Heterogeneous capital stocks and economic inertia in the US economy

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Abstract. The timescales of capital investments, and therefore the turnover dynamics of capital stock, have limited representation in macroeconomic modelling. This hinders analysis of economic inertia, particularly in the context of a rapid net zero transition in which vast quantities of long-lived investments may need to be prematurely abandoned. We set out to determine the minimum model that is required to accurately represent heterogeneous capital. We develop a quantitative framework for estimating the residence time of capital assets in the US economy, deriving an instructive annual distribution of investments across timescales which can be effectively aggregated into three major timescale components.

1 Introduction

1.1 The survival dynamics of capital

Inertia can be defined as the resistance of an object to changes in its course, and it applies as much to economies as it does any other physical object, even if the specifics of how we might represent the inertia of an entire economy may differ from that of, for example, a train. For the economy, inertia is determined not only by vested interests, mindsets, regulatory and political regimes (Seto et al., 2016); it is also critically determined by the heterogenous portfolio of capital that comprises the economy, and therefore the investments and activities riding on this capital.

Capital investments are invariably designed to provide returns over specific amounts of time. Typically these are years, often decades, into the future, and unless the investor is willing to walk away from the returns on their investments, the creation of a capital asset establishes a commitment to future activity and hence inertia. Indeed, the institutional inertia represented through vested interests, mindsets, regulatory and political regimes might be seen as subservient to, and in support of, the protection of future returns on investments (Foxon, 2002). Notwithstanding expensive retrofitting or premature scrapping, with consequential loss of planned returns on investment, infrastructure investments with lifetimes spanning several decades restrict transition to a rate which corresponds to their lifetime (Jaccard and Rivers, 2007).

Given that fossil fuel use has grown near exponentially for well over a hundred years (Jarvis et al., 2012), the transition to net-zero emissions within the timescales called for by the Paris process will mark a radical change in direction for the global economy, and in addition to the decarbonisation of new investments, this is likely to require the removal of large amounts of existing long-lived carbon-intensive infrastructure over the next three decades (Mercure et al., 2021). Davidsdottir and Ruth (2004) conclude that the rate of capital turnover is “the most important factor in permanently changing carbon emission profiles and energy efficiency”. Understanding the relationship between capital investments and inertia not only allows us to identify the components which most influence progress on climate change, it can also help us assess the risk of ‘stranded assets’ if the economy is forced to transition at rates faster than its infrastructural inertia would otherwise allow (Grubb, 1997; Jaccard and Rivers, 2007; Mercure et al., 2021).

The value of a capital asset depends not only on its projected annual productivity, but also on how close it is to its planned retirement. New assets being born through investment and old assets maturing and dying leads to a distribution of asset ages at any time, much like the demographics of human populations. Although this form of survival analysis is how asset values are compiled and tracked within sectoral national accounts (OECD, 2009), the expected lifetimes and age structure of these assets are seldom reported within that process. This is partly attempted in vintage capital theory, which accounts for the age distribution of capital and, in its models of growth and technological change, considers the effects of vintage on productivity (Solow and others, 1960; Boucekkine et al., 2011). However, the literature on vintage capital lacks analysis of, and theory on, the evolution of capital stocks and the timescales inherent in these processes. Specifically, why do we see the portfolio of asset service lives that we do in economies?

Neither is it commonly appreciated in the economic literature, nor in much mainstream modelling of climate change, as discussed below, that the turnover of these pools of capital provide critical insights into the inertia of the economy, and hence its ability to change direction. Indeed, the effects of economic inertia are invariably hidden in economic analysis by the specification of optimal general equilibrium pathways, which in effect transfer all dynamics into an idealised investment scenario.

As highlighted by Mercure et al. (2021), but seldom employed in this way, the conservation equation for capital assets used in national accounting procedures defines their inertial dynamics. If K_i is the value of the i’th stock (T$), the conservation of this capital follows

$$\dot{K}_i = u_i - D_i = u_i - d_i K_i \tag{1}$$

where u_i is the rate of investment into this stock (T$/yr), D_i is the annual depreciation of this stock (T$/yr), and d_i is the depreciation or decay rate (yr^{-1}). Although rarely portrayed in this way, d_i is an inverse timescale, $T_i = d_i{}^{-1}$.

