The Dynamics of Distributions in Continuous-Time Stochastic Models

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We study an optimal precautionary-saving problem in continuous time. The evolution of optimally evolving state variables, wealth and labour market status, can be described by stochastic differential equations. We derive conditions under which an invariant distribution for state variables exists and is unique. We also provide conditions such that initial distributions converge to the long-run distribution. By deriving Fokker-Planck equations for these state variables, we can provide an intuitive interpretation of the evolution and determinants of the implied distribution of wealth.

JEL Codes: C62, D91, J63
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1 Introduction

[Motivation] Dynamic and stochastic models are widely used for macro economic analysis and also for many analysis in labour economics. When the development of these models started with the formulation of stochastic growth models, a lot of emphasis was put on understanding formal properties of these models. Does a unique solution exist, both for the control variables and general equilibrium itself? Is there a stationary long-run distribution (of state variables being driven by optimally chosen control variables) to which initial distributions of states converge? The literature employing continuous time models only initially put some emphasis on looking at stability issues (Merton, 1975; Bismut, 1975; Magill, 1977; Brock and Magill, 1979; Chang and Malliaris, 1987). In recent decades, applications to economic questions have been the main focus. This does not mean, however, that all formal problems have been solved. In fact, we argue in this paper that formal work is badly missing for continuous time uncertainty.

[Objectives] The goal of this paper is threefold: First, we introduce methods for analysing existence and stability of distributions described by stochastic differential equations from the mathematical literature. The approach to proving the existence and uniqueness of an invariant distribution and its ergodicity, i.e. of convergence to the said distribution, builds on the work of Meyn and Tweedie (1993 a,b,c) and Down et al. (1995). Their work is especially useful for understanding properties of systems driven by jump processes.[2] The methods we use here are therefore particularly relevant for the search and matching analyses cited above.

Second, we use these methods to analyse stability properties of a precautionary-savings model where individuals can smooth consumption by accumulating wealth. Any extension

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[2]These methods are also used for understanding how to estimate models that contain jumps (e.g. Bandi and Nguyen, 2003) or for understanding long-term risk-return trade-offs (Hansen and Scheinkman, 2009).

of search and matching models in continuous time that allow for self-insurance (see e.g. Lise, 2013) would display similar stability properties. Individuals have constant relative risk aversion and an infinite planning horizon. Optimal behaviour implies that the two state variables of an individual, wealth and employment status, follow a process described by two stochastic differential equations. We analyse under which conditions an invariant (stationary) distribution for wealth and employment status exists, is unique and when the model is stable in the sense that the distribution converges for any initial distribution to the unique invariant one. The corresponding theorem is proven.

Our third objective consists in providing some economic interpretations for the determinants of the distribution of wealth implied by the matching and saving process. To this end, we provide a tool that embeds the analysis of distributions into a standard mathematical tool - the so-called Fokker-Planck equations. These equations describe the distributional properties of stochastic processes in a fairly general but still intuitive way. The advantage of these equations consists in the fact that one is no longer restricted to specific distributions for which closed-form solutions can be found. The entire dynamics of distributions is described and not simply distributions in a "steady-state". They can also be applied to much more general processes than has been done so far in the literature. By their nature, all existing distributions must be special cases of these general equations.[3]

[Findings] One crucial component of our proofs is a smoothing condition. As we allow for Poisson processes, we have to use more advanced methods based on T-processes than in the case of a stochastic differential equation driven by a Brownian motion. In the latter case the strong smoothing properties of Brownian motion can be used to obtain the strong Feller property. In this sense, the corresponding analysis will often be more straightforward than the one presented here. For the wealth-employment process of our model, we find that the wealth process is not smoothing and the strong Feller property does not hold. However, for the economically relevant parameter case (the low-interest rate regime), we can still show a strong version of recurrence (namely Harris recurrence) by using a weaker smoothing property, and thus obtain uniqueness of the invariant distribution. Ergodicity is then implied by properties of discrete skeleton chains.

Using the Dynkin formula, we compute the Fokker-Planck equations for the wealth-employment status system, a two-dimensional partial differential equation system. It describes the evolution of the density of wealth and employment status over time, given some initial condition. When we are interested in long-run properties only, we can set time derivatives equal to zero in the Fokker-Planck equations and obtain an ordinary two-dimensional non-autonomous differential equation system. Boundary conditions can be motivated from our phase diagram analysis.

The big advantage of our example for illustrating the usefulness of Fokker-Planck equations, consists in the generic nature of the resulting stochastic system. There will be one fundamental equation that describes the ins into and outs out of employment. Then, there will be one "dependent" equation that describes the accumulation of wealth. If wealth is replaced by firm-size, human capital, entitlement to benefits or duration in employment or unemployment, exactly the same structure occurs.

[Table of contents] The structure of our paper is as follows. The next section relates our analysis to the literature. Section 3 presents the consumption-saving problem and derives the stochastic differential equations describing the evolution of state variables. Section 4 proves existence and uniqueness of an invariant measure for the state variables together with conver-

[3] As Fokker-Planck equations describe densities, this method would allow for structural maximum likelihood estimation of models that include additional features to those usually captured in labour models (see e.g. van den Berg, 1990; Postel-Vinay and Robin, 2002; Flinn, 2006 or Launov and Wälde, 2013). In work in progress, we use the Fokker-Planck equations derived in this paper to understand determinants of the wealth distribution of a cohort in the US based on the NLSY79.

gence to the long-run invariant distribution. Section 5 provides a more applied approach to describing the dynamics of distributions by presenting the Fokker-Planck equations. The final section concludes. Appendix 4.1 provides some general background to stochastic processes in continuous time to which we refer in the main text. Appendix A derives the Fokker-Planck equations step by step.

2 Related literature

To illustrate the usefulness of our methods, we employ a continuous-time Bewley-Huggett-Aiyagari model of precautionary savings. Our economic background is therefore in the tradition of Huggett (1993) and Aiyagari (1994). Huggett (1993) analyses an exchange economy with idiosyncratic risk and incomplete markets. Agents can smooth consumption by holding an asset and endowment in each period is either high or low, following a stationary Markov process. This structure is similar in spirit to our setup. Huggett provides existence and uniqueness results for the value function and the optimal consumption function and shows that there is a unique long-run distribution function to which initial distributions converge. Regarding stability, he relies on the results of Hopenhayn and Prescott (1992). An overview of the various directions the precautionary savings model took is provided by Heathcote et al. (2009). Miao (2006) proves the existence of a sequential competitive equilibrium in a Bewley-Huggett-Aiyagari model. More recent analyses include Ortigueira and Siassi (2013) who focus on risk-sharing within a family in the presence of idiosyncratic risk.

The only fully-developed continuous-time model with precautionary savings we are aware of is Lise (2013). In addition to our setup, he also allows for on-the-job search. He does not employ Fokker-Planck equations and abstracts from existence and stability analyses, however. Scheinkman and Weiss (1986) study a precautionary savings setup with a borrowing constraint when the interest rate is zero (e.g. for holding cash) in a two-type economy. Lippi et al. (2015) extend their framework to time-varying money supply.[4] Achdou et al. (2014) survey continuous-time models in macroeconomics with a focus on partial differential equations emphasizing open theoretical ends like the lack of proofs of existence and uniqueness. They also present a precautionary saving model where uncertainty results from Brownian motion.[5]

The theory we will employ below provides a useful contribution to the economic literature as the latter, as just presented, focuses on related, but different methods. For one, we treat Markov processes in continuous time, while references in the macro-economic literature in the context of Markov-process stability are mostly related to discrete time.[6] But even in discrete time, the theory of T-processes of Meyn and Tweedie (a weaker version of strong Feller processes), seems new in the economics literature. While relying on other results from Meyn and Tweedie (1993a), Kamihigashi and Stachurski (2012, 2013), for instance, infer stability from order mixing properties instead.

In the economic continuous–time literature, the starting point is Merton's (1975) analysis of the continuous-time stochastic growth model. For the case of a constant saving rate and a Cobb-Douglas production function, the "steady-state distributions for all economic variables can be

[4] The two-type economy is very useful as it is the simplest economy with a wealth distribution that varies over time. At the individual level, the decision problem and therefore the wealth distribution for some future point in time has properties that we describe here by Fokker-Planck equations. The aggregate distributions in two-type economies and in economies with many types (as here) differs of course.

[5] See also Achedou et al. (2015) for a model similar to ours. One main difference to their approach is our analysis of the *dynamics* of the wealth distribution. In particular, we show convergence of the wealth distribution to the unique stationary distribution.

[6] Continuous time models are treated thoroughly, but under different conditions, in the finance literature. As an example, Raimondo (2005) proves existence of equilibrium in a model with incomplete and with complete markets. Anderson and Raimondo (2008) prove dynamic completeness of the equilibrium price process.

solved for in closed form". No such closed form results are available of course for the general case of optimal consumption. Chang and Malliaris (1987) also allow for uncertainty that results from stochastic population growth as in Merton (1975) and they assume the same exogenous saving function where savings are a function of the capital stock. They follow a different route, however, by studying the class of strictly concave production functions (thus including CES production function and not restricting their attention to the Cobb-Douglas case). They prove "existence and uniqueness of the solution to the stochastic Solow equation". The build their proof on the so-called reflection principle. More work on growth was undertaken by Brock and Magill (1979) building on Bismut (1975). Magill (1977) undertakes a local stability analysis for a many-sector stochastic growth model with Brownian motions using methods going back to Rishel (1970). All of these models use Brownian motion as their source of uncertainty and do not allow for Poisson jumps. To the best of our knowledge, not much (no) work has been done on these issues since then.

The principles behind and the derivation of the Fokker-Planck equation (FPE) for Brownian motion are treated e.g. in Friedman (1975, ch. 6.5) or Øksendal (1998, ch. 8.1). For our case of a stochastic differential equation driven by a Markov chain, we use the infinitesimal generator as presented e.g. in Protter (1995, ex. V.7). From general mathematical theory, we know that the density satisfies the corresponding FPE $\frac{\partial}{\partial t}p(t,x) = \mathcal{A}^* p(t,x)$, where p denotes the density of the process with state variable x at time t and $\mathcal{A}^*$ is the adjoint operator of the infinitesimal generator $\mathcal{A}$ of this process. We follow this approach in our framework and obtain the FPE for the law of the employment-wealth process.

In economics, versions of Fokker-Planck equations, equivalently called Kolmogorov forward equations, are rarely used or referred to so far. Lo (1988) derives a FPE for a one-dimensional process. Merton (1975) applies the method to analyse distributional properties of a stochastic Solow growth model. Bertola and Caballero (1994) study the distribution of capital when investment is irreversible. Klette and Kortum (2004) employ a method related to FPEs to derive firm-size distributions. Moscarini (2005) uses them to derive the distribution of the belief about the quality of a match. Koeniger and Prat (2007) obtain an employment distribution and Prat (2007) describes the distribution of detrended productivity. Impullitti et al. (2011) study the firm-size distribution in an international trade context. Stokey (2008) provides a text-book treatment of Kolmogorov forward and backward equations for Brownian motion.

The main difference in our application consists in its considerable generalization (as we allow for a system of stochastic differential equations with jumps), in the detailed derivation and in the explanations linking the derivation to standard methods taught in advanced graduate courses. The only new tool we require is the Dynkin formula. This approach focusing on the principles of FPEs in a tractable and accessible way should allow and encourage a much wider use of this tool for other applications. We would like to move Fokker-Planck equations much more into the mainstream. In fact, one could argue that Fokker-Planck equations should become a tool as common as Keynes-Ramsey rules.[7]

By transforming the FPEs from equations describing densities into equations describing distribution functions, we obtain a description of densities whose intuitive interpretation is very similar to derivations of less complex distributions as in Burdett and Mortensen (1998) or Burdett et al. (2011). In addition, however, our equations exhibit new "advection" terms that capture the shift of the distribution due to the evolution of the additional state variable, i.e. due to wealth.

[7] We would like to thank Philipp Kircher for having put this so nicely.

3 The model

3.1 The setup and optimal consumption

Consider an individual that maximizes a standard intertemporal utility function, $U(t) = E_t \int_t^\infty e^{-\rho[\tau - t]} u(c(\tau))\, d\tau$, where expectations need to be formed due to the uncertainty of labour income which in turn makes consumption $c(\tau)$ uncertain. The expectations operator is denoted E_t and conditions on the current state in t. The planning horizon starts in t and is infinite. The time preference rate ρ is positive. We assume that the instantaneous utility functions has a CRRA structure

$$u(c(\tau)) = \frac{c(\tau)^{1-\sigma} - 1}{1-\sigma} \tag{1}$$

with $\sigma \neq 1$. All proofs for the logarithmic case $\sigma = 1$ should work accordingly.

