conditions: in the former case, we assume that the economy becomes stationary (i.e., stops growing) at T , whereas in the latter case, the growth continues forever. If we use the exact solution at T as a terminal condition for the EFP, then the EFP solution would be indistinguishable from the exact solution everywhere in the figure. However, Fair and Taylor’s (1983) and naive methods are far less accurate; they produce solutions that are systematically lower than the exact solution everywhere in the figure; and the naive solution is the least accurate of all.

Verifying the turnpike theorem numerically We next evaluate the accuracy of EFP, Fair and Taylor (1983), and naive solutions by implementing the turnpike test outlined in Step 3 of Algorithm 1a; see Section 3.4. Specifically, we first simulate each of the four solutions 100 times and we then compute the mean and maximum absolute differences in log 10 units between the exact solution and the remaining three solutions across 100 simulations for the intervals $[0, 50]$, $[0, 100]$, $[0, 150]$, $[0, 175]$, and $[0, 200]$. These statistics show how fast the accuracy of numerical solutions deteriorates, as we approach the terminal period. The accuracy results are reported in Table 1, as well as the time needed for computing and simulating the solution of length T 100 times (in seconds). We observe that in most implementations, the approximation errors of EFP do not exceed $10^{-6} = 0.0001\%$, while the errors produced by Fair and Taylor’s (1983) and naive methods can be as large as $10^{-1.13} \approx 7.4\%$ and $10^{-0.89} \approx 12\%$. We discuss these findings below.

TABLE 1. Comparison of four solution methods

Terminal condition	Fair–Taylor (1983) method, $\tau = 1$		Naive method	EFP method					
	Steady state			$\tau = 1$			$\tau = 200$		
				Balanced growth	T -period stationary		Balanced growth	T -period stationary	
T	200	400	200	200	200	400	200	200	400
Mean errors across t periods in \log_{10} units									
$t \in [0, 50]$	-1.60	-1.60	-1.36	-7.30	-6.97	-7.15	-7.23	-6.75	-7.01
$t \in [0, 100]$	-1.42	-1.42	-1.19	-7.06	-6.81	-6.98	-7.03	-6.19	-6.81
$t \in [0, 150]$	-1.34	-1.35	-1.11	-6.96	-6.73	-6.91	-6.94	-5.47	-6.73
$t \in [0, 175]$	-1.32	-1.32	-1.09	-6.93	-6.71	-6.89	-6.91	-5.09	-6.70
$t \in [0, 200]$	-1.30	-1.31	-1.07	-6.91	-6.69	-6.87	-6.90	-4.70	-6.68
Maximum errors across t periods in \log_{10} units									
$t \in [0, 50]$	-1.29	-1.29	-1.04	-6.83	-6.63	-6.81	-6.82	-6.01	-6.42
$t \in [0, 100]$	-1.18	-1.18	-0.92	-6.69	-6.42	-6.68	-6.68	-4.39	-5.99
$t \in [0, 150]$	-1.14	-1.14	-0.89	-6.66	-6.39	-6.67	-6.66	-2.89	-5.98
$t \in [0, 175]$	-1.14	-1.13	-0.89	-6.66	-6.40	-6.66	-6.66	-2.10	-5.98
$t \in [0, 200]$	-1.14	-1.13	-0.89	-6.66	-6.37	-6.66	-6.66	-1.45	-5.92
Running time, in seconds									
Solution	1.2(+3)	6.1(+3)	28.9	216.5	8.6(+2)	1.9(+3)	104.9	99.1	225.9
Simulation	-	-	2.6	2.6	2.6	5.8	2.6	2.8	5.7
Total	1.2(+3)	6.1(+3)	31.5	219.2	8.6(+2)	1.9(+3)	107.6	101.9	231.6

Note: “Mean errors” and “Maximum errors” are, respectively, mean and maximum unit-free absolute difference between the exact solution for capital and the solution delivered by a method in the column. The difference between the solutions is computed across 100 simulations.

4.2 EFP method

In Table 1, we provide the results under three alternative implementations of EFP that illustrate how the properties of the EFP solutions depend on the choices of the terminal condition, K_T , time horizon T , and parameter τ .

