Transformative AI, existential risk, and asset pricing*

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Abstract

We study the implications of transformative artificial intelligence for asset prices, and in particular, how financial market prices can be used to forecast the arrival of such technology. We take into account the double-edged nature of transformative AI: while advanced AI could lead to a rapid acceleration in economic growth, some researchers are concerned that building a superintelligence misaligned with human values could create an existential risk for humanity. We show that under standard asset pricing theory, either possibility – aligned AI accelerating growth or unaligned AI risking extinction – would predict a large increase in *real interest rates*, due to consumption smoothing. The simple logic is that, under expectations of either rapid future growth or future extinction, agents will save less, increasing real interest rates. We contribute a variety of new empirical evidence confirming that, contrary to some recent work, higher growth expectations cause higher long-term real interest rates, as measured using inflation-linked bonds and rich cross-country survey data on inflation expectations. We conclude that monitoring real interest rates is a promising framework for forecasting AI timelines.

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1 Introduction

Background. Recent rapid progress in generative artificial intelligence has highlighted the possibility that humanity may soon develop "transformative AI": AI technology that precipitates a transition comparable to the agricultural or industrial revolutions. Leading research labs like OpenAI and Google DeepMind bluntly declare their mission to build "artificial general intelligence" that can perform at or above human level on all tasks (OpenAI 2023; DeepMind 2023). The possibility of relatively short timelines for AGI is taken seriously by leading machine learning researchers, who in a 2023 survey gave a 10% chance that by 2027 AI will outperform humans at all tasks and a median forecast for such capability by 2047 (Grace, Stewart, et al. 2024).

The prospect of such transformative AI is a "double-edged sword", in the language of Jones (2023). On the one hand, continued AI innovations like those which have occurred in protein folding or text generation could accelerate economic growth and improve well-being. In the same way that growth increased by roughly an order of magnitude with the industrial revolution, some have predicted that transformative AI automating all tasks would increase growth by another order of magnitude, with GDP growth rising to 30% or more per year (Davidson 2021). Indeed, standard models of economic growth extended to include human-level AI can predict even economic singularities: infinite output in finite time (Aghion, Jones, and Jones 2018; Trammell and Korinek 2020).

On the other hand, many in the AI research community and in the broader public are concerned that such powerful AI technology could create severe risks, even an "existential risk" for the human species. This concern is driven by the challenge of ensuring that smarter-than-human AI technology pursues goals matching human values, rather than pursuing unintended and undesirable goals: the "AI alignment problem" (Ngo 2022; Yudkowsky 2016). The 2023 survey of machine learning researchers found that – among those who chose to respond – the median believed there to be a 5% chance that human-level AI results in "human extinction or similarly permanent and severe disempowerment of the human species" (Grace, Stewart, et al. 2024). This scenario is referred to as *unaligned* AI, in contrast to the growth-enhancing scenario with *aligned* AI.

Most economists, meanwhile, have been notoriously less likely to agree that transformative AI will be developed soon, less optimistic that aligned AI would radically accelerate economic growth, and less pessimistic that unaligned AI could pose an existential risk to human survival, on average (Korinek et al forthcoming).

This paper. We study the implications of transformative AI for asset prices and show how financial market prices can be used to forecast the arrival of such technology. In particular, we show that the prospect of transformative AI would predict a large increase in *real interest rates*, and would do so under expectations of either aligned or unaligned AI. As a result, to the extent that financial markets are efficient information aggregators, the level of long-term real interest rates can be used to help forecast the development of transformative AI.

This predicted rise in real interest rates is a basic implication of all modern asset pricing models, and is simply an application of the logic of consumption smoothing. Consider the case of *aligned* transformative AI: with the prospect of growth-induced high consumption and low marginal utility in the future, agents today would want to save less or borrow more, pushing up real interest rates at the relevant maturity. Similarly, if the market were forecasting future AI to be *unaligned* and to extinguish humanity, then there would also be no desire to save for the future (due to future extinction), again pushing up real interest rates at the appropriate maturity.

Empirical results on real rates. We offer new empirical evidence confirming that indeed, in the data, higher future growth increases real interest rates.

Measuring real interest rates is challenging. Existing work estimates real interest rates by using the nominal yields on nominal bonds and attempting to construct a measure of expected inflation to subtract from the nominal yields. The estimation of expected inflation needed for this, however, is difficult. We tackle this difficulty in two ways.

First, we use real yields from *inflation-linked bonds*, which provide a cleaner direct measurement of real rates compared to estimation based on nominal yields. To our knowledge, prior literature on the topic has not used real rates from inflation-linked bonds only because these bonds are comparatively new, with 20 or 30 years of data available.

Using these real yields directly from inflation-linked bonds, we show that higher real rates today indeed predict higher future GDP growth. Figure 1 shows the correlations for the US, UK, Australia, and Canada at the 10-, 15-, and 20-year horizons, comparing real interest rates over the relevant horizon with future GDP growth at the same horizon. While this data is merely correlational, and the data points are not independent of each other, it is suggestive evidence that growth and real interest rates are significantly linked.

Second, we use rich survey data on long-term inflation expectations from across 89 countries over the last 30 years to construct real interest rates from nominal bonds. The survey data is a unique dataset of forecasts from professional forecasters collected by Consensus Economics. By using forward-looking forecasts of inflation – rather than backwards-looking statistical measures of expected inflation, as in much of the literature – we are able to construct a large panel of real interest rate data. Our results using this data are similar to the results using inflation-linked bonds, and combined, provide the best evidence we are aware of about the link between ex-ante real rates and expected growth.