As a measure of the amount of time a given capital stock is expected to survive in a cohort, T_i is the turnover timescale and is an alternative measure of asset lifetime to the mean service life of an asset – the estimated “economically useful life of an asset” used by national statistics agencies in the perpetual inventory method that creates national accounts, based on manufacturer estimates, tax records, analysis of price depreciation, and other sources (BEA, 2003; OECD, 2009), but often outdated, inconsistent between countries, and only available for selected assets and industries (Bennett et al., 2020; Rincon-Aznar et al., 2017). T_i has conceptual parallels in the dynamics of physical systems: in an equilibrium scenario, where investments and net retirements are balanced, it is functionally equivalent to residence time in a well-mixed system i.e. the average time an element is expected to remain in its pool. However, this extends beyond well-mixed systems, given it also mirrors average queuing time in queuing theory as described in the widely applicable Little's law, often invoked in microeconomics (Hendijani, 2021).

Mercure et al. (2021) point out that equation (1) defines both the dynamics of capital stocks and the timescale for these dynamics, and as such provides the appropriate vehicle for investigating economic inertia. Here T_i is the time constant or e-folding time for the temporal evolution of the first order system specified by equation (1), and therefore measures of the speed at which a stock of capital assets moves towards equilibrium for a given investment u_i. In this respect, T_i can be used as a representation of the inertia of a given asset class or sector, and if the full distribution of asset classes and their turnover timescales is known for an economy, these can aggregate to define the inertia for entire economies.

The turnover behaviour of entire sectors and economies is invariably approximated through the turnover of a single representative capital asset, with a fixed depreciation rate and hence turnover timescale. This is how the economy has been portrayed in most Integrated Assessment Models (IAMs) that have informed climate decision making. Capital depreciation rates in these models range between 2-10%, indicating turnover timescales for global capital of the order of 10-50 years (Table 1). Notably, these timescales are starting to fall outside those specified in the Paris Agreement for the full decarbonisation of the global economy, suggesting conflict between our common climate and economic objectives.

The five-fold range in turnover timescales used in IAMs suggests significant uncertainty still remains over the inertia of the global economy. This is also underscored by the lack of literature on the turnover timescales of aggregate capital stocks, suggesting that the turnover of the entire economies is poorly understood. Moreover, in an economy changing so rapidly – for example, to meet urgent climate objectives – that the lifetime of a substantial proportion of assets never reach their full lifetimes, a single representative timescale may not hold as an accurate description of the turnover dynamics of the stock; in this situation it may become necessary to represent a fuller range of capital stocks and turnover timescales. It is therefore important to have sight of the full distribution of inertia amongst assets throughout the economy to see if such systems can be faithfully reduced to a single representative stock, depreciation rate, and turnover timescale.

Table 1. Capital depreciation rates and turnover timescales in integrated assessment models.

Model	**Depreciation rate (%/yr)**	**Timescale (years)**	**Source**
DICE	2.0%	50	Nordhaus and Sztorc (2013)
WORLDSCAN	2.8%	36	Lejour and Planbureau (2006)
MERGE	4.0%	25	Manne and Richels (2005)
GTAP/GTEM-C	4.0%	25	Cai et al. (2015)
MIRAGE	4.0%	25	Bchir et al. (2003)
MEDIAM	4.5%	22	Weber et al. (2005)
SGM/Phoenix	5.0%	20	Wing et al. (2011)
MARKAL	5.0%	20	Strachan et al. (2008)
ENV-Linkages	5.0%	20	Duval and Maisonneuve (2009)
SAGE	5.0%	20	Marten et al. (2019)
FALSTAFF	6.7%	15	Jackson and Victor (2015)
E3ME	10.0%	10	Cambridge Econometrics (2019)
WITCH	10.0%	10	Emmerling et al. (2016)
G-CUBED	variable		McKibbin and Wilcoxen (1999)
GEMMA	variable		Jackson et al. (2014)
GEM-E3	variable		Capros et al. (2013)