Each individual can save in an asset a. Allowing optimal consumption to be a function of state variables, $c(a(t), z(t))$, the optimal evolution of individual wealth is given by

$$da(t) = \{ra(t) + z(t) - c(a(t), z(t))\}\, dt. \tag{2}$$

Wealth $a(t)$ increases (or decreases) per unit of time dt if capital income $ra(t)$ plus labour income $z(t)$ is larger (or smaller) than optimally chosen consumption $c(a(t), z(t))$. Labour income $z(t)$ is given by constants w and b[8] and is described by the second constraint of the household, a stochastic differential equation,

$$dz(t) = \Delta dq_\mu - \Delta dq_s, \qquad \Delta \equiv w - b. \tag{3}$$

The Poisson process q_s counts how often our individual moves from employment into unemployment. The arrival rate of this process is given by $s > 0$ when the individual is employed and by $s = 0$ when the individual is unemployed. The Poisson process related to job finding is denoted by q_μ with an arrival rate $\mu > 0$ when unemployed and $\mu = 0$ when employed (as there is no search on the job). It counts how often the individual finds a job. In effect, $z(t)$ is a continuous time Markov chain with state space $\{w, b\}$, where the transition $w \to b$ happens with rate s and the transition $b \to w$ with rate μ. This description of z will be used in the remainder of the paper. As usual, the wealth-employment process (a, z), is defined on a probability space $(\Omega, \mathcal{F}, P)$.

We now let the individual maximize her objective function by choosing a consumption path subject to the budget constraint (2) and the equation for the employment status (3). Optimal consumption is described by the following generalized Keynes-Ramsey rules which extends the approach suggested by Wälde (1999) for the case of an uncertain interest rate to our case of uncertain labour income. We suppress the time argument for readability. Consumption $c(a_w, w)$ of an employed individual with current wealth a_w follows (see app. B.1)

$$\begin{aligned}-\frac{u''(c(a_w, w))}{u'(c(a_w, w))} dc(a_w, w) = &\left\{r - \rho + s\left[\frac{u'(c(a_w, b))}{u'(c(a_w, w))} - 1\right]\right\} dt \\ &- \frac{u''(c(a_w, w))}{u'(c(a_w, w))}\left[c(a_w, b) - c(a_w, w)\right] dq_s\end{aligned} \tag{4a}$$

while her wealth evolves according to

$$da_w = [ra_w + w - c(a_w, w)]\, dt. \tag{4b}$$

[8]In some broader equilibrium perspective, w and b would be endogenous objects. As long as there is only idiosyncratic risk and income is a deterministic function of time, all of our proofs below would work as well.

Analogously, solving for the optimal consumption of an unemployed individual with current wealth a_b yields

$$-\frac{u''(c(a_b,b))}{u'(c(a_b,b))}dc(a_b,b) = \left\{r-\rho-\mu\left[1-\frac{u'(c(a_b,w))}{u'(c(a_b,b))}\right]\right\}dt \\ -\frac{u''(c(a_b,b))}{u'(c(a_b,b))}\left[c(a_b,w)-c(a_b,b)\right]dq_\mu \quad \text{(4c)}$$

and her wealth follows

$$da_b = [ra_b + b - c(a_b,b)]dt. \quad \text{(4d)}$$

Without uncertainty about future labor income, i.e. $s = \mu = dq_s = dq_\mu = 0$, the above Keynes-Ramsey rules reduce to the classical deterministic consumption rule, $-\frac{u''(c)}{u'(c)}\dot{c} = r - \rho$. The additional $s[\ldots]$ term in (4a) shows that consumption growth is faster under the risk of a job loss. Note that the expression $[u'(c(a_w,b))/u'(c(a_w,w))-1]$ is positive as consumption $c(a_w,b)$ of an unemployed worker is smaller than consumption of an employed worker $c(a_w,w)$ (see lem. B.12 for a proof) and marginal utility is decreasing, $u'' < 0$. Similarly, the $\mu[\ldots]$ term in (4c) shows that consumption growth for unemployed workers is smaller.

As the additional term in (4a) contains the ratio of marginal utility from consumption when unemployed relative to marginal utility when employed, this suggests that it stands for precautionary savings (Leland, 1968, Aiyagari, 1994, Huggett and Ospina, 2001).[9] When marginal utility from consumption under unemployment is much higher than marginal utility from employment, individuals experience a high drop in consumption when becoming unemployed. If relative consumption shrinks as wealth rises, i.e. if $\frac{d}{da}\frac{c(a,w)}{c(a,b)} < 0$, reducing this gap and smoothing consumption is best achieved by fast capital accumulation. This fast capital accumulation would go hand in hand with fast consumption growth as visible in (4a).

In the case of unemployment, the $\mu[\ldots]$ term in (4c) suggests that the possibility to find a new job induces unemployed individuals to increase their current consumption level. Relative to a situation in which unemployment is an absorbing state (once unemployed, always unemployed, i.e. $\mu = 0$), the prospect of a higher labor income in the future reduces the willingness to give up today's consumption. With higher consumption levels, wealth accumulation is lower and consumption growth is reduced.

The stochastic dq-terms in (4a) and (4c) (tautologically) represent the discrete jumps in the level of consumption whenever the employment status changes. We will understand more about these jumps after the phase-diagram analysis below.

For our analysis to follow, we assume that the interest rate is lower than the time-preference rate, $r < \rho$. For convenience, we also assume that the initial wealth level $a(t)$ is chosen inside the interval $[-b/r, a_w^*]$. The lower bound $-b/r$ is a natural borrowing constraint as discussed below and the upper bound a_w^* is endogenously determined below as well.[10]

3.2 An illustration of consumption and wealth dynamics

The dynamics of consumption and wealth can be illustrated in the wealth-consumption space. The background for this illustration results from initially focusing on the evolution between jumps and by eliminating time as exogenous variable. Computing the derivatives of consumption with respect to wealth in both states and considering wealth as the exogenous variable,

[9] If the individual knew the points in time where she moves to another state, the Keynes-Ramsey rule would not display this term. In fact, an explicit solution for the consumption *level* would be available for any wage path (see e.g. Wälde, 2012, eq. (5.6.10)).

[10] Our discussion below suggests that wealth will lie within this intervall after a finite lenght of time with probability one even when initial wealth $a(t)$ lies outside the intervall.

we obtain a two-dimensional system of non-autonomous ordinary differential equations (ODE). As wealth is now the argument for these two differential equations, there is no longer a need to distinguish between wealth of employed and unemployed workers (i.e. between a_w and a_b). The dynamics between jumps therefore follows

$$-\frac{u''(c(a,w))}{u'(c(a,w))}\frac{dc(a,w)}{da}=\frac{r-\rho+s\left[\frac{u'(c(a,b))}{u'(c(a,w))}-1\right]}{ra+w-c(a,w)}, \tag{5a}$$

$$-\frac{u''(c(a,b))}{u'(c(a,b))}\frac{dc(a,b)}{da}=\frac{r-\rho-\mu\left[1-\frac{u'(c(a,w))}{u'(c(a,b))}\right]}{ra+b-c(a,b)}. \tag{5b}$$

With two boundary conditions, this system provides a unique solution for $c(a,w)$ and $c(a,b)$. Once solved, the effect of a jump is then simply the effect of a jump of consumption from, say, $c(a,w)$ to $c(a,b)$.

Properties of this system can then be illustrated in the usual way by plotting zero-motion lines and by plotting the sign of the derivatives into a phase diagram. Following these steps, it turns out (see app. B.2) that there is an endogenous upper limit a_w^* of the wealth distribution determined by the zero-motion line for consumption. The ratio of consumption at this point is given by

$$\frac{u'(c(a_w^*,b))}{u'(c(a_w^*,w))}\equiv 1-\frac{r-\rho}{s}. \tag{6}$$

Joint with an endogenous natural borrowing limit of $a\geq -b/r$ (see app. B.3), this allows us to plot a phase diagram as in fig. 1.[11] This figure displays wealth on the horizontal and consumption $c(a,z)$ on the vertical axis. It plots dashed zero-motion lines for a_w and $c(a,w)$ and a solid zero-motion line for a_b following from (4b), (55) and (4d), respectively. We assume for this figure that the threshold level a_w^* is positive.[12] The intersection point of the zero-motion lines for $c(a,w)$ and a_w is the temporary steady state (TSS),

$$\Theta\equiv(a_w^*,c(a_w^*,w)). \tag{7}$$

We call this point *temporary* steady state for two reasons. On the one hand, employed workers experience no change in wealth, consumption or any other variable when at this point (as in a standard steady state of a deterministic system). On the other hand, the expected spell in employment is finite and a random transition into unemployment will eventually occur. Hence, the state in Θ is steady only temporarily.

As we know from the proposition in app. B.2 that consumption for the unemployed always falls, both consumption and wealth fall above the zero-motion line for a_b. The arrow-pairs for the employed workers are also added. They show that one can draw a saddle-path through the TSS. To the left of the TSS, wealth and consumption of employed workers rise, to the right, they fall.

Relative consumption when the employed worker is in the TSS is given by (6). A trajectory going through $(a_w^*,c(a_w^*,b))$ and hitting the zero-motion line of a_b at $-b/r$ is in accordance with laws of motions for the unemployed worker.

[11] App. B proves various properties of our system used for plotting this phase diagram under a mild technical condition. A proof of the existence of an optimal consumption path is in app. C.

[12] This is of course a quantitative issue. In ongoing numerical work, the threshold is positive for reasonable parameter values. It approaches infinity for r approaching ρ.

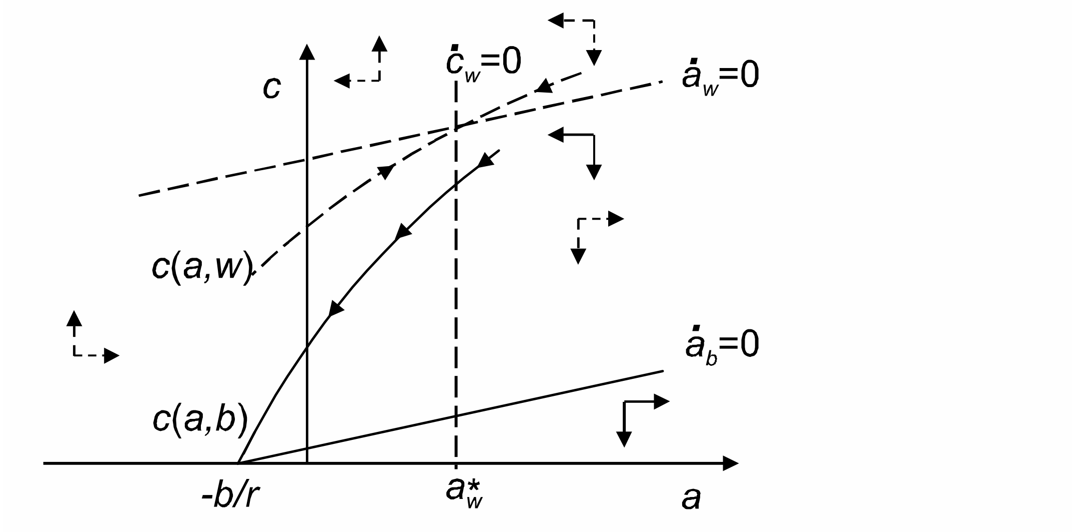

Figure 1 *Policy functions for employed and unemployed workers*

For our assumption of an interest rate being lower than the time preference rate, $r < \rho$, the range of wealth a worker can hold is bounded. Whatever the initial wealth level, there is a positive probability that the wealth level will be in the range $[-b/r, a^*_w]$ after some finite length of time. For an illustration, consider the policy functions in fig. 1: Wealth decreases both for employed and unemployed workers for $a > a^*_w$. The transition into the range $[-b/r, a^*_w]$ will take place only in the state of unemployment which, however, occurs with positive probability.

When wealth of an individual is within the range $[-b/r, a^*_w]$, consumption and wealth will rise while employed and fall while unemployed. While employed, precautionary saving motives drive the worker to accumulate wealth. While unemployed, the worker runs down current wealth as higher income for the future is anticipated – "postcautionary dissaving" takes place. When a worker loses a job at a wealth level of, say, $a^*_w/2$, his consumption level will drop from $c(a^*_w/2, w)$ to $c(a^*_w/2, b)$. Conversely, if an unemployed worker finds a job at, say, $a = 0$, her consumption increases from $c(0, b)$ to $c(0, w)$. A worker will therefore be in a permanent consumption and wealth cycle. Given these dynamics, wealth will never leave the interval $[-b/r, a^*_w]$ and one can easily imagine a distribution of wealth over the range $[-b/r, a^*_w]$.

4 Stability of the wealth-employment process

We would now like to formally understand the stability properties of the model just presented. As the fundamental state variables are wealth (2) and the employment status (3) of an individual, the process we are interested in is the wealth-employment process $X_\tau \equiv (a(\tau), z(\tau))$. All other variables (like control variables or e.g. factor rewards in a general equilibrium version) are known deterministic functions of the state variables. Hence, if we understand the process governing the state variables, we also understand the properties of all other variables in this model. The state-space of this process X_τ is $\mathbf{X} \equiv [-b/r,\ a^*_w] \times \{w, b\}$ and has all the properties required for the state space in the general ergodicity theory for Markov processes, which we review in section 4.1 below. Moreover, for the sake of simplicity, we now set the initial time $t = 0$ – following the usual practice in the mathematical literature.