Other asset prices. We also briefly discuss the implications of transformative AI for other asset prices. We highlight that the implications of transformative AI for *equity* prices are much more ambiguous than for real interest rates. Among other issues, while the prospect of *aligned* AI leading to rapid growth may increase equity valuations, expectations of *unaligned* AI on the other hand would lower valuations. The net effect is qualitatively ambiguous, making stocks more difficult to use as a barometer for market expectations for AI timelines without taking a quantitative stand on magnitudes. Moreover, even

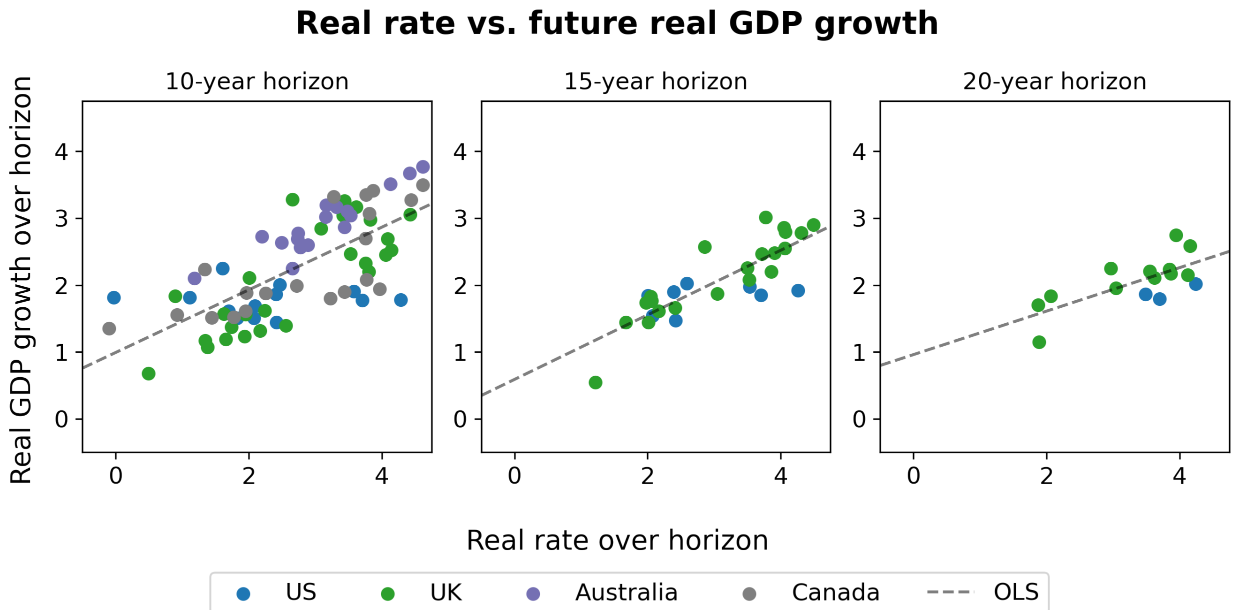

Figure 1: Real interest rates from inflation-linked bonds versus future GDP growth. Each subfigure plots a scatterplot of real interest rates of the titular maturity on the x-axis versus *future* annual GDP growth over the same horizon on the y-axis. Real interest rates are measured using yields on inflation-linked bonds on the last trading day of each year. The scatter plots show all available data up through 2022, for the US (since 1999), the UK (since 1985), Australia (since 1995), and Canada (since 1991), where the end date of the data depends on the time horizon. More details on data sources are given in section 3.

whether higher expected future growth from aligned AI raises or lowers overall equity valuations is itself unclear, and depends critically on the intertemporal elasticity of substitution: larger future cashflows due to economic acceleration may be more than offset by the higher discount rate previously discussed. Even setting these two issues to the side, additionally it is not obvious that AI companies will capture *profits* from developing advanced AI – which is necessary for the expectation of AI to show up in equity prices – or that any companies which do capture profits are currently publicly traded. Finally, we also touch on the implications of transformative AI for land and commodity prices.

Outline. The structure of this paper is as follows. In section 2, we define the "transformative AI" scenario under consideration, and provide a brief overview of existing related work, which may be less familiar to many readers with a background in economics. We also briefly review the relevant and burgeoning literature on the economics of AI. In section 3, we demonstrate the simple result that growth and death risk raise real interest rates in a very broad set of models. Section 4 presents evidence that higher growth expectations raise real rates today, and offers some commentary on existing analysis of this topic. Section 5 reviews relevant literature finding that mortality and savings behavior is related. Section 6 discusses the implications of transformative AI for equities, land, and commodities. Section 7 concludes.

2 Defining transformative AI and relevant literature

In this section, we define the "transformative AI" scenario under consideration and provide context on existing research on the topic.[1] Much of this work may be unfamiliar to economists; familiar readers may wish to skip to section 3 after reviewing the definition of transformative AI in section 2.1, which is referenced throughout the paper.

2.1 Defining transformative AI

For the purposes of this paper, we consider the prospect of "transformative AI" as defined informally by Karnofsky (2016): artificial intelligence technology that has at least as profound an impact on the human trajectory as did the industrial revolution or agricultural revolution. As Karnofsky (2016) discusses, this term is similar to other concepts such as "artificial general intelligence" and "superintelligence", but is intended to be more inclusive – capturing technology which is transformative, even if such technology is not able to match all human abilities.

We operationalize this definition of transformative AI by dividing two cases.

Definition (Aligned transformative AI)**.** Aligned transformative AI is technology that causes growth in global GDP in excess of 30% per year.

Definition (Unaligned AI)**.** Unaligned AI is technology that causes the extinction of humanity.