The full distribution of turnover timescales and their relative contributions to the inertia of an economy is provided by the relationship between T and K for all elements of an economy. We refer to this as the capital-timescale relationship, which we aim to uniquely derive for the United States in this paper. Like a retirement function describes the turnover dynamics of a single asset or cohort of assets, the capital-timescale relationship describes the turnover dynamics, and therefore the inertia, of whole economies. We contend that this relationship is a fundamental property of the economy, most crucially because it identifies the timeframes on which returns are expected on investments, and therefore how financial risk is spread through time. The specification of the capital-timescale relationship also fundamentally alters our view of capital, from classes of fixed ‘artifacts’ to their corresponding dynamic classes.

1.2 Literature on heterogeneous capital dynamics

Capital is most commonly disaggregated by sector or by geography, reflecting the way it is reported in national accounts, but some attempts have been made to understand the relationship between capital stocks and turnover timescales. Studies attempting to characterise the inertial risks of a rapid climate transition have typically focused on specific assets comprising the economy, most commonly the energy sector (Davis et al., 2010; Fisch-Romito et al., 2021). Davis and Socolow (2014), for example, estimated that the existing stock of power plants will emit between 98-578 $GtCO_2$ depending on their average lifetime which they estimate falls in the range of 20–60 years. Other technology-rich models attempt some inertial analysis by focusing on technology lifecycles (Mercure et al., 2018). However, each of these tends to consider particular types of capital independent of the remaining economy; this is to neglect the interconnectivity of assets, aggregate investments and supply chains, and the inertia produced by capital throughout the whole economy (Guivarch and Hallegatte, 2011; Grubb et al., 2021).

More complex IAMs have often modelled some form of capital heterogeneity typically through incorporating a sectoral breakdown of the economy, modelling growth and depreciation rates for individual sectors in individual countries, such as in G-CUBED (McKibbin and Wilcoxen, 1999). While this provides some depth to the treatment of capital, it rarely provides much inertial heterogeneity as there is only limited variation in the representative depreciation rates – and therefore turnover timescales – between sectors (Mercure et al., 2021). There is much greater timescale variation between types of capital, for example between equipment and buildings. This is reflected in GEMMA, which “distinguishes between two types of capital stock: 1) buildings and infrastructure; 2) machinery and equipment, each of which is expected to have different characteristics in terms of depreciation rate” (Jackson et al., 2014, p. 18). GEM-E3 similarly introduces an inertial distinction between durable and non-durable goods, in addition to a sectoral and regional disaggregation (Capros et al., 2013).

A World Bank report by Shalizi and Lecocq (2009), based on earlier work by Jaccard et al. (1997), highlighted the heterogeneity of capital stock and classified it into groups for the benefit of such modelling. In their classification Group 1 capital (lifetime 5-15 years) largely consists of consumer durables, Group 2 (15-40 years) is mostly buildings, such as factories and power plants, Group 3 (40-75+ years) is infrastructure including road, rail and power distribution networks, and Group 4 covers land use and urban form which persist for “a century or more”. In their subsequent analysis they estimate that capital with lifetimes longer than 15 years – Groups 2, 3 and 4 – directly influenced 41% of global GHG emissions in 2000.

Similar analysis by Jaccard and Rivers (2007) incorporates groups of capital disaggregated by timescale, using them to disprove suggestions that economic benefit could be gained from a delay to emissions reductions, highlighting the need to instead decarbonise long-lived capital investment in the short term as a means of avoiding the impact of capital inertia. These authors note that “there is little in the way of firm empirical analysis establishing the natural turnover rate of either individual categories of capital stock or the weighted average of all of society’s capital stock,” and that “much of the recent research that has suggested benefits to delay appears to have focused on the lower part of the capital stock hierarchy: buildings and especially equipment.” They therefore represent longer-lived capital using a three-tier structure: machinery and equipment, with an estimated lifetime of 20-30 years based on available service life information (effectively a merger of Shalizi and Lecocq (2009)’s Groups 1 and 2); housing, with a lifetime of 71.5 years; and urban form, with a lifetime of 117 years.