The goal of this section is a proof of *stability* of the Markov process X_τ in the sense that we want to show that the distribution of X_τ converges for $\tau \to \infty$ to a unique limiting distribution (no matter what the initial value X_0). (See def. 4.10 for the precise meaning of that statement.)

The general structure of the stability or ergodicity proof is quite usual:

- First we prove existence of an invariant probability measure, i.e., of a distribution μ on the state space such that the process is stationary when started with this distribution, i.e., when $X_0 \sim \mu$. Hence, the first step is looking for *candidates* for the limiting distribution, if it exists. (Note that we here use "probability measure" and "distribution" essentially as synonyms.) As our state space is already compact, existence will follow from a continuity condition on the paths of X, more precisely the *weak Feller property*, cf. def. 4.5 below. We review the theoretical underpinnings in section 4.1.2 and carry out the proofs for our model in section 4.2.

- Then we prove uniqueness of such invariant probability measures. Technically, the usual techniques actually only provide uniqueness of invariant measures (which may well be infinite if no invariant probability measure exists), but the combination with the first step, of course, gives existence and uniqueness of the invariant distribution. As in the case of Markov chains, uniqueness follows from irreducibility (def. 4.1) and recurrence (def. 4.3) of the process X. Proving the latter property requires us to have some smoothing properties of X, which is often easy to verify in a diffusion setting, but not so clear in a pure jump setting as ours. We critically rely on the notion of T*-processes* defined in def. 4.8. Verifying that our wealth-employment process X is a T-process is the main task of section 4.3.

- The unique invariant distribution identified in the last step is the natural candidate for the limiting distribution, so we only have to prove convergence in the third step. This is done in section 4.4. Note that we are using the notion of convergence in total variation sense as compared to the more usual (and weaker) convergence in distribution.

We now continue with an overview of ergodicity theory for Markov processes in continuous time with continuous state spaces. All the results in section 4.1 are well known in the mathematical literature and, hence, the reader only interested in the new results might directly proceed with section 4.2.

4.1 Review of ergodicity results for continuous time Markov processes

The wealth-employment process $(a(\tau), z(\tau))$ described by (2) and (3) is a continuous-time Markov process with a non-discrete state space $[-b/r, a_w^*] \times \{w, b\}$. Thus, we will rely on results from the general stability theory of Markov processes as presented in the works of Meyn and Tweedie and their coauthors cited above. In the present section, we will recapitulate the most important elements of the stability for Markov processes in continuous time. Here, we will discuss the theory in full generality, i.e., we assume that we are given a Markov process $(X_t)_{t\in\mathbb{R}_{\geq 0}}$ on a state space $\mathbf{X}$, which is assumed to be a locally compact separable metric space endowed with its Borel σ-algebra. All Markov processes are assumed to be time-homogeneous, i.e., the conditional distribution of X_{t+s} given $X_t = x$ only depends on s, not on t.

4.1.1 Preliminaries

Let $(X_t)_{t\in\mathbb{R}_{\geq 0}}$ be a (homogeneous) Markov process with the state space $\mathbf{X}$, where $\mathbf{X}$ is assumed to be a locally compact and separable metric space, which is endowed with its Borel σ-algebra $\mathcal{B}(\mathbf{X})$. Let $P^t(x, A)$, $t \geq 0$, $x \in \mathbf{X}$, $A \in \mathcal{B}(\mathbf{X})$, denote the corresponding transition kernel, i.e.

$$P^t(x, A) \equiv P(X_t \in A | X_0 = x) \equiv P_x(X_t \in A), \tag{8}$$

where P_x is a shorthand-notation for the conditional probability $P(\cdot | X_0 = x)$. Note that $P^t(\cdot, \cdot)$ is a *Markov kernel*, i.e. for every $x \in \mathbf{X}$, the map $A \mapsto P^t(x, A)$ is a probability measure on

$\mathcal{B}(\mathbf{X})$ and for every $A \in \mathcal{B}(\mathbf{X})$, the map $x \mapsto P^t(x, A)$ is a measurable function. Similarly, by a *kernel* we understand a function $K : (\mathbf{X}, \mathcal{B}(\mathbf{X})) \to \mathbb{R}_{\geq 0}$ such that $K(x, \cdot)$ is a measure, not necessarily normed by 1, for every x and $K(\cdot, A)$ is a measurable function for every measurable set A. Moreover, let us denote the corresponding semi-group by P_t, i.e.

$$P_t f(x) \equiv E(f(X_t)|X_0 = x) = \int_{\mathbf{X}} f(y) P^t(x, dy) \tag{9}$$

for $f : \mathbf{X} \to \mathbb{R}$ bounded measurable. For a measurable set A, we consider the stopping time τ_A and the number of visits of X in set A,

$$\tau_A \equiv \inf\{t \geq 0 | X_t \in A\}, \quad \eta_A \equiv \int_0^\infty \mathbf{1}_A(X_t) dt.$$

Definition 4.1 *Assume that there is a σ-finite, non-trivial measure φ on $\mathcal{B}(\mathbf{X})$ such that, for sets $B \in \mathcal{B}(\mathbf{X})$, $\varphi(B) > 0$ implies $E_x(\eta_B) > 0$, $\forall x \in \mathbf{X}$. Here, similar to P_x, E_x is a short-hand notation for the conditional expectation $E(\cdot|X_0 = x)$. Then X is called φ-*irreducible*.

In the more familiar case of a finite state space and discrete time, we would simply require $\eta_{\{x\}}$ to have positive expectation for any state x. In the continuous case, such a requirement would obviously be far too strong, since singletons $\{x\}$ usually have probability zero. The above definition only requires positive expectation for sets B, which are "large enough", in the sense that they are non-null for some reference measure.

A simple sufficient condition for irreducibility is given in Meyn and Tweedie (1993b, prop. 2.1), which will be used to show irreducibility of the wealth-employment process.

Proposition 4.2 *Suppose that there exists a σ-finite measure μ such that $\mu(B) > 0$ implies that $P_x(\tau_B < \infty) > 0$. Then X is φ-irreducible, where*

$$\varphi(A) \equiv \int_{\mathbf{X}} R(x, A)\mu(dx), \quad R(x, A) \equiv \int_0^\infty P^t(x, A)e^{-t} dt.$$

Definition 4.3 *The process X is called* Harris recurrent *if there is a non-trivial σ-finite measure φ such that $\varphi(A) > 0$ implies that $P_x(\eta_A = \infty) = 1$, $\forall x \in \mathbf{X}$. Moreover, if a Harris recurrent process X has an invariant probability measure, then it is called* positive Harris.

Like in the discrete case, Harris recurrence may be equivalently defined by the existence of a σ-finite measure μ such that $\mu(A) > 0$ implies that $P_x(\tau_A < \infty) = 1$. As already remarked in the context of irreducibility, in the discrete framework one would consider sets $A = \{y\}$ with only one element.

Let μ be a measure on $(\mathbf{X}, \mathcal{B}(\mathbf{X}))$. We define a measure P_μ^t by

$$P_\mu^t(A) = \int_{\mathbf{X}} P^t(x, A)\mu(dx).$$

We say that μ is an *invariant measure*, iff $P_\mu^t = \mu$ for all t. Here, the measure μ might be infinite. If it is a finite measure, we may, without loss of generality, normalize it to have total mass $\mu(\mathbf{X}) = 1$. The resulting probability measure is obviously still invariant, and we call it an *invariant distribution*. (Note that any constant multiple of an invariant measure is again invariant.) In the case of an invariant distribution, we can interpret invariance as meaning that the Markov process has always the same marginal distribution in time, when starting with the distribution μ.

4.1.2 Existence of an invariant probability measure

The existence of finite invariant measures follows from a combination of two different types of conditions. The first property is a growth property. Several such properties have been used in the literature, a very useful one seems to be *boundedness in probability on average.*

Definition 4.4 *The process X is called* bounded in probability on average *if for every $x \in \mathbf{X}$ and every $\epsilon > 0$ there is a compact set $C \subset \mathbf{X}$ such that*

$$\liminf_{t\to\infty} \frac{1}{t} \int_0^t P_x(X_s \in C) ds \geq 1 - \epsilon. \tag{10}$$

The second property is a continuity condition.

Definition 4.5 *The Markov process X has the* weak Feller property *if for every continuous bounded function $f : \mathbf{X} \to \mathbb{R}$ the function $P_t f : \mathbf{X} \to \mathbb{R}$ from (9) is again continuous. Moreover, if $P_t f$ is continuous even for every bounded measurable function f, then X has the* strong Feller property*.*

Given these two conditions, Meyn and Tweedie (1993b, th. 3.1) establish the existence of an invariant probability measure in the following

Proposition 4.6 *If a Markov process X is bounded in probability on average and has the weak Feller property, then there is an invariant probability measure for X.*

4.1.3 Uniqueness

Turning to uniqueness, the following proposition is cited in Meyn and Tweedie (1993b, page 491). For a proof see Azéma, Duflo and Revuz (1969, Théorème 2.5).

Proposition 4.7 *If the Markov process X is Harris recurrent and irreducible for a non-trivial σ-finite measure φ, then there is a unique invariant measure (up to constant multiples).*

Proposition 4.7 gives existence and uniqueness of the invariant *measure.* A simple example shows that irreducibility and Harris recurrence do not guarantee existence of an invariant *probability* measure: Let $\mathbf{X} = \mathbb{R}$ and $X_t = B_t$ denote the one-dimensional Brownian motion. The Brownian motion is both irreducible and Harris recurrent – irreducibility is easily seen, while recurrence is classical in dimension one. Therefore, there is a unique invariant measure. By the Fokker-Planck equation, the density f of the invariant measure must satisfy $\Delta f = 0$. By non-negativity, this implies that f is constant, $f \equiv c$ for some $c > 0$. Thus, any invariant measure is a constant multiple of the Lebesgue measure, and there is no invariant probability measure for this example.

Given this example and as we are only interested in invariant *probability* measures, we need to combine this proposition with the previous section: Boundedness in probability on average together with the weak Feller property gives us the existence of an invariant probability measure as used in sect. 4.1.2, whereas irreducibility together with Harris recurrence imply uniqueness of invariant measures. Thus, for existence and uniqueness of the invariant probability measure, we will need all four conditions.

Whereas irreducibility, boundedness in probability on average and the weak Feller property are rather straightforward to check in practical situations, this seems to be harder for Harris recurrence. Thus, we next discuss some sufficient conditions for Harris recurrence. If the Markov process has the strong Feller property, then Harris recurrence will follow from a very weak growth property, namely that $P_x(X_t \to \infty) = 0$ for all $x \in \mathbf{X}$, see Meyn and Tweedie (1993b, th. 3.2). While the strong Feller property is often satisfied for models driven by Brownian motion (e.g., for hypo-elliptic diffusions), it may not be satisfied in models where randomness is driven by a pure-jump process. Thus, we will next formulate an intermediate notion between the weak and strong Feller properties, which still guarantees enough smoothing for stability.

Definition 4.8 *The Markov process X is called* T-process*, if there is a probability measure ν on $\mathbb{R}_{\geq 0}$ and a kernel T on $(\mathbf{X}, \mathcal{B}(\mathbf{X}))$ satisfying the following three conditions:*

1. *For every $A \in \mathcal{B}(\mathbf{X})$, the function $x \mapsto T(x, A)$ is continuous*[13].
2. *For every $x \in \mathbf{X}$ and every $A \in \mathcal{B}(\mathbf{X})$ we have $K_\nu(x, A) \equiv \int_0^\infty P^t(x, A)\nu(dt) \geq T(x, A)$.*
3. *$T(x, \mathbf{X}) > 0$ for every $x \in \mathbf{X}$.*

The kernel K_ν is the transition kernel of a discrete-time Markov process $(Y_n)_{n\in\mathbb{N}}$ obtained from $(X_t)_{t\geq 0}$ by random sampling according to the distribution ν: more precisely, let us draw a sequence σ_n of independent samples from the distribution ν and define a discrete time process $Y_n \equiv X_{\sigma_1+\cdots+\sigma_n}$, $n \in \mathbb{N}$. Then the process Y_n is Markov and has transition probabilities given by K_ν. Using this definition and theorem 3.2 in Meyn and Tweedie (1993b), we can formulate

Proposition 4.9 *Suppose that X is a φ-irreducible T-process. Then it is Harris recurrent (with respect to φ) if and only if $P_x(X_t \to \infty) = 0$ for every $x \in \mathbf{X}$.*

Hence, in a practical sense and in order to prove existence of a unique invariant *probability* measure, one needs to establish that a process X has the weak Feller property and is an irreducible T-process which is bounded in probability on average (as the latter implies the growth condition $P_x(X_t \to \infty) = 0$ of prop. 4.9).

Let us shortly compare the continuous, but compact case – where boundedness in probability is always satisfied – with the discrete case. In the latter situation, existence of an invariant distribution always holds, while uniqueness is then given by irreducibility. In the compact, continuous case irreducibility and Harris recurrence only guarantee existence and uniqueness of an invariant measure, which might be infinite. On the other hand, existence of a finite invariant measure is given by the weak Feller property. Thus, for existence and uniqueness of an invariant probability measure, we will need the weak Feller property, irreducibility and Harris recurrence – which we will conclude from the T-property. Thus, the situation in the continuous (but compact) case is roughly the same as in the discrete case, except for some required continuity property, namely the weak Feller property.