Our definition of aligned transformative AI follows Davidson (2021), who defines "explosive growth" as growth in gross world product of at least 30%, i.e. an increase in growth rates by an order of magnitude.[2] He discusses the possibility that transformative AI could cause such explosive growth. We take this as our benchmark for the effect of aligned AI, though given the unprecedented magnitude under consideration, these numbers should clearly be taken as rough approximations rather than as precise predictions.[3] Our definition of the unaligned AI scenario follows the literature on the topic, which is summarized in section 2.4.

[1] Later sections also discuss relevant economics literature in the context of our analysis: section 4 reviews existing work on the relationship between real interest rates and growth; section 5 reviews existing work on the relationship between real interest rates and mortality or catastrophe risk; and section 6 reviews relevant work on other asset prices.

[2] See also Hanson (2000).

[3] One alternative would be to use a definition in terms of task models (Zeira 1998). For example, aligned transformative AI could be defined as technology which can perform 100% of "cognitive" tasks that human perform, as in Davidson (2023). Because such technology would plausibly rapidly accelerate GDP growth – see Davidson (2023) for structural estimates – for the purposes of this paper the distinction in definitions is not important.

2.2 Forecasting transformative AI

Analysis of the possibilities for artificial intelligence has a long history. Good (1965) originated the concept of an "intelligence explosion", a hypothesized phenomenon where AI systems gain the ability to improve their own algorithms and architectures, leading to recursive improvement and rapid increases in intelligence and power. Vinge (1993) originated and Kurzweil (2005) popularized the related concept of a "technological singularity", referring to an acceleration in technological progress occurring so quickly that it would be difficult to predict ex ante how the world would look after. While these earlier analyses were mostly speculative, rapid progress in machine learning over the last decade has resulted in analysis more grounded in the reality of modern AI.

Cotra (2020) provides an influential benchmark forecast for the development of transformative AI. Her framework is based on estimating the number of computations the human brain can perform per second. She then forecasts forward trends in the computational power of computers, using long-run trends like Moore's Law. She combines these to estimate the date by which computing power could match that of the human brain. Her analysis generates a distribution of estimates, with Cotra (2020) estimating a median arrival date of 2050 for transformative AI, and the updated analysis in Cotra (2022) forecasting a median of 2040. These estimates, however, are highly uncertain: the analysis of Cotra (2020) showed a 10% probability of transformative AI before 2030 and a 20% probability that transformative AI is not developed until after 2100.

Surveys of machine learning researchers are not too far off from the Cotra (2020) estimates. Grace, Salvatier, et al. (2018) survey 352 AI researchers on "when unaided machines can accomplish every task better and more cheaply than human workers" and find a median of 2061. Stein-Perlman, Weinstein-Raun, and Grace (2022) run an updated version of this survey with 738 respondents, and find a median of 2058 for the same question; Grace, Stewart, et al. (2024), in the latest iteration of the same survey with 2,778 published researchers, find a median of 2047. These results again come with significant dispersion.

Davidson (2023) uses a large-scale semi-endogenous growth model, a la Jones (1995), to forecast timelines for the development of transformative AI, and has a median forecast of 2043 for the development of transformative AI. This approach to forecasting the path of AI is analogous to the "dynamic integrated-climate economy" (DICE) modeling approach used in the climate literature: it is a computational integrated assessment model with an economics foundation.

Economists generally have been more cautious about forecasting the development of transformative AI. Korinek et al (forthcoming) survey economists and AI researchers about the probability of the development of "human-level machine intelligence". The median response of AI researchers in this survey was before 2050; for economists, the median response was after 2070.[4] Another survey by the Centre for Macroeconomics among European economists asked about the implications of progress in AI for global economic growth over the next decade. 64% of respondents answered growth would "in-

[4] These results were sensitive to how the question was asked.

crease (to 4-6%)", though in open-ended comments many of these respondents noted that they thought the increase would be smaller; 36% of respondents answered growth would "remain unchanged" (CFM 2023).

2.3 The economics of transformative AI

A small but important economics literature has analyzed the economics of transformative AI. A larger literature studies the economics of prosaic AI more broadly.[5]

The seminal contribution to this literature is Aghion, Jones, and Jones (2018), who consider a range of possible scenarios for the effects of artificial intelligence on economic growth. Of particular interest is their result that if AI automates tasks in the *ideas* production function (rather than the goods production function), then speeding up the rate of automation is equivalent to speeding up the rate of population growth. It is well-known that in semi-endogenous growth models, the rate of growth on the balanced growth path is proportional to population growth. Under some conditions, they show there can be a 'singularity' in the sense of reaching infinite output in finite time. They also highlight the critical role of potential bottleneck tasks in preventing (long-run) growth explosions.[6]

Trammell and Korinek (2020) offer a literature review of how the many permutations of different assumptions on the role of AI in growth models have differential implications for growth and for macroeconomic aggregates like the labor share. Their review highlights a wide range of possibilities, depending on what is assumed about the structure of production.[7]

2.4 The alignment problem and the economics of existential risk

Concern over risks from artificial intelligence technology are widespread not just among the public and in fiction, but also among many scientists across many fields. This has recently been captured by the "Statement on AI Risk" signed by a long list of AI scientists and public figures, stating, "Mitigating the risk of extinction from AI should be a global priority alongside other societal-scale risks such as pandemics and nuclear war" (Center for AI Safety 2023).

[5]See, for example: Agrawal, McHale, and Oettl (2018), Acemoglu and Restrepo (2018), Beraja, Kao, et al. (2023), and Brynjolfsson and McAfee (2014).

[6]Clancy (2022) offers a readable summary. Korinek and Stiglitz (2018), in the same volume as Aghion, Jones, and Jones (2018), analyzes how the development of AI could affect the income distribution (see also Korinek 2019).