This attention to the heterogeneity of capital stock has not become common practice in IAMs or other climate-economy analysis, and the categorisations adopted by Jaccard and Rivers (2007) and Shalizi and Lecocq (2009) have not appeared in much further work. Grubb et al., (2021, p. 12) state that with the exception of some dedicated models, “treatment of dynamic realism in standard stylized IAMs is patchy at best”. Like Jaccard and Rivers (2007), we suggest that this is heavily influenced by the lack of data on, and a framework for applying, the timescale dynamics of capital. Contrary to some of the approaches taken in the transition risks literature, we are also conscious that the capital stock of macroeconomies is heavily interlinked and that both emissions and inertia are produced by capital in a broad range of sectors, with a broad range of timescales, therefore necessitating an understanding of capital inertia at the complete macroeconomic level, not just for individual sectors or types of fixed capital.

The economic risk from a rapid economic transition discussed in section 1.1 cannot be estimated, and the necessary planning cannot be conducted to mitigate the risk to economies and to populations, without an accurate inclusion of capital inertia in IAMs and other climate-economy models. We propose in this paper a method for empirically deriving turnover timescales for capital assets that is not reliant on estimated service lives, and for aggregating these into a capital-timescale relationship, which will not only be critical to understanding how inertia is distributed in the economy, and provide a highly instructive description of capital investment patterns, their and structural change of the US economy over time, but will also reveal whether a single representative timescale can provide an appropriate approximation of macroeconomic capital dynamics. If a single timescale is not appropriate, we aim to derive the simplest representative model that can represent capital inertia in IAMs, short of modelling the full capital-timescale relationship.

In section 2 we will outline our method for deriving turnover times using equation (1), using data from the US as an example. In section 3 we will aggregate these to a capital-timescale relationship for the US economy, and investigate the minimum model necessary to represent this relationship in IAMs and other models that simulate capital dynamics, with evidence provided in section 4 for the effectiveness of this model.

2 Deriving turnover times for US capital assets

The US Bureau of Economic Analysis (BEA) publish detailed estimates of the total capital value of 96 private non-residential fixed asset classes in 63 industries (giving a total of 2972 sector-specific assets with a non-zero capital value), as well as 51 types of residential fixed assets, and 28 consumer durable goods asset classes. This provides nearly 3000 unique asset classes comprising components of the US economy – a far larger number than those for which service lives are typically provided for. For each class the BEA identify not only the current value, but unlike most other published national accounts, they also report levels of investment and depreciation in any given year from 1947.

Given the way depreciation, D, is handled in the perpetual inventory method, the depreciation rate d is an effective cohort-level property reflecting two features of the perpetual inventory approach. Firstly, it describes the turnover of assets within the cohort as determined by the assumed representative 'service life' for the cohort and any assumed survival function around this. Secondly, depreciation also relates to the rate of production of capital services from a cohort because this is modelled as the outflow of capital into the allied production processes (OECD, 2009; Katz, 2015). This outflow serves two purposes. On the one hand it forms part of the forward valuation of the stock, because it is the future flow of all capital services that determine future productive returns, corrected to net present value assuming a particular discount rate (OECD, 2009; Katz, 2015). However, this capital services outflow, just like the effects of physical depreciation, also describes the loss of capital at a rate proportional to the magnitude of the capital stock. As a result, it behaves like physical depreciation, and the net effect of these two different capital loss functions is an expectation that equation (1) holds for every asset class in the BEA database.

Given the array of definitions and deployments of depreciation in national accounts like that of the BEA it is perhaps more appropriate to define the turnover dynamics of an asset class directly using the perpetual inventory equation (1). If all losses of capital from an asset class are proportional to the value size of that class, then from equation (1) T_i can be estimated directly for every asset class as:

$$T_i = \frac{K_i}{D_i} \qquad (2).$$

This provides direct estimates of the turnover timescale associated with each asset class including not only the physical effects of depreciation of cohorts, but also the perceived consumption of capital in value production. Figure 1 shows the relationship between depreciation and capital value for all 3015 BEA asset classes we consider, covering the period 1947-2018. From this we can see that, despite the complexities and heterogeneity of practice associated with specifying depreciation and value production in the BEA perpetual inventory, in practically every class K_i is near linear in D_i across time reflecting the fact that d_i and hence T_i are near constant within each class.