4.1.4 Stability

By now we have established a framework for showing existence and uniqueness of an invariant distribution, i.e., probability measure. However, under *stability* we understand more, namely the convergence of the marginal distributions to the invariant distribution, i.e., that for any starting distribution μ, the law P_μ^τ of the Markov process at time τ converges to the unique invariant distribution for $\tau \to \infty$. In the context of T-processes, we are going to discuss two methods which allow to derive stability. But first, let us define the notion of stability in a more precise way.

[13] A more general definition requires lower semi-continuity only. As we can show continuity for our applications, we do not need this more general version here.

Definition 4.10 *For a signed measure μ consider the total variation norm*

$$\|\mu\| \equiv \sup_{|f|\leq 1} \left| \int_{\mathbf{X}} f(x)\mu(dx) \right|.$$

Then we call a Markov process $(X_t)_{t\in\mathbb{R}_{\geq 0}}$ stable *or* ergodic *iff there is an invariant probability measure π such that*

$$\forall x \in \mathbf{X}: \quad \lim_{t\to\infty} \|P^t(x,\cdot) - \pi\| = 0.$$

Note that this implies in particular that the law P^t_μ of the Markov process converges to π, which is the unique invariant probability measure.

In the case of a finite state space in discrete time, ergodicity follows (inter alia) from aperiodicity. Down, Meyn and Tweedie (1995), also give one continuous result in this direction.

Definition 4.11 *A ψ-irreducible Markov process (X_t) is called* aperiodic *iff there is a measurable set C with $\psi(C) > 0$ satisfying the following properties:*

1. *there is $\tau > 0$ and a non-trivial measure ν on $\mathcal{B}(\mathbf{X})$ such that*

$$\forall x \in C,\ \forall A \in \mathcal{B}(\mathbf{X}): \quad P^\tau(x, A) \geq \nu(A);$$ [14]

2. *there is $T > 0$ such that*

$$\forall t \geq T,\ \forall x \in C: \quad P^t(x, C) > 0.$$

If we are given an irreducible, aperiodic Markov process, then stability is implied by conditions on the *infinitesimal generator*. In the following proposition we give a special case of Down, Meyn and Tweedie (1995, th. 5.2) suitable for the employment-wealth process in our model.

Proposition 4.12 *Given an irreducible, aperiodic T-process X_t with infinitesimal generator $\mathcal{A}$ on a compact state space. Assume we can find a measurable function $V \in \mathcal{D}(\mathcal{A})$ with $V \geq 1$ and constants $d, c > 0$ such that*

$$\mathcal{A}V \leq -cV + d.$$

Then the Markov-process is ergodic.

The problem with aperiodicity in the continuous time framework is that it seems hard to characterize the small sets appearing in def. 4.11. For this reason, we also give an alternative theorem, which avoids small sets (but is clearly related with the notion of aperiodicity). Given a fixed $\tau > 0$, the process $Y_n \equiv X_{\tau n}$, $n \in \mathbb{N}$, clearly defines a Markov process in discrete time, a so-called *skeleton* of X. These skeleton chains are a very useful construction for transferring results from Markov processes in discrete time to continuous time. In particular, Meyn and Tweedie (1993b, th. 6.1) gives a characterization of stability in terms of irreducibility of skeleton chains.

Proposition 4.13 *Given a Harris recurrent Markov process X with invariant probability measure π. Then X is stable iff there is some irreducible skeleton chain.*

[14] Such a set C is then called *small*.

4.2 Existence

After the review of the general ergodicity theory, we now come back and implement the scheme for our particular model. Hence, from now on we again work with the two-dimensional Markov process $X(\tau) = (a(\tau), z(\tau))$. As seen above, in order to show existence for an invariant probability measure for X, we need (i) some compactness result for X like boundedness in probability on average recalled in def. 4.4 and (ii) a continuity property like the weak Feller property, see prop. 4.6. Showing that X is bounded in probability on average is straightforward: According to def. 4.4 we need to find a compact set for any initial condition x and any small number ϵ such that the average probability to be in this set is larger than $1 - \epsilon$. As our process $X_\tau \equiv (a(\tau), z(\tau))$ is bounded, we can choose the state-space $\mathbf{X} \equiv [-b/r,\ a_w^*] \times \{w, b\}$ as our set for any x and ϵ. Concerning the weak Feller property, we offer the following

Lemma 4.14 *The wealth-employment process has the weak Feller property.*

Proof. Let us first show that the wealth-employment process depends continuously on its initial values. To see this, fix some $\omega \in \Omega$, the probability space, on which the wealth-employment process is defined. Notice that $z_\tau(\omega)$ is certainly continuous in the starting values, because any function defined on $\{w, b\}$ is continuous by our choice of topology. Thus, we only need to consider the wealth process. For fixed ω, $a_\tau(\omega)$ is a composition of solutions to deterministic ODEs, each of which are continuous functions of the respective initial value. Therefore, $a_\tau(\omega)$ is a continuous function of the initial wealth.

Now assume, without loss of generality, that the wealth-employment process has a deterministic initial value (a_0, z_0) and fix some bounded, continuous function $f : [-b/r,\ a_w^*] \times \{w, b\} \to \mathbb{R}$. For the weak Feller property, we need to show that

$$P_\tau f(a_0, z_0) = E\left(f(a_\tau, z_\tau)\right)$$

is a continuous function in (a_0, z_0). Thus, take any sequence (a_0^n, z_0^n) converging to (a_0, z_0) and denote the wealth-employment process started at (a_0^n, z_0^n) by (a_τ^n, z_τ^n). Then, by continuous dependence on the initial value, $(a_\tau^n(\omega), z_\tau^n(\omega)) \to (a_\tau(\omega), z_\tau(\omega))$, for every $\omega \in \Omega$. By continuity of f, this implies convergence of $f\left(a_\tau^n(\omega), z_\tau^n(\omega)\right)$. Since f is bounded, we may conclude convergence $P_\tau f\left(a_0^n, z_0^n\right) \to P_\tau f(a_0, z_0)$ by the dominated convergence theorem. Thus, $P_\tau f$ is, indeed, bounded and continuous whenever f is bounded and continuous, and the weak Feller property holds. ■

4.3 Uniqueness

Given existence of an invariant distribution, uniqueness will follow from (Harris) recurrence together with irreducibility of the process X. The details are spelled out in section 4.1.3, in particular in prop. 4.7.

4.3.1 Irreducibility

We prove irreducibility in the following

Lemma 4.15 *In the low-interest-regime with $r < \rho$, $(a(\tau), z(\tau))$ is an irreducible Markov process, with the non-trivial irreducibility measure φ introduced in prop. 4.2.*

Proof. Let $-b/r < a < a_w^*$, $z \in \{w, b\}$. Then, regardless of the initial point $a_t \in [-b/r, a_w^*]$ and regardless of z_t, it is possible to attain the state (a, z) in finite time with probability greater than zero. Thus, prop. 4.2 implies irreducibility with irreducibility measure

$$\varphi(A) \equiv \int_{\mathbf{X}} R(x, A)\mu(dx), \quad R(x, A) \equiv \int_0^\infty P^t(x, A)e^{-t}dt,$$

where we can take the Lebesgue measure on $[-b/r, a_w^*]$ times the counting measure on $\{w, b\}$ as measure μ. ■

4.3.2 Harris recurrence

The proof of Harris recurrence is more elaborate and builds on some auxiliary results, most importantly on being a T-process, compare Definition 4.8 which will be proved in Theorem 4.17 below. We start by giving an auxiliary result on the distribution of jumps in the employment status.

Lemma 4.16 *The conditional density of the time of the first jump in employment given that there is precisely one such jump in $[0, \tau]$ and that $z(0) = w$ is given by*

$$g_\tau^{(1)}(u) = \begin{cases} \frac{\mu - s}{e^{(\mu-s)\tau}-1} e^{(\mu-s)u}, \ 0 \le u \le \tau, & \mu \neq s, \\ 1/\tau, \ 0 \le u \le \tau, & \mu = s. \end{cases}$$

Proof. Since the formula is well-known for $\mu = s$, we only prove the result for $\mu \neq s$. The joint probability of the first jump $\tau_1 \le u \le \tau$ and $N_\tau = 1$, where N_τ denotes the number of jumps in $[0, \tau]$, is given by

$$P(\tau_1 \le u, \ N_\tau = 1) = P(\tau_1 \le u, \ \tau_2 \ge \tau - \tau_1) = \int_0^u P(\tau_2 \ge \tau - v) s e^{-sv} dv$$
$$= \int_0^u e^{-\mu(\tau - v)} s e^{-sv} dv = \frac{s}{\mu - s} e^{-\mu\tau} \left(e^{(\mu-s)u} - 1 \right).$$

Here, τ_2 denotes the time between the first and the second jump, and we have used independence of τ_1 and τ_2. Dividing through the probability of $N_\tau = 1$, we get

$$P(\tau_1 \le u | N_\tau = 1) = \frac{e^{(\mu-s)u} - 1}{e^{(\mu-s)t} - 1},$$

and we obtain the above density by differentiating with respect to u. ■

Before starting the somewhat elaborate proof of the T-property, let us shortly discuss why the conventional way to uniqueness of invariant measures is not open to us. As discussed in section 4.1, uniqueness of the invariant distribution of a Markov process is implied by smoothing properties of the process, and this approach is usually employed in the literature of continuous time models. However, the wealth-employment process (a, z) does not satisfy the strong Feller property (see def. 4.5). Indeed, assume that $f : [a_b^*, a_w^*] \times \{w, b\} \to \mathbb{R}$ is bounded measurable, but not continuous. For the sake of concreteness, let us assume that f has a jump at some point $a_b^* < a_0 < a_w^*$. If there is no jump in the employment status until time τ (an event with positive probability), then the trajectory of the wealth process a is deterministic until time τ and z is even constant. Hence, on this event the jump cannot be smeared out.

On the other hand, the distribution of the jump times has a smooth density. If there is at least one jump until time τ, we, therefore, expect the discontinuity of f to be smeared out due to the density of the jump times. If both these heuristics are true, then

- the wealth-employment process is not strong Feller, as

$$P_\tau f(a_0, z_0) = E\left[f(a_\tau, z_\tau)\right] = \underbrace{E\left[f(a_\tau, z_\tau) \mathbf{1}_{N_\tau = 0}\right]}_{\text{discontinuous in } (a_0, z_0)} + \underbrace{E\left[f(a_\tau, z_\tau) \mathbf{1}_{N_\tau > 0}\right]}_{\text{continuous in } (a_0, z_0)}$$

  is discontinuous in (a_0, z_0) – where N denotes the number of jumps in the employment status;

- the wealth-employment status conditioned on the number of jumps being greater then zero should satisfy the strong Feller condition. Hence, the kernel $T((a_0, z_0), A) = P^\tau((a_0, z_0), A \cap \{N_\tau > 0\})$ should be a continuous component of P^τ in the sense of def. 4.8. In other words, the wealth-employment process is a T-process.

Indeed, it turns out that these heuristic considerations lead to a correct conclusion.

Theorem 4.17 *The wealth-employment process $(a(\tau), z(\tau))$ is a T-process.*

Given that there are some technical difficulties concerning the proof of th. 4.17, we first give a detailed heuristic sketch of the proof. A formal proof is provided afterwards. The main step in establishing that a kernel T is a continuous component of P^τ in the sense of def. 4.8 is to show continuity. To this end, let us consider a measurable set $A \subset [a_b^*, a_w^*] \times \{w, b\}$ and define

$$T_{>0}((a_0, z_0), A) \equiv P^\tau((a_0, z_0), A \cap \{N_\tau > 0\}) = \int \mathbf{1}_A(a, w) p^\tau_{>0}((a_0, z_0), (a, w)) da P(N_\tau > 0) + \int \mathbf{1}_A(a, b) p^\tau_{>0}((a_0, z_0), (a, b)) da P(N_\tau > 0),$$

where $p^\tau_{>0}((a_0, z_0), (a, z))$ denotes the transition density of the wealth-employment process *conditioned on* $\{N_\tau > 0\}$. Obviously, continuity of $T_{>0}$ is equivalent to continuity of $a_0 \mapsto p^\tau_{>0}((a_0, z_0), (a, w))$ and $a_0 \mapsto p^\tau_{>0}((a_0, z_0), (a, b))$. Moreover, if the heuristic argument is correct, we may actually restrict ourselves to the case when there is exactly one jump in the employment process until time τ. This means, we consider the kernel

$$T_1((a_0, z_0), A) \equiv P^\tau((a_0, z_0), A \cap \{N_\tau = 1\}) = \int \mathbf{1}_A(a, z_0') p_1^\tau((a_0, z_0), (a, z_0')) da P(N_\tau = 1),$$

where $z_0' \in \{w, b\}$, $z_0' \neq z_0$ and p_1^τ denotes the transition density conditioned on the event that there is exactly one jump until time τ. Now the picture becomes much clearer. Indeed, let us assume that the jump in employment status happens at some time $u < \tau$. Up to time u, the wealth process moves deterministically according to the ODE (2), after time u it again moves in a deterministic way according to (2). Hence, there is a deterministic function ϕ_{z_0} (see (13) for the precise definition) such that

$$a_\tau = \phi_{z_0}(a_0, u; \tau)$$

provided that there is precisely one jump of the employment status at time u (and no other jump before τ). Hence, we may express T_1 by

$$T_1((a_0, z_0), A) = \int_0^\tau \mathbf{1}_A(\phi_{z_0}(a_0, u; \tau), z_0') g_\tau^{(1)}(u) du P(N_\tau = 1).$$

If $u \mapsto \phi_{z_0}(a_0, u; \tau)$ were smooth and invertible with smooth inverse $y \mapsto \phi_{z_0}^{-1}(a_0, y; \tau)$, then we could re-write the equation as

$$T_1((a_0, z_0), A) = \int_{low(a_0)}^{up(a_0)} \mathbf{1}_A(y, z_0') g_\tau^{(1)}(\phi_{z_0}^{-1}(a_0, y; \tau)) \left| \frac{\partial}{\partial y} \phi_{z_0}^{-1}(a_0, y; \tau) \right| dy, \tag{11}$$

which is continuous in a_0 provided that $a_0 \mapsto \left| \frac{\partial}{\partial y} \phi_{z_0}^{-1}(a_0, y; \tau) \right|$ and $a_0 \mapsto low(a_0)$, $a_0 \mapsto up(a_0)$ are continuous (plus some boundedness assumption). Assuming that we can make all these steps rigorous, we thus have proved the theorem.