[7]Nordhaus (2021) builds a model of one specific set of assumptions of these many permutations, and considers whether the empirical predictions of those assumptions are born out in the data, as an attempt to forecast "are we approaching an economic singularity?". Korinek (2019) analyzes the Malthusian implications of AI that can substitute for humans. Besiroglu, Emery-Xu, and Thompson (2022) show that if the capital share in the ideas production function increases, then the long-run growth rate also increases. They show that the capital share of deep learning for computer vision is substantially higher than the capital share for prior research technologies, and estimate that if the capital share of the economy-wide ideas production function rose to the level of that for computer vision, then growth would be three to eight times higher.

The basic concern is that it may be technically challenging to successfully program artificial intelligence technology in such a way that it behaves in line with human values. Just as software bugs can have large negative consequences in more mundane computer systems, software bugs in very powerful artificial intelligence systems could have correspondingly impactful negative consequences.

Ngo (2022) provides an overview of this "AI alignment problem" from the perspective of modern deep learning methods. Bostrom (2014) provides a book-length treatment from just before the deep learning revolution. Yudkowsky (2016) provides a conceptual argument for why the task of ensuring agents which are more intelligent than humans will act in line with human values should be perceived as challenging. Karnofsky (2021) offers a comprehensive and updated summary of these arguments. There is limited analysis of the AI alignment problem from an economics perspective. Hadfield-Menell and Hadfield (2019), Gans (2018), and Ely and Szentes (2023) are three exceptions.

In the economics literature, an important set of papers has analyzed how we should think about the tradeoffs between technology which brings positive benefits but creates existential risks. The important work of Aschenbrenner (2020) builds a model of directed technical change, extending the work of Jones (2016), where society can invest either in technology that increases consumption or technology that reduces the risk of death. Aschenbrenner shows that under reasonable parameters, optimally, existential risk follows a Kuznets-style curve: first rising, as society values consumption, and then falling, as the diminishing marginal utility of additional consumption is outweighed by the benefit of lower existential risk. Trammell (2020) shows a similar result in the context of an exogenous growth model. Jones (2023) summarizes these frameworks. Acemoglu and Lensman (2023) study the optimal regulation of technology adoption when that technology poses a (non-existential) disaster risk, motivated by AI technology. They show that if adoption is irreversible, then the path of adoption should be gradual, taking a 'wait-and-see' approach.[8]

3 Real interest rates, growth, and mortality in theory

In this section, we demonstrate that real interest rates are connected to both expected economic growth and mortality across a broad range of modeling frameworks. The connection is driven by the same, simple economic logic across all modeling frameworks: higher expected growth and higher mortality risk both reduce the supply of savings, which pushes up real interest rates. We show this logic holds in the three classes of models, covering the modern asset pricing modeling frameworks:

(i) Representative agent models

(ii) Incomplete markets models

(iii) Overlapping generations models

[8] See also Gans (2024), Beraja and Zorzi (2022), and Lehr and Restrepo (2022)

Since these results are known in the literature, we focus on results and intuition, and refer interested readers to relevant papers for full derivations. We also consider extensions with behavioral frictions (rule-of-thumb behavior and household myopia); nonstandard preferences (recursive preferences and habit formation); and models with new goods, which create nonstationary utility functions.

We conclude the section by emphasizing how the relationship between real rates and growth depends critically on the time horizon. In the short run – at business cycle horizons – *real interest rates that are too high cause low growth*, due to nominal rigidities. In the long run, nominal rigidities fade, and *high growth causes high real rates*. Hence, our empirical analyses in sections 4 and 5 focus on long-term real rates.

3.1 Representative agent models

It is well-known that in the canonical infinitely-lived representative agent model that the real interest rate is closely tied to growth and death.

The Ramsey rule. In the deterministic case with time-separable utility over the level of consumption, the real interest rate has a particularly simple expression – the canonical "Ramsey rule":

$$r = \rho + \frac{1}{\sigma} g \tag{1}$$

Here, r is the real interest rate over some time horizon, $\rho > 0$ is the rate of pure time preference, $\sigma > 0$ is the elasticity of intertemporal substitution, and g is the growth rate of consumption. With σ usually calibrated somewhere between 0.2 and 2 – an issue to which we return – we see that higher growth implies a higher real rate. Higher existential risk shows up here as a higher rate of time discounting ρ, thus also implying a higher real rate.

Benchmark calibration under transformative AI. Consider briefly a benchmark calibration at the annual frequency with $\sigma = 1$ (log utility) and $\rho = 0.01$ for a back-of-the-envelope calculation. Then, a growth rate of 1% per capita would imply a real interest rate of 2% under the Ramsey rule – not far off the level seen in advanced economies today. Meanwhile, a transformative AI-induced growth explosion causing the growth rate g to rise to 30% (as defined in section 2.1) would raise real interest rates to 31%. This would be an unprecedentedly high level.

The Euler equation. The Ramsey rule analysis above importantly assumed away uncertainty, among other things. Consider an infinitely-lived household with expected, discounted, time-separable utility over the level of consumption. Denote the period utility function $u(C_t)$ where C_t is consumption and u has diminishing marginal utility, $u' > 0$

and $u'' < 0$. Denote the subjective discount rate as β, and the probability of death in period t as δ. In this representative agent framework, the probability of death δ is equivalent to the probability of extinction.

The resulting intertemporal optimality condition is the well-known Euler equation:

$$1 = \beta\delta\mathbb{E}_t\left[\frac{u'(C_{t+1})}{u'(C_t)}\right](1 + r_t) \tag{2}$$

Suppose the path of consumption does not adjust, as in an endowment economy, for simplicity.