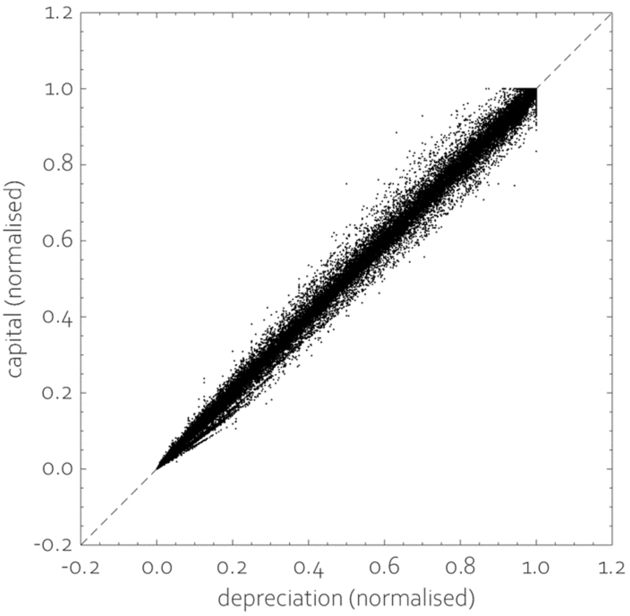

Figure 1. The relationship between annual depreciation and capital value for all 3015 asset classes comprising the US economy presented in the BEA database, 1947-2018 (N = 217,080). Both capital value and depreciation are normalised by the within class maximum. The 1:1 line (--) shows compliance with the linear model (2).

In line with equation (2) and the evidence for linearity between K_i and D_i seen in Figure 1, we estimate T_i using simple least squares applied to each of the 3015 asset categories assuming T_i doesn't change across the 72 year sample. The corresponding relationship between T_i and K_i for each asset class is shown in Figure 2.

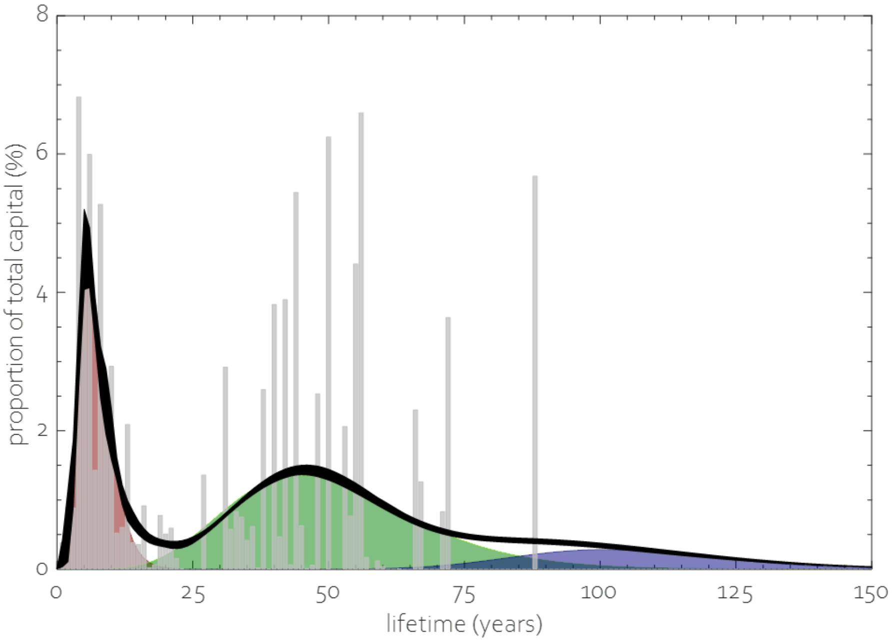

Figure 2. The relationship between turnover timescale and capital value. Bars represent the 3015 BEA asset categories. Black envelope is the 95 % confidence interval of the corresponding survival function. The three coloured regions are a statistical partitioning of the survival function into constituent gamma distributions (see Table 2 for details).