The role of the terminal condition: Better terminal condition gives more accurate solutions The results in Table 1 show that if we use the balanced-growth terminal condition that is equal to the infinite-horizon solution at T , the EFP approximation is very accurate everywhere independently of τ and T , namely, the difference between the exact and EFP solutions is less than $10^{-6} = 0.0001\%$. In turn, if the terminal condition is given by a solution to a T -period stationary model, the accuracy critically depends on the choice of τ and T , and deteriorates dramatically when the economy approaches the time horizon T , as predicted by the turnpike theorem.

To study how the approximation errors in the tail of the solution depend on the time horizon, terminal condition, and model parameters, we also solved the model under $T = \{200, 300, 400, 500\}$ and $\eta = \{1/3, 1, 3\}$; these results are shown in Appendix E of the Supplemental Material; see Figure S2. We consider two terminal conditions: one is a T -period stationary economy and the other is a zero-capital assumption. When solving the model for $T = 200$, the maximum errors produced at $\tau = 100$ are about one order

of magnitude higher with zero terminal capital than with T -period stationary terminal condition. As we increase T , the errors become smaller independently of the terminal condition. For $T = 300$, the maximum approximation errors vary from $10^{-6} = 0.0001\%$ to $10^{-5} = 0.001\%$. Overall, EFP provides a sufficiently accurate solution for the first 100 periods when we solve the model for $T \geq 250$.

The choice of τ : A trade-off between accuracy and cost We analyze two different values of τ such as $\tau = 1$ and $\tau = 200$. Under $\tau = 1$, EFP constructs a path of function in the same way as Fair and Taylor's (1983) method constructs a path of variables. First, given K_T , EFP solves for (K_{T-1}, \dots, K_0) , stores K_0 , and discards the rest. Next, given K_{T+1} , EFP solves for (K_T, \dots, K_1) , stores K_1 , and discards the rest. It proceeds for τ steps forward until the path (K_0, \dots, K_τ) is constructed.

As we see from the table, EFP method with $\tau = 1$ is very accurate independently of T and a specific terminal condition used, namely, the EFP and exact solutions again differ by less than $10^{-6} = 0.0001\%$. This result illustrates the implication of the turnpike theorem that the effect of any terminal condition on the very first element of the path $\tau = 1$ is negligible if the time horizon T is sufficiently large.

A shortcoming of the version of EFP with $\tau = 1$ is its high computational expense: the running time under $T = 200$ and $T = 400$ is about 20 and 30 minutes, respectively. The cost is high because we need to recompute entirely a sequence of decision functions each time when we extend the path by one period ahead. Effectively, we recompute the EFP solution T times, and this is what makes it so costly.

The choice of T : Making EFP cheap Our turnpike theorem suggests a cheaper version of EFP in which we construct a longer path (i.e., we use $\tau > 1$) but we do it just once; the results for this version of the EFP method are provided in the last three columns of Table 1. For $\tau = 200$, the terminal condition plays a critical role in the accuracy of solutions near the tail. Namely, if we use the terminal condition from the T -period stationary economy, and use the time horizon $T = 200$, then the approximation errors near the tail reach $10^{-1.45} \approx 4\%$.

However, the approximation errors are dramatically reduced when the time horizon T increases, as the last column of Table 1 shows. Namely, if we construct a path of length $T = 400$ but use only the first $\tau = 200$ decision functions and discard the remaining path, the solution for the first $\tau = 200$ periods is almost as accurate as that produced under $\tau = 1$. This is true even though the terminal condition from the T -period stationary economy is far away from the exact terminal condition. Importantly, the construction of a longer path is relatively inexpensive: the running time increases from about 2 minutes to 4 minutes when we increase the time horizon from $T = 200$ to $T = 400$, respectively.

Sensitivity analysis On the basis of the results in Table 1, we advocate a version of EFP that constructs a sufficiently long path $\tau > 1$ by using $T \gg \tau$. We assess the accuracy and cost of this preferred EFP version by using $\tau = 200$ and $T = 400$ under several alternative parameterizations for $\{\eta, \sigma_\epsilon, \gamma_A\}$ such that $\eta \in \{0.1; 1; 5; 10\}$, $\sigma_\epsilon \in \{0.01; 0.03\}$, and $\gamma_A \in \{1; 1.01; 1.05\}$. As a terminal condition, we use decision rules produced by the T -period stationary economy. These sensitivity results are provided in Table 2 of Appendix E of the Supplemental Material.