First, observe that higher death risk causes a higher real rate. A higher death risk is a lower probability of surviving until the next period, δ. A lower δ in (2) requires a higher real rate r_t. The intuition is that a higher probability of death shifts in the willingness to supply savings.

Second, observe that higher consumption growth, all else equal, also raises the real rate. Consider a shock that increases next-period consumption in at least one state of the world and shrinks it in none of them. Then, due to diminishing marginal utility, expected marginal utility $\mathbb{E}_t[u'(C_{t+1})]$ decreases, requiring a higher real rate r_t.

A risky shock – one which increases next-period consumption in some states but lowers it in others – does not unambiguously increase the real interest rate. The Euler equation (2) shows that what matters is *expected* growth *in marginal utility* – i.e. growth expectations taken over the risk-neutral measure. Thanks to diminishing marginal utility, this means that low-growth states of the world are weighted more highly.

For example, if consumption growth is lognormally distributed around the mean g and variance Var, then:

$$r_t = \rho + \frac{1}{\sigma}g - \frac{1}{2\sigma^2}\text{Var} \tag{3}$$

Here, $\rho \equiv -\ln(\beta\delta)$ and σ is once again the intertemporal elasticity of substitution.

The fact that the real rate is decreasing in the variance term shows how a shock which increases expected consumption growth could still push down the real rate if the shock also increases the variance of growth sufficiently. This again is due to the fact that what matters is expected growth in marginal utility. Diminishing marginal utility ensures that low-growth states of the world are weighted more highly. We return to this when discussing inequality.

3.2 Incomplete markets models and heterogeneous agents

The analysis above of the representative agent model demonstrates the importance of savings and borrowing decisions for understanding the effect of expected growth and mortality on real interest rates. This suggests it is worth considering how including realistic borrowing frictions affects the analysis.

Werning (2015) provides a benchmark analysis. In a world where idiosyncratic income risk does not covary with aggregate output, assuming isoelastic utility, and taking the "zero-liquidity limit" so that all agents are hand-to-mouth, then the *slope* of the relationship between growth and the real interest rate is the same, but the *level* is lowered. The analog to the Ramsey equation (1) is:

$$r = \rho + \frac{1}{\sigma} g - \gamma_1 \tag{4}$$

All the terms are as before, with the addition of $-\gamma_1$. $\gamma_1 > 0$ reflects the idiosyncratic risk facing the "marginal saver", which is the agent who *most* wants to save. The slope of the relationship between real rates and growth is still governed by the inverse of the intertemporal elasticity of substitution. Thus the real rate still increases with growth g and the existential risk probability embedded in ρ.

Moving away from the Werning (2015) benchmark, if idiosyncratic risk does covary with aggregate output, the relationship is more complicated. Auclert, Rognlie, and Straub (2018) show that an analog of the Ramsey equation can be written, for a particular form of idiosyncratic risk, as:

$$r_t = \rho + \frac{1}{\sigma \gamma_2} \left[C_{t+1} - \gamma_3 C_t \right] - \gamma_1 \tag{5}$$

Recall C_t is aggregate consumption at time t. If $\gamma_2 = \gamma_3 = 1$, then (5) is the same as (4), but they diverge due to cyclical income risk. γ_2 is the cyclicality of income of the marginal saver: the elasticity of individual income to aggregate income. γ_3 is the ratio of average cyclicality of income across all types, relative to the cyclicality of the marginal saver. Holding all else equal, higher C_{t+1} unambiguously increases the real rate.

Summarizing. While the relationship between output or consumption growth and real rates in these models is more complicated, a positive shock to growth still causes higher real rates. An increase in mortality risk has the same effect on the real rate as previously.

3.3 Overlapping generations models

The overlapping generations (OLG) framework is closely related to the incomplete markets framework of the prior section. Consider a simple version of this framework, where each agent lives for two periods and has log utility. There is Cobb-Douglas production technology with capital share α, population growth of n, and exogenous Hicks-neutral productivity growth of g. Then it can be shown that the analog of the Ramsey rule is:

$$r = \rho + g + \gamma_4 \tag{6}$$

Here, the coefficient on growth is 1, since log utility implies that the elasticity of intertemporal substitution is 1. The new term is γ_4, which is a function of the capital share α and population growth n.[9] Once again, the slope of the relationship between the real interest rate and growth is governed by the intertemporal elasticity of substitution; and the relationship between the real rate and mortality risk is direct.[10]

3.4 Recursive preferences and habit formation

Flynn, Schmidt, and Toda (2023) study the relationship between consumption growth and real interest rates under recursive preferences, such as the form studied in Epstein and Zin (1991) and Weil (1989). They show that the relationship is again determined by the elasticity of intertemporal substitution, where this elasticity must be defined appropriately given the recursive nature of preferences. The relationship betwen real rates and existential risk is unaffected by recursive preferences.

Bhamra and Uppal (2014), Hamilton et al. (2016), and Dennis (2009) study the relationship between consumption growth and real rates under habit formation. They show that with internal habits, the real rate is increasing in consumption growth. On the other hand, consider the extreme case with external habit where utility is determined entirely by the difference between individual consumption and average consumption. In such a world, a rapid acceleration in growth that lifts the consumption of all equally would not lower future marginal utility at all, and would not provide any incentive to save less or borrow more today. The real interest rate would be unaffected by the prospect of *aligned* transformative AI under this assumption, though it would still rise under the prospect of misaligned, extinction-causing AI. However, to the extent that preferences are not *purely* based on external habit, then rapid growth caused by transformative AI would still raise the real rate. This discussion emphasizes the importance of whether transformative AI will decrease marginal utility, rather than growth rates per se.