Further, we validate the accuracy of our turnover timescale estimates by comparing them to the mean service lives used in national accounts to complete the perpetual inventory method. These are taken from BEA (2003) where a good match is possible; where this is not possible, mean values from other global sources quoted in Rincon-Aznar et al. (2017) are used; where no agency has a reliable estimate, the asset class is not plotted. From Figure 3 we can see there is broad agreement between our turnover timescales based on equation (2) and the mean service lives used in various ways to define depreciations, reflecting the dominance of natural retirement at the end of service life in the turnover dynamics of many asset classes in the BEA perpetual inventory. However, there are also significant differences between the two, particularly in asset classes with mean service lives greater than 20 years. This is likely to reflect the effects of nonlinearity in the assumed survival function for certain classes (Katz, 2015), and the complex effects of capital flows on the loss of capital through their productive use.

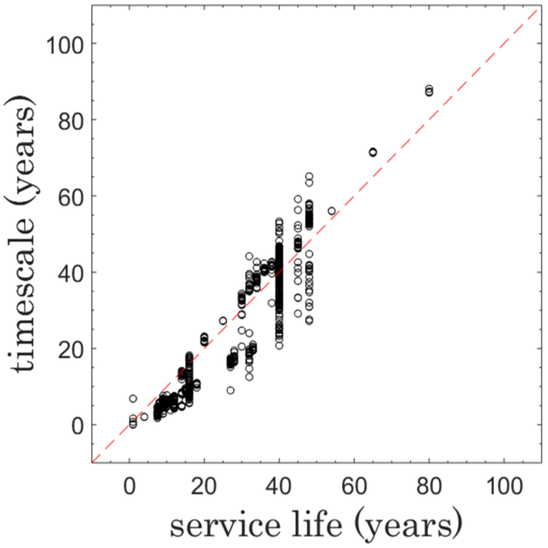

Figure 3. The relationship between the quoted mean service lives of asset classes, where they are available in the literature (BEA, 2003; Rincon-Aznar et al., 2017), and the corresponding turnover timescale estimated from equation (2) using linear least squares.

We hold that it is the turnover timescale T_i that more accurately reflects the inertial dynamics in each asset class, due to the quality issues with service lives raised in section 1.1, and because it is the aggregate effects of all effective forms of capital loss including natural retirement, physical deterioration, obsolescence and accidental damage. Allied to this, capital is defined by the conservation equation (1) and hence it is logical for its turnover dynamics to be derived from this first order process.

3 The capital-timescale relationship of the US economy

The method described in Section 2 provides a representative turnover timescale for each of the 3015 capital asset classes in the BEA account of the US economy, but like service lives, these invariably reflect only the first moment of a range of expected lifetimes within that class; the asset class 'Aircraft', as an example, will contain a diversity of aircraft types and models each with different expected lifetimes, and aircraft built to the same model will have a probabilistic chance of retirement according to a particular survival function. If we want to capture the fact that each asset class is comprised of large cohorts of elements, and that this should be accounted for in the inertial dynamics, we need to populate each asset class accordingly. The BEA assume symmetrical (bell-shaped) Winfrey mortality functions, where discards are spread over the period ±55% of the average service life, except for residential buildings which are spread over ±95% of the average service life (OECD, 1993). We replicate this, using a normal distribution with the same spread to redistribute the capital value in any given asset class across all timescales of interest.

Having estimated the full cohort of timescales for each unique asset class, we can now group capital with respect to these timescales. This is significant in reassigning capital from its familiar artefact-orientated ‘asset’ classification into the corresponding ‘timescale’, and hence inertial, class. From this, we can then assess the extent of investments made that contribute to the overall inertia of the US economy.

The result is shown in Figure 2. The first thing to note is how remarkably stationary this capital-timescale relationship is. Many of the 3015 sectors come and go in their relative importance over the 72 years. Computer hardware and software have surged in prominence, for example, while equipment for heavy industry has shrunk. However, in the timescale space this ebb and flow is lost, as if the more important feature of investment is not what things are called, but rather how long they reside in the economy providing returns. Allied to this, it appears to be the spectrum of timescales of these returns that is preserved, which may suggest that capital heterogeneity is important as a means of spreading risk and opportunities.