The accuracy and cost of EFP in these experiments are similar to those reported in Table 1 for the benchmark parameterization. The difference between the exact and EFP solutions varies from $10^{-7} = 0.00001\%$ to $10^{-6} = 0.0001\%$ and the running time varies from 155 to 306 seconds. The exception is the model with a low degree of risk aversion $\eta = 0.1$ for which the running time increases to 842 seconds. (We find that with a low degree of risk aversion, the convergence of EFP is more fragile, so that we had to use a larger degree of damping for iteration, decreasing the speed of convergence.)

4.3 Fair and Taylor's (1983) method

As Table 1 shows, EFP dominates the EP method in both accuracy and cost. Fair and Taylor's (1983) method has relatively low accuracy (namely, its approximation errors are $10^{-1.6} \approx 2.5\%$) because the certainty equivalence approach does not produce sufficiently accurate approximation to conditional expectations under the given parameterization. We find that Fair and Taylor's (1983) method is far more accurate with a smaller variance of shocks and/or smaller degrees of nonlinearities; for example, under $\eta = 1$, $\sigma_\epsilon = 0.01$, $\gamma_A = 1.01$, and $T = 200$, the difference between the exact solution and Fair and Taylor's (1983) solutions is around 0.1% (this experiment is not reported). A comparison of $T = 200$ and $T = 400$ shows that the accuracy of Fair and Taylor's (1983) method cannot be improved by increasing the time horizon.

The high cost of Fair and Taylor's (1983) method is explained by two factors. First, $\tau = 1$ is the only possible choice for Fair and Taylor's (1983) method. To solve for variables of period $t = 0$, this method assumes that productivity shocks are all zeros starting from period $t = 1$, so that the path for $t = 1, \dots, T$ has no purpose other than helping to approximate the variables of period $t = 0$. In contrast, EFP can use much longer τ 's as long as the resulting solution is sufficiently accurate, which reduces the cost.

Second, for Fair and Taylor's (1983) method, the cost of simulating the model is high because the solution and simulation steps are combined together: in order to produce a new simulation, it is necessary to entirely recompute the solution under a different sequence of shocks. In contrast, the simulation cost is low for EFP: after we construct a path of decision functions once, we can use the constructed functions to produce as many simulations as we need under different sequences of shocks. For example, the time that Fair and Taylor's (1983) method needs for computing/simulating 100 solutions is about 30 minutes and 1 hour, respectively (recall that the corresponding times for EFP method are 2 and 4 minutes, respectively).

4.4 Naive method: Understanding the importance of anticipatory effects

For the naive method, we report the solution only for $T = 200$ since neither time horizon nor terminal condition is relevant for this method. The performance of the naive method is poor: the difference between the exact and naive solutions can be as large as $10^{-0.89} \approx 12\%$. The naive solution is so inaccurate because the naive method completely neglects anticipatory effects. In each time period t , this method computes a stationary solution by assuming that technology will remain at the levels $A_t = A_0 \gamma_A^t$ and

$A_{t+1} = A_0 \gamma_A^{t+1}$ forever, meanwhile the true nonstationary economy continues to grow. Since the naive agent is “unaware” about the future permanent productivity growth, the expectations of such an agent are systematically more pessimistic than those of the agent who is aware of future productivity growth. It was pointed out by [Cooley, LeRoy, and Raymon \(1984\)](#) that naive-style solution methods are logically inconsistent and contradictory to the rational expectation paradigm: agents are unaware about a possibility of parameter changes when they solve their optimization problems; however, they are confronted with parameter changes in simulations. Our analysis suggests that naive solutions are particularly inaccurate in growing economies.

To gain intuition into why the accuracy of the naive method is low and how the expectation about the future can affect today’s economy, we perform an additional experiment. We specifically consider a version of the model (1)–(3) with the production function $f_t(k, z) = z_t k_t^\alpha A_t$, in which the technology level A_t can take two values, $\underline{A} = 1$ (low) and $\bar{A} = 1.2$ (high). We consider a scenario when the economy starts with \underline{A} at $t = 0$, switches to \bar{A} at $t' = 250$, and then switches back to \underline{A} at $t'' = 550$ (e.g., the UK joins the EU in 1973 and it exits the EU in 2020). We show the technology profile in the upper panel of Figure 5.

We parameterize the model by using $T = 900$, $\eta = 1$, $\alpha = 0.36$, $\beta = 0.99$, $\delta = 0.025$, $\rho = 0.95$, $\sigma = 0.01$. To make the anticipatory effects more visible, we shut down the stochastic shocks in simulation by setting $z_t = 1$ for all t .