In order to verify the various assumptions made in the above sketch , we need to understand the solution of the ODE

$$\frac{da_z(\tau)}{d\tau} = ra_z(\tau) + z - c(a_z(\tau), z) \tag{12}$$

better. Indeed, the properties would be essentially trivial, if it were not for the (possible) singularity of the consumption function $c(a, z)$ at $a = a_b^*$ and $a = a_w^*$ induced by the explosion of the right hand side in (5). Nevertheless, by careful analysis we can establish the assumptions made above, at least when we further restrain the domain.

We denote the solution of (12) started at $a_0 \in [a_b^*, a_w^*]$ at time 0 evaluated at time $\tau = u$ by $\psi_z(a_0, u)$, i.e., $\psi_z(a_0, 0) = a_0$. Let $\mathfrak{T}(a, z) \in [0, \infty]$ be the time it takes for the deterministic function $\psi_z(a, \cdot)$ to reach the boundary $\{a_b^*, a_w^*\}$ of the domain. Note that $\mathfrak{T}$ may be infinite, which is actually the good situation, as the consumption function $c(a, z)$ is actually C^1 in that case—and, hence, stability holds. While it seems not clear how to obtain C^1 on the whole interval $[a_b^*, a_w^*]$, it is clear how to get it on the interior of the domain. Of course, if $\mathfrak{T}(a, z) = \infty$ for some $a \in]a_b^*, a_w^*[$, then it is infinite for any such a.

Lemma 4.18 *For $z = w, b$, the map $a \mapsto c(a, z)$ is C^1 in the interior $]a_b^*, a_w^*[$ of the domain.*

Proof. $x(a) \equiv (c(a, w), c(a, b))$ solves an ODE in a (the reduced form ODE system), with a right hand side which is locally Lipschitz in the interior of the domain. Fix some interior value a_0 and consider the initial value problem for x started at $x(a_0)$ on the a-domain $[a_0, a_w^*[$. As the right hand side is locally Lipschitz, we can apply the usual existence and uniqueness theorem, which gives, in particular, that the solution is C^1 up to (but not necessarily including) $a = a_w^*$. On the other hand, for $a \in]a_b^*, a_0]$, we just revert the direction, which gives another locally Lipschitz right hand side, and, hence, C^1 follows in the same way. ■

This directly implies that $\psi_z(a, u)$ is C^1 in both a and u for $u < \mathfrak{T}(a, z)$, and continuous in both variables even for $u \le \mathfrak{T}(a, z)$.

Lemma 4.19 *The map $a \mapsto \mathfrak{T}(a, z)$ is continuous on $[a_b^*, a_w^*] \setminus \{a_z^*\}$. Moreover, if $\mathfrak{T}(a, z) < \infty$ for any $a_b^* < a < a_w^*$, then $\mathfrak{T}(\cdot, z)$ is continuous on the whole domain.*[15]

Proof. Let $\psi_z(a, u)$ denote the solution map of the ODE driving a_z evaluated at time u for initial value $\psi_z(a, 0) = a$. Obviously, $\psi_w(a, \cdot)$ is strictly increasing (until the time that a_w^* is hit), while $\psi_b(a, \cdot)$ is strictly decreasing. Hence, they have continuous inverse functions (in t, for fixed a).

Fix any point $a^0 \in]a_b^*, a_w^*[$ and the corresponding value $\mathfrak{T}^0(z) \equiv \mathfrak{T}(a^0, z)$. For any positive t we obviously have

$$\mathfrak{T}(\psi_z(a, t), z) = \mathfrak{T}(a, z) - t.$$

Denoting $\psi_z^0(t) \equiv \psi_z(a^0, t)$, we get for any $a < a^0$ for $z = b$ and any $a > a^0$ for $z = w$ that

$$\mathfrak{T}(a, z) = \mathfrak{T}(\psi_z^0((\psi_z^0)^{-1}(a)), z) = T^0(z) + (\psi_z^0)^{-1}(a),$$

which is continuous in a. As a^0 was arbitrary in the interior of the interval, the claim follows. ■

Let us introduce a little bit of notation: for $z \in \{w, b\}$ we denote by z' the *other* element of $\{w, b\}$. Moreover, we define

$$\phi_z(a, u; \tau) \equiv \psi_{z'}(\psi_z(a, u), \tau - u), \quad 0 \le u \le \tau, \ z \in \{w, b\}. \tag{13}$$

In words, ϕ_z denotes the value of the wealth process at time τ given that the wealth process at time 0 has the value a and there is precisely one change of the employment status (from z to z') in $[0, \tau]$, which takes place at time u. We are going to identify a sufficiently large set of us on which $u \mapsto \phi_z(a, u; \tau)$ is differentiable and invertible with differentiable inverse.

[15] Otherwise, we have a jump from $+\infty$ to 0 at $a = a_z^*$.

Lemma 4.20 *Define the set*

$$\mathfrak{S}(a,z;\tau) \equiv \{u \in [0,\tau] \mid u > \tau - \mathfrak{T}\left(\psi_z(a,u), z'\right)\}.$$

If $\mathfrak{T}(a,z') = \infty$ for some $a_b^* < a < a_w^*$, then

$$\mathfrak{S}(a,z;\tau) = \begin{cases} [0,\tau], & a \neq a_{z'}^*, \\ ]0,\tau], & a = a_{z'}^*. \end{cases}$$

Otherwise, the following three properties hold:

1. *There are numbers $\mathfrak{s}(a,z;\tau)$ such that $\mathfrak{S}(a,z;\tau) =]\mathfrak{s}(a,z;\tau),\tau]$.*
2. *$a \mapsto \mathfrak{s}(a,z;\tau)$ is continuous on $]a_b^*, a_w^*[$.*
3. *For every $(a,z) \in [a_b^*, a_w^*] \times \{w,b\}$ we have (uniformly) $\tau - \mathfrak{s}(a,z;\tau) > 0$.*

Proof. The description for $\mathfrak{T}(a,z') = \infty$ is obvious, so we assume that $\forall a \in [a_b^*, a_w^*] \setminus \{a_{z'}^*\}$: $\mathfrak{T}(a,z') < \infty$.

First note that $\tau \in \mathfrak{S}(a,z;\tau)$. Moreover, for $u < v < \tau$ we have that $u \in \mathfrak{S}(a,z;\tau)$ implies $v \in \mathfrak{S}(a,z;\tau)$, since

$$\tau - \mathfrak{T}\left(\psi_z(a,v), z'\right) \leq \tau - \mathfrak{T}\left(\psi_z(a,u), z'\right) < u < v,$$

which shows that $\mathfrak{S}(a,z;\tau)$ is an interval. However, for its lower endpoint the inequality is no longer strict, implying that the interval is closed to the right, but open to the left.

For the continuity of $\mathfrak{s}$, let us consider any (monotone) converging sequence $a_n \to a \in [a_b^*, a_w^*]$. First, assume that $u \in \mathfrak{S}(a_n,z;\tau)$ for all $n \geq N$. Then $u > \tau - \mathfrak{T}(\psi_z(a_n,u),z')$. Thus, continuity of $\psi_z(\cdot,u)$ and $\mathfrak{T}(\cdot,z')$ (cf. Lemma 4.19) imply that

$$u \geq \tau - \mathfrak{T}\left(\psi_z(a,u), z'\right).$$

The right hand side of the inequality is decreasing in u, so that we can infer that every $u' > u$ is contained in $\mathfrak{S}(a,z;\tau)$, hence $u \in \overline{\mathfrak{S}(a,z;\tau)}$. In a similar way, we can show that $u \in [0,\tau] \setminus \overline{\mathfrak{S}(a_n,z;\tau)}$ for every $n \geq N$ implies that $u \in [0,\tau] \setminus \mathfrak{S}(a,z;\tau)$. However, this is only possible if $\mathfrak{s}(a_n,z;\tau) \to \mathfrak{s}(a,z;\tau)$, proving continuity in the interior of the domain.

It is obvious that $\tau > \mathfrak{s}(a,z;\tau)$ as $\tau \in \mathfrak{S}(a,z;\tau)$ and $\mathfrak{S}(a,z;\tau)$ is half-open. The uniformity is also clear. ■

Lemma 4.21 *The map $u \mapsto \phi_z(a,u;\tau)$ is differentiable on $\mathfrak{S}(a,z;\tau)$ and we have*

$$\left| \frac{\partial}{\partial u} \phi_z(a,u;\tau) \right| > 0.$$

Proof. By (13), ϕ_z is differentiable in u provided that $a' \mapsto \psi_{z'}(a', \tau - u)$ is differentiable at $a' = \psi_z(a,u)$. It is a well-known fact that the solution map of an ODE is differentiable in its initial value provided that the right hand side is C^1. By Lemma 4.18, the right hand side of (12) (for $z = z'$) is C^1 (in a) as long as we do not hit $a_{z'}^*$, which is precisely guaranteed by $u \in \mathfrak{S}(a,z;\tau)$. Hence, we can apply the chain rule and obtain

$$\begin{aligned} \frac{\partial}{\partial u} \phi_z(a,u;\tau) &= -\frac{\partial \psi_{z'}}{\partial u}\left(\psi_z(a,u), \tau - u\right) + \frac{\partial \psi_{z'}}{\partial a}\left(\psi_z(a,u), \tau - u\right) \frac{\partial \psi_z}{\partial u}(a,u) \\ &= -\underbrace{\left[r\phi_z(a,u;\tau) + z' - c(\phi_z(a,u,\tau), z')\right]}_{I} + \\ &\quad + \underbrace{\frac{\partial \psi_{z'}}{\partial a}\left(\psi_z(a,u), \tau - u\right)}_{II} \underbrace{\left[r\psi_z(a,u) + z - c(\psi_z(a,u), z)\right]}_{III}. \end{aligned}$$

For $z = w$, we have $I < 0$ (with strict inequality as $u \in \mathfrak{S}(a,z;\tau)$), and $II \geq 0$, $III \geq 0$, implying that

$$\frac{\partial}{\partial u}\phi_w(a,u;\tau) > 0.$$

On the other hand, for $z = b$, we have $I > 0$ (again, with strict inequality), $II \geq 0$ and $III \leq 0$, implying that

$$\frac{\partial}{\partial u}\phi_b(a,u;\tau) < 0.$$

■

By Lemma 4.21 together with Lemma 4.20 we now understand rigorously on which domains of integration we can do the change of variables in (11), which is crucial for establishing continuity. Therefore, we are now prepared to finish the proof of the theorem.