We find from the capital-timescale relationship that the US economy can be described as the sum of three timescale-distinct sets of timescales which we refer to as fast, medium and slow capital (Fig. 2). Of these, medium capital makes up a majority of capital (57%) and has a first moment of 51 years (Table 2). This maps relatively well to Group 2 and much of Group 3 identified by Shalizi and Lecocq, (2009). The fast capital component has a first moment of 7 years and contributes some 30 percent of all capital, paralleling Shalizi and Lecocq's (2009) Group 1.

Table 2. Partitioning of the capital-timescales distribution shown in Figure 3. Each distribution is a gamma function simultaneously fitted to the overall distribution. The table reports the first moment T and percent contribution to total capital f. Numbers in brackets are the recession time constants from Figure 5.

Parameter	Value	Units
$\boldsymbol{T_{fast}}$	7.16 (5.34)	yrs
$\boldsymbol{f_{fast}}$	30.0	%
$\boldsymbol{T_{medium}}$	50.64 (32.14)	yrs
$\boldsymbol{f_{medium}}$	56.8	%
$\boldsymbol{T_{slow}}$	104.25 (91.05)	yrs
$\boldsymbol{f_{slow}}$	13.2	%

The slow group, meanwhile, dominates the distribution beyond 75 years, making up just 13 % of total capital. These have a large spread of timescales stretching beyond 200 years. It is dominated by real estate, but also includes some other long-lived asset classes that fit the description of ‘urban form’ used for the uppermost capital group in both Shalizi and Lecocq (2009) and Jaccard and Rivers (2007), such as sewer systems (Table 2). This group therefore maps to Group 4 and the ‘urban form’ group in these papers respectively, with the addition of some longer-lived real estate, which they situate as part of Group 3/‘Buildings’.

4 What is representative?

The first moment for the full capital-timescale distribution for the US economy shown in Figure 2 is 44.7 years, suggesting a representative depreciation rate on an aggregate capital stock of 2.24 %/yr, very much at the lower end of values currently used in IAM frameworks attempting to capture the inertia of produced capital (Table 1). However, if we divide total capital by total depreciations in the BEA database following equation (2) we get a representative timescale of only 16.1 years and hence a depreciation rate of 6.22 %/yr, closer to the upper end of the IAM spectrum. This difference possibly explains the lack of consensus in macroeconomics over aggregate depreciation rate values, with on the one hand observed capital portfolio turnovers suggesting low depreciation rates and long timescales, while on the other growth models suggesting much shorter effective turnover and hence higher depreciation. These effective estimates give lower turnover timescales because of growth differentially amplifying the effects of shorter timescales.

To illustrate the minimum representative model of inertia, we simulate the decay dynamics of the aggregate capital of the US economy as if new investment were suddenly withdrawn, with existing capital depreciating according to equation (1). This parallels an idealised structural shift where investment is diverted from ‘brown’ to ‘green’ assets (Mercure et al., 2021). The decay profile of total capital is shown in Figure 4, and we find that the recession dynamics have three characteristic timescales of 91, 32 and 5 years (Table 2). Although not perfectly aligning with the first moments of the capital-timescale distribution shown in Figure 2, this demonstrates that the single timescales used in IAMs are probably inadequate when describing any transition involving declining high carbon capital stocks.