For a naive agent, regime switches are unexpected. The naive agent believes that the economy will always be in a stationary solution with \underline{A} until the first switch at $t' = 250$, then the agent believes that the economy will always be in a stationary solution with \bar{A} until the second switch at $t'' = 550$, and finally, the agent switches back to the first stationary solution for the rest of the simulation.

In contrast, the EFP method constructs a solution of an informed agent who solves the utility-maximization problem at $t = 0$ knowing the technology profile in Figure 5. Re-

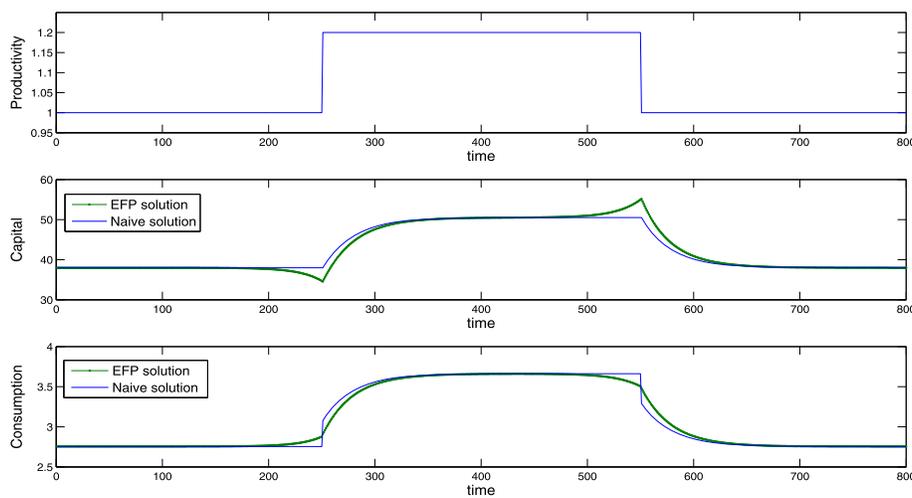


FIGURE 5. EFP versus naive solutions in the model with parameter shifts.

markably, under the EFP solution, we observe a strong anticipatory effect: about 50 periods before the switch from \underline{A} and \bar{A} takes place, the agent starts gradually increasing her consumption and decreasing her capital stock in order to bring some part of the benefits from future technological progress to present. When a technology switch actually occurs, it has only a minor effect on consumption. (The tendencies reverse when there is a switch from \bar{A} to \underline{A}). Such consumption-smoothing anticipatory effects are entirely absent in the naive solution. Here, unexpected technology shocks lead to large jumps in consumption in the exact moment of technology switches. The difference in the solutions is quantitatively significant under our empirically plausible parameter choice.

Note that anticipated regime changes cannot be effectively approximated by conventional Markov switching models; see, for example, Sims and Zha (2006), Davig and Leeper (2007, 2009), Farmer, Waggoner, and Zha (2011), Foerster et al. (2016), etc. In that literature, regime changes come at random and thus, the agents anticipate the possibility of regime change and not the change itself. However, there is a recent literature on Markov chains with time-varying transition probabilities that makes it possible to model the effect of expectation on equilibrium quantities and prices; see, for example, Bianchi (2019) for a discussion and further references. Also, Schmitt-Grohé and Uribe (2012) proposed a perturbation-based approach that deals with anticipated parameter shifts of a fixed time horizon (e.g., shocks that happen each four or eight periods) in the context of stationary Markov models. In turn, EFP can handle any combination of unanticipated and anticipated shocks of any periodicity and duration.

5. USING EFP TO SOLVE AN UNBALANCED GROWTH MODEL

Real business cycle literature heavily relies on the assumption of labor-augmenting technological progress leading to balanced growth. However, there are empirically relevant models in which growth is unbalanced. For example, Acemoglu (2002) argued that technical change is not always directed to the same fixed factors of production but to those factors of production that give the largest improvement in the efficiency of production.¹¹ One implication of this argument is that technical change can be directed to either capital or labor depending on the economy's state. Furthermore, Acemoglu (2003) explicitly incorporated capital-augmenting technological progress into a deterministic model of endogenous technical change by allowing for innovations in both capital and labor. Evidence in support of capital-augmenting technical change is provided in, for example, Klump, Mc Adam, and Willman (2007) and León-Ledesma, Mc Adam, and Wilman (2015).¹²

¹¹Namely, endogenous technical change is biased toward a relatively more scarce factor when the elasticity of substitution is low (because this factor is relatively more expensive); however, it is biased toward a relatively more abundant factor when the elasticity of substitution is high (because technologies using such a factor have a larger market).