Proof of th. 4.17. We choose the measure $\nu(dt) = \delta_\tau(dt)$ for some fixed $\tau > 0$ and define a candidate $\widetilde{T}$ for a continuous component of P^τ by

$$\widetilde{T}((a,z),A) \equiv \int_0^\tau \mathbf{1}_A(\phi_z(a,u;\tau),z')\mathbf{1}_{\mathfrak{S}(a,z;\tau)}(\phi_z(a,u;\tau))g_\tau^{(1)}(u)duP(N(\tau)=1), \tag{14}$$

for $a \in [a_b^*, a_w^*]$, $z \in \{w,b\}$, $A \subset [a_b^*, a_w^*] \times \{w,b\}$ measurable, i.e.,

$$\widetilde{T}((a,z),A) = P^\tau((a,z), A \cap \{N_\tau = 1\} \cap \{T_1 \in \mathfrak{S}(a,z;\tau)\}),$$

where T_1 denotes the first jump time of the Poisson process N. Hence, it is clear that $\widetilde{T} \leq P^\tau$. Now, introduce a change or variables $u \to y \equiv \phi_z(a,y;\tau)$ as in (11). By Lemma 4.21, we get

$$\widetilde{T}((a,z),A) = \int_{L(a,z;\tau)}^{U(a,z;\tau)} \mathbf{1}_A(y,z')\mathbf{1}_{\mathfrak{S}(a,z;\tau)}\left(\phi_z^{-1}(a,y;\tau)\right) \times \cdots$$
$$\cdots \times g_\tau^{(1)}\left(\phi_z^{-1}(a,y;\tau)\right)\left|\frac{\partial}{\partial y}\phi_z^{-1}(a,y;\tau)\right| dy, \tag{15}$$

where the lower and upper limits of the integration are given by

$$L(a,z;\tau) \equiv \begin{cases} \phi_z(a,0;\tau), & z = w, \\ \phi_z(a,\tau;\tau), & z = b, \end{cases} \quad U(a,z;\tau) \equiv \begin{cases} \phi_z(a,\tau;\tau), & z = w, \\ \phi_z(a,0;\tau), & z = b, \end{cases}$$

respectively. Here, $y \mapsto \phi_z^{-1}(a,y;\tau)$ denotes the inverse function of $u \mapsto \phi_z(a,u;\tau)$. Comparing (15) with (14), we note two important differences: the integrand (including the limits of the integration) in (15) is continuous in a almost everywhere but, on the other hand, generally unbounded.

By a slight abuse of notation, let us denote $\mathfrak{S}(a,z;\tau) \equiv]\mathfrak{s}(a,z;\tau),\tau]$.[16] Lemma 4.20 implies that we may choose $0 < \epsilon < \inf_{(a,z)}(\tau - \mathfrak{s}(a,z;\tau))$. Now define $\mathfrak{S}_\epsilon(a,z;\tau) \equiv]\mathfrak{s}(a,z;\tau)+\epsilon,\tau]$ and

$$T((a,z),A) \equiv \int_0^\tau \mathbf{1}_A(\phi_z(a,u;\tau),z')\mathbf{1}_{\mathfrak{S}_\epsilon(a,z;\tau)}(\phi_z(a,u;\tau))g_\tau^{(1)}(u)duP(N(\tau)=1). \tag{16}$$

By the same change of variables as above, we arrive at

$$T((a,z),A) = \int_{L(a,z;\tau)}^{U(a,z;\tau)} \mathbf{1}_A(y,z')\mathbf{1}_{\mathfrak{S}_\epsilon(a,z;\tau)}\left(\phi_z^{-1}(a,y;\tau)\right) \times \cdots$$
$$\cdots \times g_\tau^{(1)}\left(\phi_z^{-1}(a,y;\tau)\right)\left|\frac{\partial}{\partial y}\phi_z^{-1}(a,y;\tau)\right| dy. \tag{17}$$

[16] This means that $\mathfrak{s}(a,z;\tau) \equiv 0$ in the case $\mathfrak{T}(a,z') = \infty$ and $\mathfrak{S}(a,z;\tau) = [0,\tau]$ is replaced by $]0,\tau]$ in that case.

Since the term I in the proof of Lemma 4.21 only gets close to 0 when u is close to $\mathfrak{s}(a,z;\tau)$, now

$$\mathbf{1}_{\mathfrak{S}_\epsilon(a,z;\tau)}\left(\phi_z^{-1}(a,y;\tau)\right)\left|\frac{\partial}{\partial y}\phi_z^{-1}(a,y;\tau)\right|$$

is uniformly bounded, implying that $(a,z)\mapsto T((a,z),A)$ is continuous for any measurable set A.

As, by construction, $\tau-(\mathfrak{s}(a_0,z_0;\tau)+\epsilon)>0$ we have $T((a,z),[a_b^*,a_w^*]\times\{w,b\})>0$. Finally, it is obvious that $T((a,z),A)\leq\widetilde{T}((a,z),A)\leq P^\tau((a,z),A)$ for any (a,z) and any measurable function A. ■

Corollary 4.22 *The wealth-employment process $(a(\tau),z(\tau))$ is Harris recurrent.*

Proof. By lemma 4.15 and theorem 4.17, the employment-wealth process $(a(\tau),z(\tau))$ is an irreducible T-process. Thus, prop. 4.9 implies that $(a(\tau),z(\tau))$ is Harris recurrent, given that $P_x(X_t\to\infty)=0$ holds for our bounded state space. ■

4.3.3 Uniqueness

We can now complete our proof of uniqueness.

Theorem 4.23 *Suppose that $r<\rho$. Then there is a unique invariant probability measure for the wealth-employment process $(a(\tau),z(\tau))$.*

Proof. By prop. 4.7, there is a unique invariant measure (up to a constant multiplier), and prop. 4.6 implies that we may choose the invariant measure to be a probability measure. ■

4.4 Stability

Stability, i.e., convergence of the distribution of $(a(\tau),z(\tau))$ to the unique invariant distribution for any given initial distribution is implied by the existence of an irreducible skeleton chain, see prop. 4.13.

Corollary 4.24 *Under the assumptions of theorem 4.23, the employment-wealth process is stable in the sense of def. 4.10.*

Proof. Recall that the employment-wealth-process is a T-process, see theorem 4.17. Moreover, we have shown irreducibility in lemma 4.15. Proposition 4.13 will imply the desired conclusion, if we can show irreducibility of a skeleton chain. Take any $\tau>0$ and consider the corresponding skeleton Y_n, $n\in\mathbb{N}$, with transition probabilities P^τ. By the proof of theorem 4.17, we see that (Y_n) is also a T-process, where the definition of T-processes is generalized to discrete-time processes in the obvious way. By Meyn and Tweedie (1993, prop. 6.2.1), the discrete-time T-process Y is irreducible if there is a point $x\in\mathbf{X}$ such that for any open neighborhood O of x, we have

$$\forall y\in\mathbf{X}:\quad\sum_{n=1}^{\infty}P^{n\tau}(y,O)>0.\tag{18}$$

This property, however, can be easily shown for the wealth-employment process (a,z) as illustrated in fig. 1 and formally analysed in app. B and C. Indeed, take $x=(-b/r,b)$. Then any open neighborhood O of x contains $[-b/r,-b/r+\epsilon[\times\{b\}$ for some $\epsilon>0$. We start at some point $y=(a_0,z_0)\in\mathbf{X}$ and assume the following scenario: if necessary, at some time between 0 and τ, the employment status changes to b, then it stays constant until the random time $N\tau$ defined by $N \equiv \inf\{n \mid a(n\tau) < -b/r + \epsilon\}$. Note that the wealth is decreasing in a deterministic way while $z = b$. Thus, we can find a deterministic upper bound $N \leq K(a_0)$. The event that the employment attains the value b during the time interval $[0, \tau]$ and retains this value until time $K(a_0)\tau$ has positive probability. In this case, however, the trajectory of the wealth-employment process reaches O, implying that $\sum_{n=1}^{\infty} P^{n\tau}(y, O) > 0$. Thus, the τ-skeleton chain is irreducible and the wealth-employment process is stable. ■

5 Describing the distribution of labour income and wealth

We now come to the applied part of this paper where we describe distributional properties of $z(\tau)$ and $a(\tau)$ by Fokker-Planck equations. This is of importance per se for our setup and serves as an example that can be adapted for many other applications.

5.1 Labour market probabilities

Consider first the distribution of the labour market state. Given that the transition rates between w and b are constant, the conditional probabilities of being in state $z(\tau)$ follow e.g. from solving Kolmogorov's backward equations as presented e.g. in Ross (1993, ch. 6). As an example, the probability of being employed in $\tau \geq t$ conditional on being in state $z \in \{w, b\}$ in t are

$$P(z(\tau) = w | z(t) = w) \equiv p_{ww}(\tau) = \frac{\mu}{\mu + s} + \frac{s}{\mu + s} e^{-(\mu+s)(\tau - t)}, \tag{19}$$

$$P(z(\tau) = w | z(t) = b) \equiv p_{bw}(\tau) = \frac{\mu}{\mu + s} - \frac{\mu}{\mu + s} e^{-(\mu+s)(\tau - t)}. \tag{20}$$

The complementary probabilities are $p_{wb}(\tau) = 1 - p_{ww}(\tau)$ and $p_{bb}(\tau) = 1 - p_{bw}(\tau)$. Letting $p_w(t)$ denote the probability of $z(t) = w$, i.e. letting it describe the initial distribution of $z(t)$, the unconditional probability of being in state z in τ is

$$p_z(\tau) = p_w(t)\, p_{wz}(\tau) + (1 - p_w(t))\, p_{bz}(\tau). \tag{21}$$

Equations (19) and (20) nicely show the influence of the initial condition on the probability of having a job. Consider a point in time τ which is just an instant after t. Let this instant be so small that τ is basically identical to t. Then, the probability of being employed in τ (where $\tau = t$) is given by $\frac{\mu}{\mu+s} + \frac{s}{\mu+s} = 1$. Similarly, the probability of being unemployed in τ where τ is very close to t is given by (set $\tau = t$ in (20)) $\frac{\mu}{\mu+s} - \frac{\mu}{\mu+s} = 0$. The longer the point τ lies into the future, the less important the initial state becomes and the closer both probabilities approach the unconditional probability of being employed, which is $\frac{\mu}{\mu+s}$.

5.2 Fokker-Planck equations for wealth

5.2.1 The question and how to answer it

Our individual faces an uncertain future labour income stream $z(\tau)$. We would like to understand the joint distribution of $a(\tau)$ and $z(\tau)$ for $\tau \geq t$. To this end, we consider the stochastic processes of $a(\tau)$ in (2) and $z(\tau)$ in (3). After defining the (joint) density of $(a(\tau), z(\tau))$, we apply the "Fokker-Planck machinery" to obtain a description of the densities.

We denote the joint density by $p(a, z, \tau)$. For each point in time τ, there is obviously a discrete and a continuous random variable. We can therefore split the density into two "subdensities" $p(a, w, \tau)$ and $p(a, b, \tau)$, both drawn in fig. 2 for some $\tau \geq t$. The subdensities can be understood as the product of a conditional density $p(a,\tau|z)$ times the probability of being in employment state z,

$$p(a,z,\tau) \equiv p(a,\tau|z)\,p_z(\tau)\,. \tag{22}$$

The probability $p_z(\tau)$ of an individual to be in a state z in τ is given by (21). As is clear from (22), $p(a,z,\tau)$ are not conditional densities – they rather integrate to the probability of $z(\tau)=z$. Looking at an individual who is in state z in τ, we get

$$\int p(a,z,\tau)\,da = \int p(a,\tau|z)\,p_z(\tau)\,da = p_z(\tau)\int p(a,\tau|z)\,da = p_z(\tau)\,. \tag{23}$$

The density of a at some point in time τ is then simply

$$p(a,\tau) = p(a,w,\tau) + p(a,b,\tau)\,. \tag{24}$$

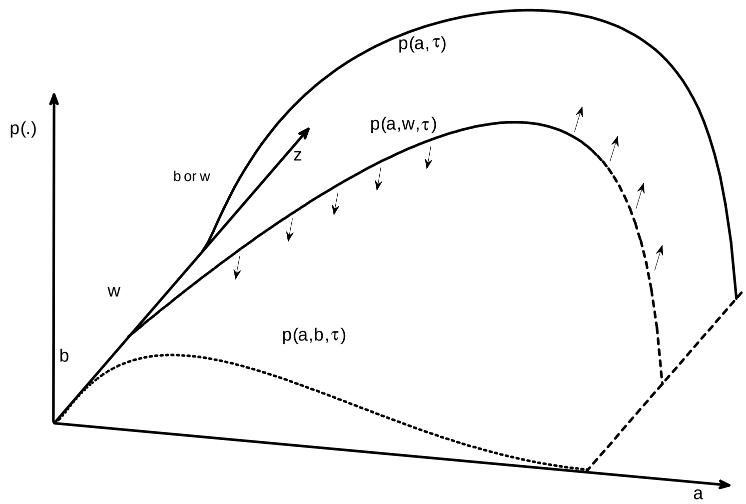

Figure 2 *The subdensities $p(a,b,\tau)$ and $p(a,w,\tau)$ and the density $p(a,\tau)$*

Note that the distribution of $(a(\tau),z(\tau))$ certainly depends on the initial condition $(a(t),z(t))$, which needs to be specified in order to calculate $p(a,z,\tau)$. In the notation we do not distinguish between the following two possibilities. Firstly, $(a(t),z(t))$ can be deterministic numbers, in which case $p(a,z,t)$ is a Dirac-distribution centered in $(a(t),z(t))$ (more precisely, the mapping $a\rightarrow p(z,a,t)$ is a Dirac-distribution). Secondly, $(a(t),z(t))$ can itself be random, either because we regard them as outcomes of the employment-wealth-process started at an even earlier time, or because there is some intrinsic uncertainty in measuring $a(t)$ (as e.g. the exact value of some asset, think e.g. of a house, is not known).