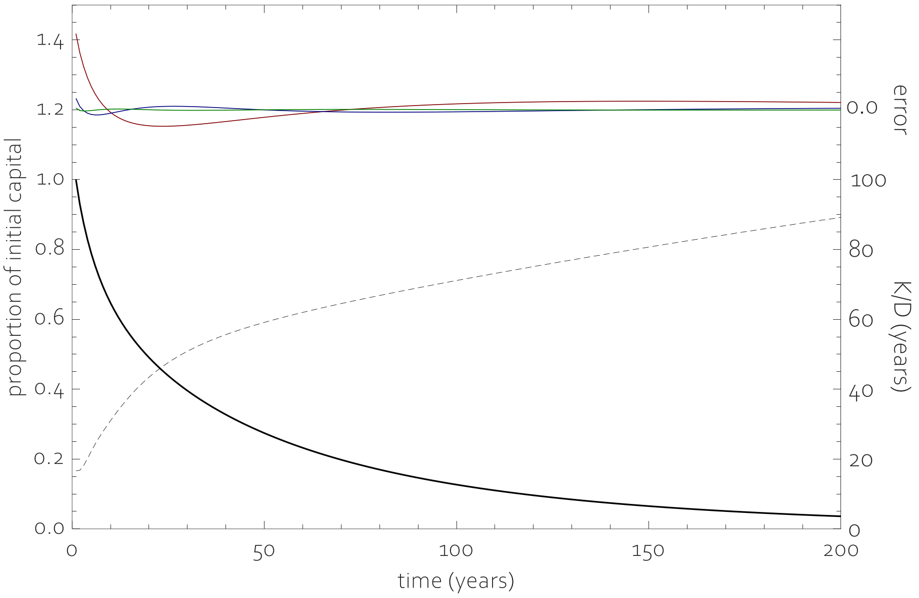

Figure 4. The decay response of capital given the capital-timescale relationship shown in Figure 3 (black solid). The error when fitting a first (red), second (blue) and third (green) order response to the decay are also shown, and the third order time constants are presented in Table 2. Lastly, the effective turnover timescale given by the ratio of capital to depreciation is also shown (dashed).

5 Discussion and conclusions

The capital-timescales structure of the US economy has remained remarkably consistent over time, with little change in the shape, the contributions of the three groups, or their representative timescales between 1947 and 2018 (Fig. 2). It holds throughout this period despite almost a dozen recessions including the Great Recession and the 1970 energy crises, technological innovation, wars, and a greater than 60-fold increase in the total capital value. During this time, many asset types have come and gone, and the relative importance of sectors has ebbed and flowed significantly, yet the timescales at which investments are being made and returns expected are not. This suggests to us that, despite our attachment to the names of the things we create, how long they live and hence the returns they produce is far more important. We also conclude that the spread of investment to create the distinct capital-timescale pattern we observe, with three distinct modes, is significant, and suggest that it possibly reflects a form of emergent strategy in which the frequency spectrum of returns is important.

Practically, our results support a similar timescale grouping to Shalizi and Lecocq (2009), highlighting that in anything other than business-as-usual growth scenarios, single timescale/depreciation rate IAMs will not adequately capture the inertial dynamics of the economy, and a minimum of three representative stocks – one fast, one intermediate, one slow turnover – is required. This is an urgent consideration as these scenarios, and the stationarity described above, are under threat as the climate crisis looms. Investment decisions over the past century have largely been made on the assumed stationarity of the climate, relying on investments playing out their lifetimes and delivering returns in a climate that is as predictable as it was in the past, but climate change will affect the attrition rate on capital structures requiring infrastructure planning and investment strategies to be revised (Giordano, 2012).

Even where the survival of capital is not directly under threat from the impacts of climate change, the lifetime and therefore the return on investments may be cut short by a rapid climate transition which requires the removal of active carbon-emitting infrastructure. For instance, the 2050 deadline to fully decarbonise the economy, identified by the IPCC as necessary to avoid dangerous climate change and established in law as a target for the US, is likely to necessitate capital with remaining lifetimes beyond that timescale – our medium and slow groups – to be adapted to produce net zero carbon emissions, or to be decommissioned before that date (Jaccard and Rivers, 2007). The potential for economic impact as a result of this adaptation or loss of future returns produces a form of infrastructural inertia in the economy, with past investment decisions binding future pathways for society; this path dependence offers a powerful argument for a precautionary approach to current such decisions (Seto et al., 2016; Hoepner and Rogelj, 2021) and for urgent action on those sectors with the greatest inertia (Vogt-Schilb et al., 2018). Although the turnover timescale method and the capital-timescale relationship we have developed here are important for understanding these risks and how to prioritorise any such retirements (Mercure et al., 2021; Semieniuk et al., 2021), the effects of climate change and any climate transition will reshape the survival functions of capital, taking us into uncharted territory.

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