¹²There are other empirically relevant types of technological progress that are inconsistent with balanced growth, for example, investment-specific technological progress considered in Krusell et al. (2000).

Constant elasticity of substitution production function In line with this literature, we consider the stochastic growth model (1)–(3) with a constant elasticity of substitution (CES) production function, and we allow for both labor- and capital-augmenting types of technological progress

$$F(k_t, \ell_t) = [\alpha(A_{k,t}k_t)^v + (1 - \alpha)(A_{\ell,t}\ell_t)^v]^{1/v}, \quad (22)$$

where $A_{k,t} = A_{k,0}\gamma_{A_k}^t$; $A_{\ell,t} = A_{\ell,0}\gamma_{A_\ell}^t$; $v \leq 1$; $\alpha \in (0, 1)$; and γ_{A_k} and γ_{A_ℓ} are the rates of capital- and labor-augmenting technological progresses, respectively. We assume that labor is supplied inelastically and normalize it to 1, $\ell_t = 1$ for all t , and we denote the corresponding production function by $f(k_t) \equiv F(k_t, 1)$. The Euler equation for the studied model is

$$u'(c_t) = \beta E_t [u'(c_{t+1})(1 - \delta + \alpha A_{k,t+1}^v (k_{t+1})^{v-1} \times [\alpha(A_{k,t+1}k_{t+1})^v + (1 - \alpha)A_{\ell,t+1}^v]^{(1-v)/v})]. \quad (23)$$

The above model is generically nonstationary; specifically, the growth rate of endogenous variables changes over time in an unbalanced manner even if we assume that $A_{k,t}$ and $A_{\ell,t}$ grow at constant growth rates.

A growth path for the economy with unbalanced growth Our goal is to construct an unbalanced growth path $\{k_t^*\}_{t=0}^{T+1}$ around which the sequence of EFP grids will be centered. We shut down uncertainty by assuming that $z_t = 1$ for all t . First, we construct a terminal condition k_{t+1}^* by assuming that all variables grow at the same rates at T and $T - 1$. For this model, it is convenient to target the following two growth rates:

$$\frac{k_{t+2}^*}{k_{t+1}^*} = \frac{k_{t+1}^*}{k_t^*} = \gamma_k \quad \text{and} \quad \frac{u'(c_{t+1}^*)}{u'(c_t^*)} = \frac{u'(c_t^*)}{u'(c_{t-1}^*)} = \gamma_u. \quad (24)$$

With this restriction, the Euler equation (23) written for $T - 1$ and T implies

$$1 = \beta [\gamma_u (1 - \delta + \alpha A_{k,t+1}^v (\gamma_k k_t^*)^{v-1} [\alpha(A_{k,t+1}\gamma_k k_t^*)^v + (1 - \alpha)A_{\ell,t+1}^v]^{(1-v)/v})], \quad (25)$$

$$1 = \beta [\gamma_u (1 - \delta + \alpha A_{k,t}^v (k_t^*)^{v-1} [\alpha(A_{k,t}k_t^*)^v + (1 - \alpha)A_{\ell,t}^v]^{(1-v)/v})], \quad (26)$$

where γ_u is determined by the budget constraint (2):

$$\gamma_u = \frac{u'[(1 - \delta)\gamma_k k_t^* + [\alpha(A_{k,t+1}\gamma_k k_t^*)^v + (1 - \alpha)A_{\ell,t+1}^v]^{1/v} - \gamma_k^2 k_t^*]}{u'[(1 - \delta)k_t^* + [\alpha(A_{k,t}k_t^*)^v + (1 - \alpha)A_{\ell,t}^v]^{1/v} - \gamma_k k_t^*]}. \quad (27)$$

Therefore, we obtain a system of three equations (25)–(27) with three unknowns γ_k , γ_u , and k_t^* , which we solve numerically. Once the solution is known, we find $k_{t+2}^* = \gamma_k^2 k_t^*$ and $k_{t+1}^* = \gamma_k k_t^*$, calculate c_{t+1}^* from the budget constraint (2), and recover the rest of the growth path k_{T-1}^*, \dots, k_0^* by iterating backward on the Euler equation (23).