Let us now step back and ask how this approach can be applied to other setups. If one would like to understand the process of accumulation and depreciation of skills and experience during different employment states, one would have to specify a differential equation for skill similar to the budget constraint (2). Joint with the fundamental process (3) one could then derive Fokker-Planck equations for densities. If one would like to model the endogenous distribution of entitlement to unemployment benefits, one would have to "translate" regulations concerning entitlement into a differential equation, add again (3) and proceed to derive Fokker-Planck equations. Similar procedures are possible for analysing distributions over the business cycle where some aggregate shock process would be added to (2), (3) or both. Note that this approach works for processes driven e.g. by Brownian motion just as well.

5.2.2 The equations and their economic interpretation

The derivation of the Fokker-Planck equations is in app. A. The result is a system of two non-autonomous quasi-linear partial differential equations in $p(a, w, \tau)$ and $p(a, b, \tau)$,

$$\frac{\partial}{\partial \tau} p(a, w, \tau) + \{ra + w - c(a, w)\} \frac{\partial}{\partial a} p(a, w, \tau) =$$
$$-\left\{r - \frac{\partial}{\partial a} c(a, w) + s\right\} p(a, w, \tau) + \mu p(a, b, \tau), \tag{25a}$$
$$\frac{\partial}{\partial \tau} p(a, b, \tau) + \{ra + b - c(a, b)\} \frac{\partial}{\partial a} p(a, b, \tau) =$$
$$sp(a, w, \tau) - \left\{r - \frac{\partial}{\partial a} c(a, b) + \mu\right\} p(a, b, \tau). \tag{25b}$$

The system is a *partial* differential equation system as there are two derivatives, one with respect to time τ and one with respect to wealth a – which is not surprising: As the FPEs describe the evolution of the density for wealth over time, two derivatives are needed. The derivative with respect to a describes the "cross-sectional" property of the density for a given τ. The time derivative describes how a density changes over time.[17] The differential equations are called *quasi*-linear as the factors in front of the wealth-derivatives are functions of a. The PDEs are *non-autonomous* as some of the terms (other than the densities) also depend explicitly on one of the exogenous variables (exogenous in a differential equation sense), i.e. on wealth a.

As we can see, the density depends on properties of optimizing behaviour through the consumption levels $c(a, w)$ and $c(a, b)$ and through the marginal propensities to consume out of wealth, $\partial c(a, w) / \partial a$. These FPEs therefore describe the evolution of wealth for any specification of the utility function (e.g. CRRA, CARA, log, etc.). Modifying the utility function (e.g. allowing for labour supply or separating the intertemporal elasticity of substitution from risk aversion) affects the density of wealth through the effect on the optimal consumption plan $c(a, z)$.

Before we give an economic interpretation to these equations, we transform them such that they do not describe densities but distribution functions. To this end, define "subdistribution" functions as

$$P(a, z, \tau) \equiv \int_{-b/r}^{a} p(a, z, \tau)\, da. \tag{26}$$

The term $P(a, w, \tau)$ gives the probability that an individual will be employed in τ and own wealth equal or lower to a. Given our definition of subdensities and their property in (23), we know that $\lim_{a\to\infty} P(a, w, \tau) = p_{zw}(\tau)$ where the term $p_{zw}(\tau)$ is given in either (19) or (20), depending on the initial state in t.

The transformation of our FPEs is subject to the condition that $p\left(-\frac{b}{r}, z, \tau\right) = 0$ for all τ. This means that there is no worker with wealth equal to $-b/r$. As a wealth of $-b/r$ for unemployed workers would imply zero consumption, $c(-b/r, b) = 0$, this can be ruled out indeed as marginal utility from consumption would then be infinity. This would violate optimality. As employed workers with wealth of $-b/r$ can only originate from unemployed workers with this wealth level (as wealth of employed workers increases) and as $p\left(-\frac{b}{r}, b, \tau\right) = 0$ for all τ, we know that $p\left(-\frac{b}{r}, w, \tau\right) = 0$ for all τ as well.

[17] Compare this to the Pearson system of distributions that describes densities by ordinary non-autonomous differential equations (see e.g. Johnson, Kotz and Balakrishnan, 1994, ch. 12). These ordinary differential equations describe the density of one random variable. Here, we analyse a stochastic process, i.e. a sequence of random variables, and therefore need two derivatives.

The subdistribution functions in (26) obey the following system (cf. app. D.2)

$$\frac{\partial}{\partial \tau} P(a, w, \tau) = -\{ra + w - c(a, w)\} \frac{\partial}{\partial a} P(a, w, \tau) - sP(a, w, \tau) + \mu P(a, b, \tau), \tag{27a}$$

$$\frac{\partial}{\partial \tau} P(a, b, \tau) = -\{ra + b - c(a, b)\} \frac{\partial}{\partial a} P(a, b, \tau) + sP(a, w, \tau) - \mu P(a, b, \tau). \tag{27b}$$

This system is now extremely easy to understand: Starting with the first equation, the evolution of the distribution function over time, i.e. the time derivative $\partial P(a, w, \tau) / \partial \tau$ on the left hand side depends on three terms. Starting at the end, there is an increase in the probability $P(a, w, \tau)$ if there is a high flow from the state of being unemployed. This flow can be high if the matching rate μ, the probability of being unemployed $P(a, b, \tau)$ or if a combination of the two is high. Similarly, the probability $P(a, w, \tau)$ decreases (ceteris paribus) exponentially at the rate s, and the faster so, the higher the separation rate. The interpretation of the last two terms in the second equation (27b) is identical (subject to reversed signs). These two terms are very familiar from derivations of wage distributions in the Burdett-Mortensen (1998) tradition.

We can think of these equations as describing how wealth of a worker flows up and down depending on her current state. The labor income levels of workers are stochastically moving back and forth between the different states w and b. The effect of these stochastic jumps on the distribution of wealth are captured by the two terms at the end of (27a,b). Wealth is moving non-stochastically within the states, either upwards (when employed) or downwards (when unemployed). The direction of the movement is on the wealth line, i.e. the partial derivative $\partial P(a, w, \tau) / \partial a$ gives the direction of a. The speed of this movement is determined by savings $ra + z - c(a, z)$. The speed is positive when employed and negative when unemployed. The overall effect of positive savings for the probability $P(a, w, \tau)$ of employed workers is then to *decrease* this probability. As wealth increases, the probability of having a wealth level equal to or lower than a certain level a obviously falls as there is a permanent flow towards higher wealth levels. This flow is then reversed in the state of unemployment where the speed (i.e. savings $ra - b - c(a, b)$) is negative. As a consequence, the probability $P(a, b, \tau)$ ceteris paribus increases over time as unemployed workers "gather" towards the lower end of the wealth distribution.

5.2.3 Initial conditions

Obtaining a unique solution for ODEs generally requires certain differentiability conditions and as many initial conditions as differential equations. Conditions for obtaining a unique solution for PDEs differ in various respects, of which the most important one from an intuitive perspective is the fact that instead of initial conditions (i.e. an initial value or vector), initial functions are required. This can easily be understood for our case: Let us assume two initial functions for a, one for each labour market state $z \in \{w, b\}$. The obvious interpretation for these initial functions are densities, just as illustrated in fig. 2. Initial functions would therefore be given by $p(a, b, t) = p^{ini}(a, b)$ and $p(a, w, t) = p^{ini}(a, w)$. Clearly, they take positive values on the range $[-b/r, a_w^*]$ only and need to jointly integrate to unity. Given these initial functions, one can then compute the partial derivatives with respect to a in (25). This gives an ODE system which allows us to compute the density for the "next" τ. Repeating this gives us the densities for all z, a and τ we are interested in.

5.2.4 A density gives a density

The Fokker-Planck equations have a very convenient property that easily allows to show that they indeed describe densities (in the sense that their solutions integrate to one). The only condition is that the initial functions integrate to one. We summarize this in the following

Proposition 5.1 *Define* $I(\tau) \equiv \int_{-\infty}^{\infty} p(a,w,\tau) + p(a,b,\tau)\, da$. *Given the laws of motion for* $p(a,z,\tau)$ *from (25) and the fact of a bounded support* $[-b/r, a_w^*]$, *this integral is mass-preserving, i.e.* $dI(\tau)/d\tau = 0$ *for all* τ. *Assuming initial densities, i.e. initial functions* $p(a,z,t) \geq 0$ *such that* $I(t) = 1$, *the PDEs in (25) indeed describe the dynamics of distributions over time.*

Proof. see app. D.1 ■

This is an extremely useful property as this implies that with an initial density we know that all other functions $p(a,w,\tau) + p(a,b,\tau)$ integrate to one and therefore represent densities.

5.2.5 The long-run distribution of individual wealth

When we are interested in the long-run distribution of wealth and income only, the time derivatives of the densities would be zero and the long-run densities would be described by two linear ordinary differential equations. This is true both for the system in densities (25) and for the system for distributions (27).

Initial conditions for this ordinary differential equations are given by

$$p(a_w^*, w) = 0, \quad p(a_w^*, b) = 0. \tag{28}$$

The intuition for $p(a_w^*, w) = 0$ comes from the saddle-path nature of the TSS Θ in (7): There is one path going into Θ from the left and one going into Θ from the right and two (not drawn) starting from Θ and going North and South. In saddle-points of ODE systems, one can prove by linearization around the fix point that local solutions of the ODE approach the saddle point asymptotically. Linearization here is more involved given the special structure of our system (see fn. 20). Assuming that the qualitative properties of local behaviour are not affected by this structure, we would observe asymptotic behaviour here as well and the TSS Θ would actually never be reached: $p(a_w^*, w) = 0$ would follow. The second boundary condition is then an immediate consequence. As the state (a_w^*, b) can occur only through a transition from (a_w^*, w) but the density at (a_w^*, w) is zero, $p(a_w^*, b) = 0$ as well.

6 Conclusion

This paper has introduced methods that allow to prove existence, uniqueness and stability of distributions described by stochastic differential equations driven by a jump process. These methods were applied to a model of precautionary saving. Existence, uniqueness and stability of the optimal process for the state variables, wealth and labour market status, were proven. The results hold for an interest rate being lower than the time-preference rate.

The T-property turned out to be especially useful for models where randomness is introduced by finite-activity jump processes, i.e., by compound Poisson processes. In diffusion models, usually even the strong Feller property holds, which makes it easy to conclude the T-property. On the other hand, in models driven by infinite-activity jump processes, e.g., Lévy processes with infinite activity, it does not seem clear whether the T-property can lead to useful results. Indeed, in these models, the strong Feller property may and may not hold, see, for instance, Picard (1995/97). On the other hand, the weak Feller property is satisfied for all Lévy processes, implying existence of invariant distributions, see Applebaum (2004, theorem 3.1.9). Looking at these issues in economic applications offers many fascinating research projects for years to come.

From a more applied perspective, we derived Fokker-Planck equations for wealth and labour market status. We saw inter alia how matching and separation rates and savings shape the evolution of the wealth distribution over time. Our approach and our derivation provides a considerable generalization to existing applications in economics. This will facilitate the use these equations in many other applications in future work.

A Appendix on deriving the Fokker-Planck equations

This appendix derives the Fokker-Planck equations (25) of the wealth-employment process $(a(t), z(t))$. We proceed step by step as this facilitates applications for other purposes. Step 1: We start with some function f having as arguments the variables whose density we would like to understand. We compute the differential of this function in the usual way and also compute its expected change. Step 2: The starting point here is Dynkin's formula. This formula, intuitively speaking, gives the expected value of some function f, whose arguments are the random variables we are interested in, as the sum of the current value of f plus the integral over expected future changes of f. The expected change of f is expressed by using the density of our random variables. The Dynkin formula is differentiated with respect to time. Step 3: By using integration by parts or the adjoint operator, we get an expression for the change of the expected value of f. Step 4: A different expression for this change of the expected value can be obtained by starting from the expected value and differentiating it. Step 5: Equating the two gives the differential equations for the density.

It should be kept in mind that this approach can be applied to systems beyond (2) and (3). As long as there are one to several stochastic processes described by stochastic differential equations, this approach can be used to obtain a description of the corresponding densities. Uncertainty can stem from Brownian motion, Poisson processes, a combination of the two or Levy processes.

A.1 The expected change of some function f

Assume there is a function f having as arguments the state variables a and z. This function has a bounded support S, i.e. $f(a, z) = 0$ outside this support.[18] Heuristically, the differential of this function, using a change of variable formula,[19] gives

$$\begin{aligned} df\left(a\left(\tau\right), z\left(\tau\right)\right) = {} & f_a\left(.\right)\left\{ra\left(\tau\right) + z\left(\tau\right) - c\left(a\left(\tau\right), z\left(\tau\right)\right)\right\} d\tau \\ & + \left\{f\left(a\left(\tau\right), z\left(\tau\right) + \Delta\right) - f\left(a\left(\tau\right), z\left(\tau\right)\right)\right\} dq_\mu \\ & + \left\{f\left(a\left(\tau\right), z\left(\tau\right) - \Delta\right) - f\left(a\left(\tau\right), z\left(\tau\right)\right)\right\} dq_s. \end{aligned}$$

Due to the state-dependent arrival rates, see after (3), only one Poisson process is active at a time.