3.5 Myopic consumers

If all agents in the economy are fully myopic and do not recognize an impending acceleration in growth or extinction event, then real interest rates are unaffected by such prospects. However, even if *consumers* are fully myopic, as long as *financial markets* can foresee these events, then these prospects will be priced in to real interest rates. Dupraz, Le Bihan, and Matheron (2022) consider a model where consumers are myopic but financial markets are fully forward-looking.

[9] Population growth does not affect the real rate in the canonical representative agent model, unlike the OLG model. Baker, De Long, and Krugman (2005) discuss how under imperfect altruism, population growth increases the real rate even in the representative agent model.

[10] In general without more assumptions than we have made so far, the OLG framework can lead to multiple or degenerate equilibria (see Acemoglu 2009, ch. 9).

3.6 New goods

Scanlon (2019) and Trammell (2023) both show that the introduction of new goods can keep marginal utility perpetually high, even as consumption grows without bound. In this case, there would not be any incentive to save less or borrow more today in response to higher expected growth. The real interest rate would be unaffected by the prospect of *aligned* transformative AI under this assumption, though it would still rise under the prospect of misaligned, extinction-causing AI.

3.7 Distinguishing the short and long run

The time horizon in question is critical to understanding the relationship between real interest rates and growth. In the short run, nominal rigidities play an important role, while they dissipate at a long enough horizon.

The business cycle literature shows that – under nominal rigidities – when real interest rates are "too" high, short-term growth is lower. Think about central banks raising the nominal policy rate. In a flexible price world, then all nominal prices and wages immediately jump to offset this increase. Inflation rises one-for-one with the nominal rate increase, leaving the real rate unchanged. However, in a world with nominal rigidities, then price or wage inflation cannot immediately jump to fully offset the increase in the nominal rate, so the real interest rate rises. Under standard assumptions about the transversality condition (Cochrane 2017), this jump in the real rate requires the *level* of consumption to jump down immediately, so that the *growth rate* of consumption can be higher, per the Euler equation (2).[11]

To be clear, at business cycle horizons, it is not high real rates *per se* which cause low growth, but real rates which are *higher than they would be* in a world without nominal rigidities. (The real rate in such a flexible world – the "natural rate of interest" – is of course unobservable, however.)

In the long run, on the other hand, it is thought that nominal rigidities relax as prices and wages have time to adjust, and it is higher consumption growth that causes higher real rates. Thus, in the short run, too high real rates cause low growth; in the long run, high growth causes high real rates.

Due to this flipping of signs, empirical work must carefully distinguish between short-run analysis and long-run analysis. This is an important issue with existing literature, an issue to which we turn in the next section – on the relationship between real rates and growth in the data.

3.8 Summarizing

Real rates and growth. The common thread across models is: if growth lowers the marginal utility of consumption, then growth increases real interest rates. We showed

[11] The textbook references on this topic under the canonical New Keynesian model are Galí (2015) and Woodford and Walsh (2005).

that this holds broadly across models, and highlighted two ways in which it might not. First, for a shock which increases consumption in some states of the world but lowers it in others, real interest rates could fall depending on how these net out. Second, marginal utility could stay high even with rapid consumption growth if utility is a function of relative consumption (i.e. external habit) or if the introduction of new goods keeps marginal utility high.

Real rates and mortality risk. Across all models, higher expected mortality risk raises real interest rates.

4 Empirical evidence on real rates versus growth: r vs. g

In the last section, we presented theoretical intuition for why higher expected growth would result in higher interest rates: expectations for such high growth would lead people to want to save less and borrow more today. In this section, we provide some simple empirical evidence that the predicted relationship holds in the available data.

First, we use cross-country survey data from Consensus Economics to show that, indeed, when long-term growth expectations are higher, long-term real interest rates are higher. Furthermore, *changes* in growth expectations are positively associated with *changes* in real rates. Second, we show that "market expectations" are rational: when 10-year real rates are higher, subsequent 10-year *realized* growth is also higher. Finally, we present simple evidence that quasi-exogenous shocks resulting in higher growth expectations *causally* increase real rates.

Before presenting our results, we explain how our measures of real rates differ from those use previously used in the literature.

4.1 Measuring real rates

The traditional approach. Most bonds historically have been *nominal*, where the yield is not adjusted for changes in inflation. Therefore, the vast majority of research studying the relationship between real interest rates and growth starts with nominal interest rates and attempts to construct real rates from the nominal rates.

Recalling that real interest rates are nominal interest rates minus expected inflation, such methodology requires estimating inflation expectations to subtract from the nominal rates. However, measures of historical inflation expectations do not exist for many countries or only have short histories – especially for measures of historical *long-term* inflation expectations. Therefore, most papers in this literature have attempted to construct ex-ante inflation expectations using available data, rather than using a direct measure of expectations.

Papers with this approach typically construct inflation expectations using a backwards-looking statistical model – usually simply a rolling AR(1) forecast based on past inflation.

This is the approach used in the careful archival work of Schmelzing (2019); and in the analyses of Lunsford and West (2019) or Borio et al. (2022).

However, such an approach is inherently backwards-looking and fails to capture the forward-looking nature of inflation expectations. For example, consider the environment as of September 2023 where inflation was falling rapidly from its highs of the previous year. An AR(1) forecast using US data would assume that the year-over-year 3.7% CPI inflation rate was an appropriate forecast for the year ahead. However, more direct measurements of inflation expectations show substantially lower inflation expectations. For example, the Survey of Professional Forecasters shows a consensus inflation forecast of 2.7%. In short, crude autoregressive statistical models often diverge sharply from more direct measures of inflation expectations, for time periods when such ground truth is available.