Results of numerical experiments For numerical experiments, we assume $T = 260$, $\eta = 1$, $\alpha = 0.36$, $\beta = 0.99$, $\delta = 0.025$, $\rho = 0.95$, $\sigma_\epsilon = 0.01$, $v = -0.42$; the last value is taken in line with Antrás (2004) who estimated the elasticity of substitution between capital and labor to be in a range of $[0.641, 0.892]$ that corresponds to $v \in [-0.12, -0.56]$. We solve two models: the model with labor-augmenting progress parameterized by $A_{\ell,0} = 1.1123$, $\gamma_{A_\ell} = 1.0015$, and $A_{k,0} = \gamma_{A_k} = 1$, and the model with capital-augmenting progress parameterized by $A_{k,0} = 1$, $\gamma_{A_k} = 0.9867$, and $A_{\ell,0} = \gamma_{A_\ell} = 1$. The parameters $A_{\ell,0}$, γ_{A_ℓ} , $A_{k,0}$, γ_{A_k} for both models are chosen to approximately match the capital stocks at $t = 0$ and $t = 154$ for the growth paths of capital, so that the cumulative growth is the same for both models over the target period given by $\tau = 154$. To this purpose, we first fix $A_{k,0}$ and γ_{A_k} for the model with capital-augmenting technological change, and we find the values of k_0 and k_{154} . Then, we solve a system of two nonlinear equations (given by a closed-form solution for the model with labor-augmenting technical change) to find the corresponding $A_{\ell,0}$ and γ_{A_ℓ} . The numerical costs of calculating solutions to the model with labor-augmenting and capital-augmenting technological changes are about 1 and 12 minutes, respectively. We implement the turnpike test by verifying that the simulated trajectories are insensitive to the specific time horizon and terminal conditions assumed. Finally, we construct the unit-free residuals in the Euler equation (23), and we find that such residuals do not exceed $10^{-4} = 0.01\%$ across 100 test simulations.

Figure 6 plots the time-series solutions of the models with labor- and capital-augmenting technological progresses, as well as the corresponding growth paths.

The properties of the model with labor-augmenting technological progress are well known. There is an exponential growth path with a constant growth rate and cyclical fluctuations around the growth path. (In the figure, the growth path in the model with labor-augmenting technological progress is situated slightly below the linear growth path shown by a solid line). In contrast, the model with capital-augmenting technological progress is not studied yet in the literature in the presence of uncertainty (to the

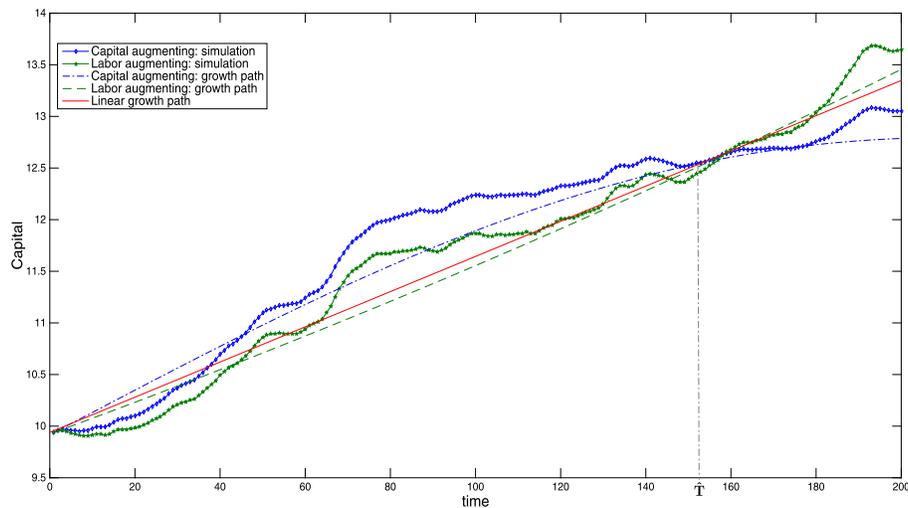


FIGURE 6. Time-series solution in the model with a CES production function.

best of our knowledge). Here, we observe a pronounced concave growth pattern indicating that the rate of return to capital decreases as the economy grows. (In the figure, the growth path in the model with capital-augmenting technological progress is situated above the linear growth path shown by a solid line.) The cyclical properties of both models look similar (provided that growth is detrended).