When we are interested in the expected change, we need to form expectations. Applying the conditional expectations operator E_τ and dividing by $d\tau$ yields the heuristic equation

$$\begin{aligned} \frac{E_\tau df\left(.\right)}{d\tau} = {} & f_a\left(.\right)\left\{ra\left(\tau\right) + z\left(\tau\right) - c\left(a\left(\tau\right), z\left(\tau\right)\right)\right\} \\ & + \mu\left(z\left(\tau\right)\right)\left[f\left(a\left(\tau\right), z\left(\tau\right) + \Delta\right) - f\left(a\left(\tau\right), z\left(\tau\right)\right)\right] \\ & + s\left(z\left(\tau\right)\right)\left[f\left(a\left(\tau\right), z\left(\tau\right) - \Delta\right) - f\left(a\left(\tau\right), z\left(\tau\right)\right)\right] \end{aligned} \tag{29}$$

In what follows, we denote this expression by

$$\mathcal{A}f\left(a\left(\tau\right), z\left(\tau\right)\right) \equiv \frac{E_\tau df\left(a\left(\tau\right), z\left(\tau\right)\right)}{d\tau} \tag{30}$$

which is, more precisely, the infinitesimal generator $\mathcal{A}$ defined by

$$\mathcal{A}f(a, z) = \lim_{\epsilon \searrow 0} \frac{E\left(f(z(\tau+\epsilon), a(\tau+\epsilon)) | z(\tau) = z,\ a(\tau) = a\right) - f(a, z)}{\epsilon}.$$

[18] We can make this assumption without any restriction. As we will see below, this function will not play any role in the determination of the actual density.

[19] There are formal derivations of this equation in mathematical textbooks like Protter (1995). For a more elementary presentation, see Wälde (2012, part IV).

Notice that $\mathcal{A}f(a,z)$ does not depend on τ, because the Markov-process $(a(\tau), z(\tau))$ is time-homogeneous. We understand $\mathcal{A}$ as an operator mapping functions (in a and z) to other such functions. Moreover, note that all test-functions, i.e. C^∞ functions of bounded support, are in the domain of the operator $\mathcal{A}$, i.e. the domain of all functions f such that the above limit exists (for all a and z).

A.2 Dynkin's formula and its manipulation

To abbreviate notation, we now define $x(\tau) \equiv (a(\tau), z(\tau))$. The expected value of our function $f(x(\tau))$ is by Dynkin's formula (e.g. Yuan and Mao, 2003) given by

$$Ef(x(\tau)) = Ef(x(t)) + \int_t^\tau E(\mathcal{A}f(x(s)))\,ds. \tag{31}$$

To understand this equation, use the definition in (30) and formally write it as

$$Ef(x(\tau)) = Ef(x(t)) + \int_t^\tau \frac{Edf(x(s))}{ds}ds = Ef(x(t)) + \int_t^\tau Edf(x(s)).$$

Intuitively speaking, Dynkin's formula says that the expected value of $f(x(\tau))$ is the expectation for the current value, $Ef(x(t))$ (given that we allow for a random initial condition $x(t)$), plus the "sum of" expected future changes, $\int_t^\tau Edf(x(s))$.

Let us now differentiate (31) with respect to time τ and find

$$\frac{\partial}{\partial\tau}Ef(x(\tau)) = \frac{\partial}{\partial\tau}\int_t^\tau E(\mathcal{A}f(x(s)))\,ds = E(\mathcal{A}f(x(\tau))), \tag{32}$$

where the first equality used that $Ef(x(t))$ is a constant and pulled the expectations operator into the integral. This equation says the following: We form expectations in t about $f(x(\tau))$. We now ask how this expectation changes when τ moves further into the future, i.e. we look at $\frac{\partial}{\partial\tau}E[f(x(\tau))]$. We see that this change is given by the expected change of $f(x(\tau))$, where the change is $\mathcal{A}f(x(\tau))$.

We now introduce the densities we defined in sect. 5.2.1. The expectation operator E in (32) integrates over all possible states of $x(\tau)$. When we express this joint density as $p(a,z,\tau) \equiv p(a,\tau|z)\,p_z(\tau)$, we can write (32) as

$$\begin{aligned}\frac{\partial}{\partial\tau}Ef(x(\tau)) &= E(\mathcal{A}f(x(\tau)))\\ &= p_w(\tau)\int_{-\infty}^{\infty}\mathcal{A}f(a,w)\,p(a,\tau|w)\,da + p_b(\tau)\int_{-\infty}^{\infty}\mathcal{A}f(a,b)\,p(a,\tau|b)\,da.\end{aligned}$$

Now pull $p_w(\tau)$ and $p_b(\tau)$ back into the integral and use $p(a,z,\tau) \equiv p(a,\tau|z)\,p_z(\tau)$ again for $z = w$ and $z = b$. Then

$$\begin{aligned}\frac{\partial}{\partial\tau}Ef(x(\tau)) &= \int_{-\infty}^{\infty}\mathcal{A}f(a,w)\,p(a,w,\tau)\,da + \int_{-\infty}^{\infty}\mathcal{A}f(a,b)\,p(a,b,\tau)\,da\\ &\equiv \phi_w + \phi_b.\end{aligned} \tag{33}$$

A.3 The adjoint operator and integration by parts

This is now the crucial step in obtaining a differential equation for the density. It consists in applying an integration by parts formula which allows to move the derivatives in $\mathcal{A}f(x(\tau))$ into the density $p(x,\tau)$. Let us briefly review this method, without getting into technical details. Given two functions $f, g : \mathbb{R} \to \mathbb{R}$ and two fixed real numbers $c < d$, the factor rule of differentiation

$$d(f(x) \cdot g(x)) = df(x) \cdot g(x) + f(x) \cdot dg(x) \tag{34}$$

implies that $f(d)g(d) - f(c)g(c) = \int_c^d f'(x)g(x)dx + \int_c^d f(x)g'(x)dx$, a formula referred to as partial integration rule. In particular, it also holds for $c = -\infty$ and $d = +\infty$, if the function evaluations are understood as limits for $c \to -\infty$ and $d \to +\infty$, respectively. If f has bounded support, i.e. is equal to zero outside a fixed bounded set, then the function evaluations at $\pm\infty$ vanish and we get

$$\int_{-\infty}^{+\infty} f'(x)g(x)dx = -\int_{-\infty}^{+\infty} f(x)g'(x)dx. \tag{35}$$

We now apply (35) to equation (33). We can do this as the expressions in (33) "lost" all stochastic features. To this end, insert the definition of $\mathcal{A}$ given in (30) together with (29) into (33). To avoid getting lost in long expressions, we look at the both integrals in (33) in turn. For the second, observe that

$$\mathcal{A}f(a,b) = f_a(.)\{ra + b - c(a,b)\} + \mu[f(a,w) - f(a,b)],$$

i.e. the term with s in (29) is missing given that we are in state b. Hence,

$$\begin{aligned}
\phi_b &= \int_{-\infty}^{\infty} [f_a(a,b)\{ra + b - c(a,b)\} + \mu[f(a,w) - f(a,b)]]\, p(a,b,\tau)\, da \\
&= \int_{-\infty}^{\infty} f_a(a,b)\{ra + b - c(a,b)\}\, p(a,b,\tau)\, da \\
&+ \int_{-\infty}^{\infty} \mu[f(a,w) - f(a,b)]\, p(a,b,\tau)\, da.
\end{aligned}$$

Now integrate by parts. As this integral shows, we only need to integrate by parts for the f_a term. The rest remains untouched. This gives with (35), where $g(x)$ stands for $\{ra + b - c(a,b)\}\, p(a,b,\tau)$ and x for a,

$$\begin{aligned}
\phi_b = &-\int_{-\infty}^{\infty} f(a,b)\left[\left\{r - \frac{\partial}{\partial a}c(a,b)\right\} p(a,b,\tau) + \{ra + b - c(a,b)\}\frac{\partial}{\partial a}p(a,b,\tau)\right] da \\
&+ \int_{-\infty}^{\infty} \mu[f(a,w) - f(a,b)]\, p(a,b,\tau)\, da.
\end{aligned} \tag{36}$$

Now look at the first integral of (33). After similar steps (as the principle is the same, we replace b by w and the arrival rate μ by s in the last equation), this reads

$$\begin{aligned}
\phi_w = &-\int_{-\infty}^{\infty} f(a,w)\left[\left\{r - \frac{\partial}{\partial a}c(a,w)\right\} p(a,w,\tau) + \{ra + w - c(a,w)\}\frac{\partial}{\partial a}p(a,w,\tau)\right] da \\
&+ \int_{-\infty}^{\infty} s[f(a,b) - f(a,w)]\, p(a,w,\tau)\, da.
\end{aligned} \tag{37}$$

Summarizing, we find

$$\frac{\partial}{\partial \tau} Ef(x(\tau)) = \phi_w + \phi_b$$

$$
\begin{aligned}
&= \int_{-\infty}^{\infty} f(a,w)\left[-\left\{r-\frac{\partial}{\partial a}c(a,w)\right\}p(a,w,\tau)-\{ra+w-c(a,w)\}\frac{\partial}{\partial a}p(a,w,\tau)\right]da \\
&+ \int_{-\infty}^{\infty} s\left[f(a,b)-f(a,w)\right]p(a,w,\tau)\,da \\
&+ \int_{-\infty}^{\infty} f(a,b)\left[-\left\{r-\frac{\partial}{\partial a}c(a,b)\right\}p(a,b,\tau)-\{ra+b-c(a,b)\}\frac{\partial}{\partial a}p(a,b,\tau)\right]da \\
&+ \int_{-\infty}^{\infty} \mu\left[f(a,w)-f(a,b)\right]p(a,b,\tau)\,da. \qquad (38)
\end{aligned}
$$

A.4 The expected value again

Let us now derive the second expression for the change in the expected value. By definition, and as an alternative to the Dynkin formula (31), we have

$$
Ef(x(\tau)) = \int_{-\infty}^{\infty} f(a,b)\,p(a,b,\tau)\,da + \int_{-\infty}^{\infty} f(a,w)\,p(a,w,\tau)\,da. \qquad (39)
$$

When we differentiate this expression with respect to time, we get

$$
\begin{aligned}
\frac{\partial}{\partial\tau}Ef(x(\tau)) &= \int_{-\infty}^{\infty} f(a,b)\,\frac{\partial}{\partial\tau}p(a,b,\tau)\,da \\
&+ \int_{-\infty}^{\infty} f(a,w)\,\frac{\partial}{\partial\tau}p(a,w,\tau)\,da. \qquad (40)
\end{aligned}
$$

Note that we can use

$$
\frac{\partial}{\partial\tau}\int_{-\infty}^{\infty} f(a,z)\,p(a,z,\tau)\,da = \int_{-\infty}^{\infty} f(a,z)\,\frac{\partial}{\partial\tau}p(a,z,\tau)\,da
$$

as z and a inside this integral are no longer functions of time.

A.5 Equating the two expressions

We now equate (38) with (40). Collecting terms belonging to $f(a,w)$ and $f(a,b)$ gives

$$
\int_{-\infty}^{\infty} f(a,w)\,\varphi_w da + \int_{-\infty}^{\infty} f(a,b)\,\varphi_b da = 0, \qquad (41)
$$

where

$$
\begin{aligned}
\varphi_w \equiv &-\left\{r-\frac{\partial}{\partial a}c(a,w)+s\right\}p(a,w,\tau)-\{ra+w-c(a,w)\}\frac{\partial}{\partial a}p(a,w,\tau) \\
&+\mu p(a,b,\tau)-\frac{\partial}{\partial\tau}p(a,w,\tau)
\end{aligned}
$$

and

$$
\begin{aligned}
\varphi_b \equiv &-\left\{r-\frac{\partial}{\partial a}c(a,b)+\mu\right\}p(a,b,\tau)-\{ra+b-c(a,b)\}\frac{\partial}{\partial a}p(a,b,\tau) \\
&+sp(a,w,\tau)-\frac{\partial}{\partial\tau}p(a,b,\tau).
\end{aligned}
$$

Obviously, the above equation is satisfied if

$$
\varphi_b = \varphi_w = 0. \qquad (42)
$$

These are the Fokker-Planck equations used in (25).

It is easy to see that the integral equation can only be satisfied for all functions f if these Fokker-Planck equations are satisfied. Indeed, assume that $\varphi_b > 0$ on an interval $I = [d-\epsilon, d+\epsilon]$. One can find a non-negative function f smooth in a such that $f(a,w) = 0$ for all a and

$$f(a,b) = \begin{cases} 1, & a \in [d-\epsilon/2, d+\epsilon/2], \\ 0, & a \in]-\infty, d-\epsilon] \cup [d+\epsilon, \infty[. \end{cases}$$

Inserting this test function into the integral equation gives

$$\int_{-\infty}^{\infty} f(a,w)\,\varphi_w da + \int_{-\infty}^{\infty} f(a,b)\,\varphi_b da = 0 + \int_{d-\epsilon}^{d+\epsilon} f(a,b)\,\varphi_b da > 0$$

by construction. Therefore, $\varphi_b = 0$ has to hold for all $a \in \mathbb{R}$, and similarly for φ_w.

B Referee appendix

For all further appendices, please see the Referees' appendix

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