Finally, another – sometimes severe – problem with measurement of real rates using historical bonds is credit risk. While modern sovereign bonds from countries like the US are closer to risk-free, this is not the case for all sovereign bonds, and especially was not always so historically. This is relevant, for example, in the long-run historical trends estimated by Schmelzing (2019). He estimates a steady long-run decline in real rates using historical sovereign nominal bonds. Besides also finding an explanation in declining time preference (Clark 2007; Stefanski and Trew 2022), this plausibly reflects a long-run decline in credit risk. For example, the estimates of Schmelzing show a sharp rise in real rates during the Napoleonic wars. It seems natural to suspect this reflects heightened credit risk on sovereign bonds during the conflict, rather than a true increase in risk-free real interest rates.

Our approach. We take a more direct approach.

For our primary analysis, we use two different sources to construct ex-ante real rates. 1) Where available, we use market real interest rates from *inflation-linked bonds*. These are bonds for which the payout is adjusted for realized inflation. As a result, the yields on these bonds directly reflect ex ante *real* interest rates, not nominal interest rates. This allows us to avoid needing to estimate inflation expectations.

2) If TIPS are not available, we use nominal rates less inflation expectations as measured in the Consensus Economics survey. Consensus Economics data covers 89 countries and directly asks professional forecasters who work at banks for their 10-year inflation forecasts. As such, these survey expectations are a direct measure of the appropriate horizon inflation expectation, and no further assumptions are needed to construct ex-ante real rates.

To our knowledge, prior literature analyzing the determinants of real interest rates has not used data from inflation-linked bonds only because these bonds are comparatively new. In the United States, inflation-linked bonds (known as Treasury Inflation-Protected Securities, or TIPS) only began to be issued in 1997, for example. Many countries do not issue such bonds at all. The Consensus Economics data has been used in other work — for example, Engel and Rogers (2009) — but as far as we know, no other paper using this data has included a similarly large time span and country sample.

The yields on inflation-linked bonds do not perfectly reflect real interest rates because of various wedges, but these wedges are plausibly not too large. First, yields on such bonds also reflect term premia: risk compensation for uncertainty about the future path of real rates (Christensen, Lopez, and Rudebusch 2010). Additionally, such bonds are commonly thought to offer a (negative) convenience yield due to their relative illiquidity; and they have some embedded optionality due to deflation floors, among other complexities related to the bond structuring. See D'Amico, Kim, and Wei (2018), Christensen, Lopez, and Rudebusch (2010), and Fleckenstein, Longstaff, and Lustig (2014) for more. However, the literature finds that such wedges are not too large, and the advantage these bonds offer in terms of being direct measures of ex-ante real rates is substantial.

Inflation-linked bond data. For the US, we use the fitted real yield curve from Gürkaynak, Sack, and Wright (2007), as updated by the Federal Reserve and available online. These fitted rates are available at 10-year, 15-year, and 20-year horizons, since January 1999.[12] For the UK, we use the fitted real yield curve produced by the Bank of England. The 10-year and 15-year horizons that we use are available since January 1985; the 20-year horizon since June 1986.[13] For Australia and Canada, we use fitted 10-year real rates from Augur Labs. These data are available since 1995 and 1991, respectively. We also use Bloomberg's "generic 10-year inflation indexed bond" series for France, Israel, Sweden, Chile, Mexico, South Africa, Brazil, Japan, Germany, and Italy (with varying start dates).

Nominal bond data. When TIPS are unavailable and we subtract Consensus surveyed inflation expectations from nominal bonds, we use two different data sources. Some 10-year nominal rates come from Bloomberg; others come from the OECD's "long-term interest rates" database. Appendix X gives a precise breakdown.

When subtracting inflation expectations from our measures of 10-year nominal rates, the dates of Consensus surveys do not always perfectly align with the dates on which we have 10-year nominal rate data. We always subtract our inflation expectations from the closest possible measured rate, and only keep data points where the gap between survey and rate measure is less than one month.

4.2 Real rates and *expected* growth

All theoretical results presented above demonstrate the positive relationship between (risk-free) real interest rates and expected *consumption* growth. In addition to the inflation forecasts already discussed, Consensus Economics also asks for GDP growth and consumption growth expectations. For the results we present in the main body of this text, we use GDP growth expectations, rather than consumption growth. This is because

[12] Indeed, they are available at any yearly horizon up to 20 years.

[13] Since the 25-year horizon is only available since January 1998, there is not yet enough data to include it in our analysis.

the sample of GDP growth expectations is 34% bigger than the sample of consumption growth expectations and the two measures track each other closely (0.95 correlation). The fact that the two measures track each other so closely is consistent with a failure of international risk-sharing while an own-country aggregate Euler still holds. Appendix A1 shows that all our main results hold when using consumption growth expectations instead.

Consensus surveys of 10-year expectations — for GDP, consumption, and inflation — are conducted twice a year before 2014 and quarterly since then.

Given that our interest rate data does not always align with the exact dates of survey dates and that our default-risk controls are imperfect, our measures of risk-free rates around times of extreme volatility are noisy. To avoid outliers, we remove observations where the ex-ante real rate is > 10 pp or the change in the rate is > 10 pp. Our main results hold regardless, as shown in appendix A2.

Proceeding to the results, we run panel regressions of the following forms:

$$r_{i,t} = \alpha + \beta_1 \mathbb{E}_t(g_{i,t}) + \beta_2 X_{i,t} + \epsilon_{i,t} \tag{7}$$

$$\Delta r_{i,t} = \alpha + \beta_1 \mathbb{E}_t(\Delta g_{i,t}) + \beta_2(\Delta X_{i,t}) + \epsilon_{i,t} \tag{8}$$

The dependent variable is either the level or the change in country i's 10-year real interest rate; the primary independent variable of interest is either the level or the change in average expected GDP growth from five years ahead to ten years ahead. We use Δ to denote the change in a variable's value across Consensus survey dates and present results below using one, three, and five-year changes. Standard errors are Newey-West with appropriate lags to account for overlapping samples.