6. EFP LIMITATIONS

We now discuss two limitations of the EFP framework related to the turnpike property and the assumption of Markov structure of the model.

6.1 Turnpike theorem does not always hold

The key assumption behind the EFP analysis is the turnpike property that says that today's decisions are insensitive to events that happen in a distant future. However, not all economic models possess this property. Below, we show a version of the new Keynesian economy in which anticipated future changes in the interest rate have immediate and unrealistically large effects on the current decisions, an implication which is known as a *forward guidance puzzle*; see, for example, Del Negro et al. (2015), Carlstrom, Fuerst, and Paustian (2015), McKay, Nakamura, and Steinsson (2016), Maliar and Taylor (2018).

Consider a stylized new Keynesian framework developed in Woodford (2003) that consists of an IS equation and Phillips curve given by

$$x_t = E_t[x_{t+1}] - \sigma(r_t - E_t[\pi_{t+1}] - r_t^n), \quad (28)$$

$$\pi_t = \beta E_t[\pi_{t+1}] + \kappa x_t, \quad (29)$$

where x_t , π_t , r_t , and r_t^n are the output gap, inflation, nominal interest rate, and natural rate of interest, respectively; β and σ are the discount factor and the intertemporal elasticity of substitution, respectively; κ is the slope of the Phillips curve. Suppose that the monetary policy is determined by the following rule:

$$r_{t+j} = E_{t+j}[\pi_{t+j+1}] + r_{t+j}^n + \epsilon_{t,t+j}, \quad (30)$$

where $\epsilon_{t,t+j}$ denotes a $t + j$ -period shock to the interest rate announced in period t , interpreted as a forward guidance shock; see Reifschneider and Williams (2000) for a general discussion on monetary policy rules. By applying forward recursion to (28) and by imposing the transversality condition $\lim_{j \rightarrow \infty} E_t[x_{t+j}] = 0$, we obtain $x_t = -\sigma \sum_{j=0}^{\infty} E_t(r_{t+j} - E_{t+j}[\pi_{t+j+1}] - r_{t+j}^n)$ which together with (30) yields

$$x_t = -\sigma \sum_{j=0}^{\infty} \epsilon_{t,t+j}. \quad (31)$$

This result implies that today's shock $\epsilon_{t,t}$ to the interest rate has the same effect as the shock $\epsilon_{t,t+j}$ that happens j years from now. In Figure 7, we show two alternative anticipated future interest rate shocks that happen in period 20 (we assume $\beta = 0.99$, $\kappa = 0.11$, and $\sigma = 1$).

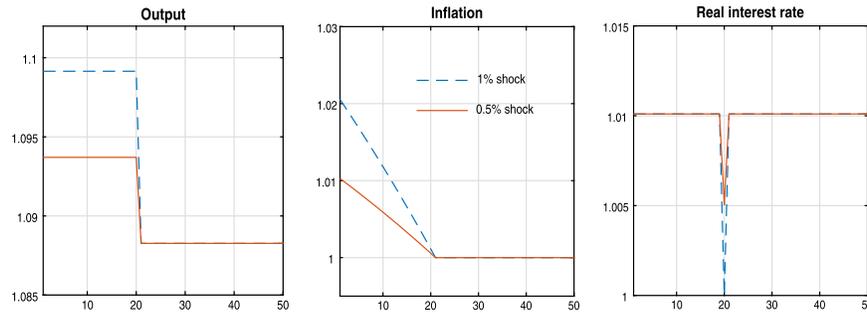


FIGURE 7. Anticipated future interest-rate shocks in the new Keynesian model.

As we see, decisions in $t = 0, 1, \dots, 19$ are dramatically affected by anticipated future interest-rate shocks in period $t = 20$ (such shocks can be viewed as variations in the terminal condition for the interest rate). This example illustrates the failure of numerical verification of the turnpike property in Step 3 of EFP. Specifically, we try out different terminal conditions and different time horizons for the interest rate, and we observe they have a nonvanishing effect on the EFP approximation. We conclude that the turnpike property does not hold and that the EFP methodology is not suitable for analyzing this particular version of the new Keynesian model.¹³

6.2 Not all models are Markov

Another essential assumption of the EFP method is that exogenous variables follow although time-inhomogeneous but still Markov process. If the process for exogenous variables is not Markov, the probability distributions today depend not only on the current state but on the entire historical path of the economy. Hence, the number of states grows exponentially over time and the EFP method becomes intractable. The implications of Markov and history-dependent models may differ dramatically. This fact can be seen by using the example of a new Keynesian model with a zero lower bound on nominal interest rates.

Consider again the IS equation (28) and Phillips curve (29), and assume that the central bank announces that it will peg the nominal interest at zero in some periods j and $j + 1$. If the peg is finite and the subsequent terminal condition is consistent with a unique equilibrium, the entire path is uniquely determined; see, for example, Carlstrom, Fuerst, and Paustian (2015). However, if we construct a Markov solution in which the interest rate is pegged in all states, then equilibrium is indeterminate (this is equivalent to indeterminacy under a perpetual peg; see Galí (2009)).

While the EFP method is not applicable to history-dependent models, there are competing methods that can work with such models. In particular, the EP method of Fair

¹³Nonetheless, the version of the model with the forward guidance puzzle is a very special and degenerate case. Maliar and Taylor (2018) showed that under empirically relevant parameterizations of the monetary policy rules, new Keynesian models satisfy the turnpike property as well, so that the EFP method can be used.

and Taylor (1983) does not rely on the assumption of Markov process and can be used to construct history-dependent equilibria; however, its accuracy is limited by the certainty equivalence approach. Adjemian and Juillard (2013) proposed a stochastic extended path method that improves on certainty equivalence approach of the baseline Fair and Taylor's (1983) method. They constructed and analyzed a tree of all possible future paths for exogenous state variables. Although the number of tree branches and paths grows exponentially with the path length, the authors proposed a clever way of reducing the cost by restricting attention to paths that have the highest probability of occurrence. However, the implementation of this method is nontrivial, in particular, in models with multiple state variables. Ajevskis (2017) proposed a method in which the certainty equivalent solution à la Fair and Taylor (1983) is improved by incorporating higher order perturbation terms. Furthermore, Krusell and Smith (2015) developed a related numerical method that combines perturbation of distributions and approximate aggregation in line with Krusell and Smith (1998) to solve for a transition path in a multi-region climate change model. Finally, another potentially useful method for analyzing nonstationary applications is a nonlinear particle filter; see, for example, Fernández-Villaverde, Guerrón-Quintana, and Schorfheide (2016) for a discussion of this method.

7. CONCLUSION

Conventional dynamic programming and Euler-equation methods are designed to solve stationary models by constructing time-invariant rules. In turn, path-solving methods, including Fair and Taylor's (1983) method, can solve nonstationary models by constructing a path for variables. Our analysis combines these two classes of methods by constructing a path for rules. As long as the model satisfies the turnpike property, the path for rules produced by EFP is an accurate approximation of time-varying value and decision functions in the infinite-horizon nonstationary economy. For a simple optimal growth model, the turnpike property can be established analytically, but for more complex models, analytical characterizations may be infeasible. As an alternative, we propose to verify the turnpike property numerically by analyzing the sensitivity of the final-horizon EFP solution to terminal conditions and terminal dates. Such “numerical proofs” of turnpike theorems can extend greatly the class of tractable nonstationary models and applications.

Our simple EFP framework has an important value-added in terms of applications that can be analyzed quantitatively. Here are some examples: First, EFP can be applied to solve models with any type of technological progresses (capital, Hicks neutral, investment-specific), as well as any other parameter drifts (e.g., drifts in a depreciation rate, discount factor, utility-function parameters, etc.). Second, EFP can handle any combination of unanticipated and anticipated shocks of any periodicity and duration in a fully nonlinear manner including seasonal adjustments. Third, EFP can be used to analyze models in which volatility has both stochastic and deterministic components. Finally, the EFP framework provides a novel tool for policy analysis: It allows to study time-dependent policies, complementing the mainstream of the literature that focuses on state-dependent policies. In the time-dependent case, a policy maker commits to

adopt a new policy on a certain date, independently of the economy's state (e.g., forward guidance about raising the interest rate on a certain future date), whereas in the state-dependent case, a policy maker commits to adopt a new policy when the economy reaches a certain state, independently of the date (e.g., to raise the interest rate when certain economic conditions are met); see Maliar and Taylor (2018) for related forward guidance policy experiments. Both of these cases are empirically relevant and can be of interest in empirical analysis.

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