X is a vector of controls which includes three variables: the standard deviation of the Consensus five-to-ten year ahead growth forecast, Consensus surveyed average expected growth from zero-to-five years, and credit default swap (CDS) rates on the country's ten-year debt. Using CDS rates allows us to control for country default risk, an important issue even for advanced economies like the US, as shown by Chernov, Schmid, and Schneider (2020), which many other papers in the literature have neglected. CDS rates come from either Bloomberg or Longstaff et al. (2011).

The reason we use the "long-term" GDP growth forecast (five-to-ten year average) rather than simply ten-year average expected growth is because short-term expected growth can be confounded by monetary factors. In the short-run, expansionary monetary policy can lower real interest rates while increasing growth expectations. We isolate the relationship between long-term growth and real rates by using the five-to-ten year horizon expected growth. Controlling for zero-to-five year expected growth allows us to get rid of any business cycle dynamics that lead to correlation between short-term monetary driven growth and long-term growth expectations.

Table 1 shows the results from (7), where the regression is in levels. Figure 2 shows a raw scatterplot of the same data, illustrating the relationship absent any controls or fixed

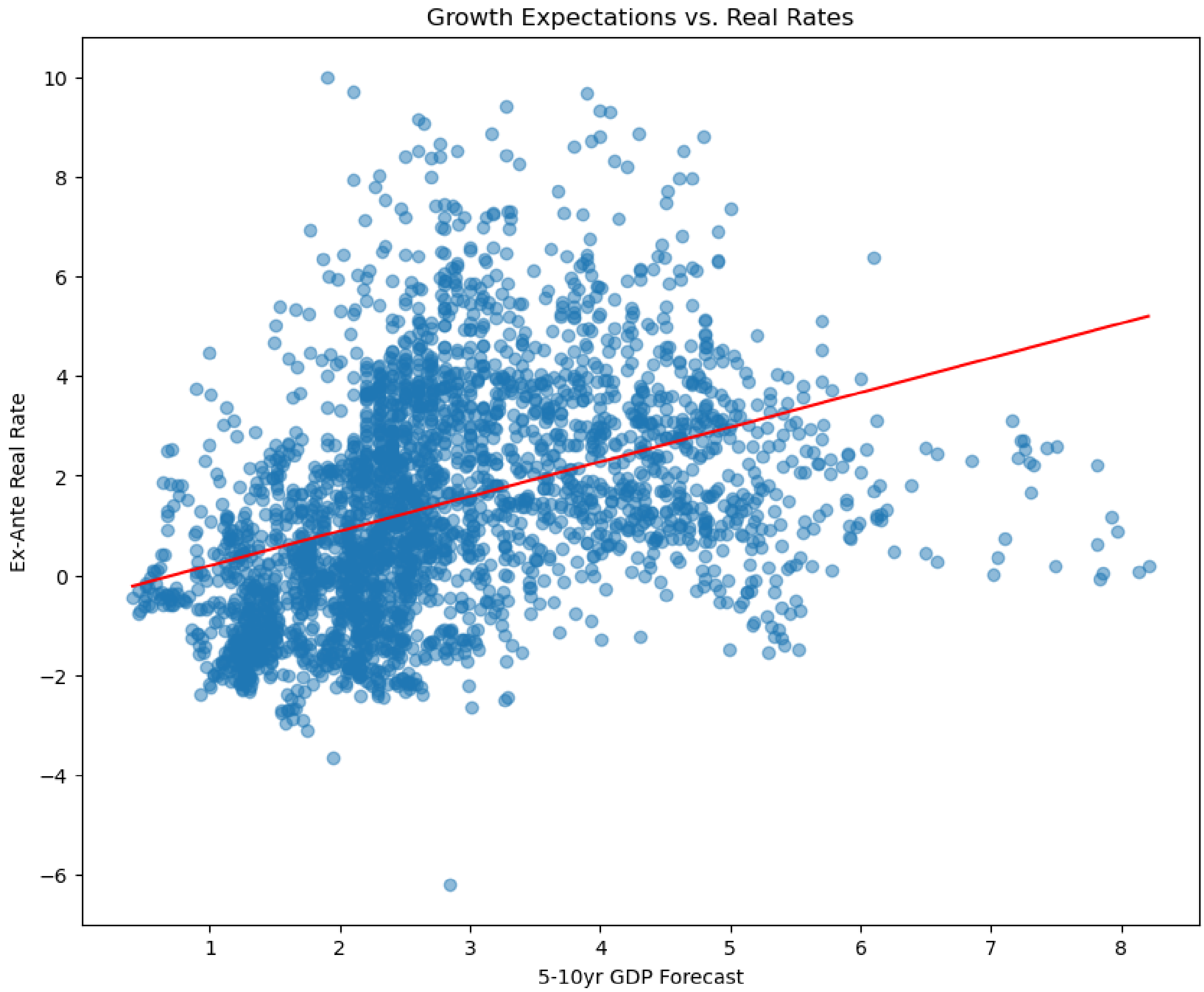

Figure 2: Ex ante real interest rates versus expected GDP growth, both at 10-year horizons. Real interest rates are measured using inflation-linked bonds when available, otherwise using benchmark nominal interest rates minus expected inflation; expected inflation is measured using the consensus of professional forecasters from Consensus Economics. Expected GDP growth is also the consensus of professional forecasters. More details on data construction are given in the text.Appendix figure 5 shows the same, where real interest rates are adjusted for credit risk.

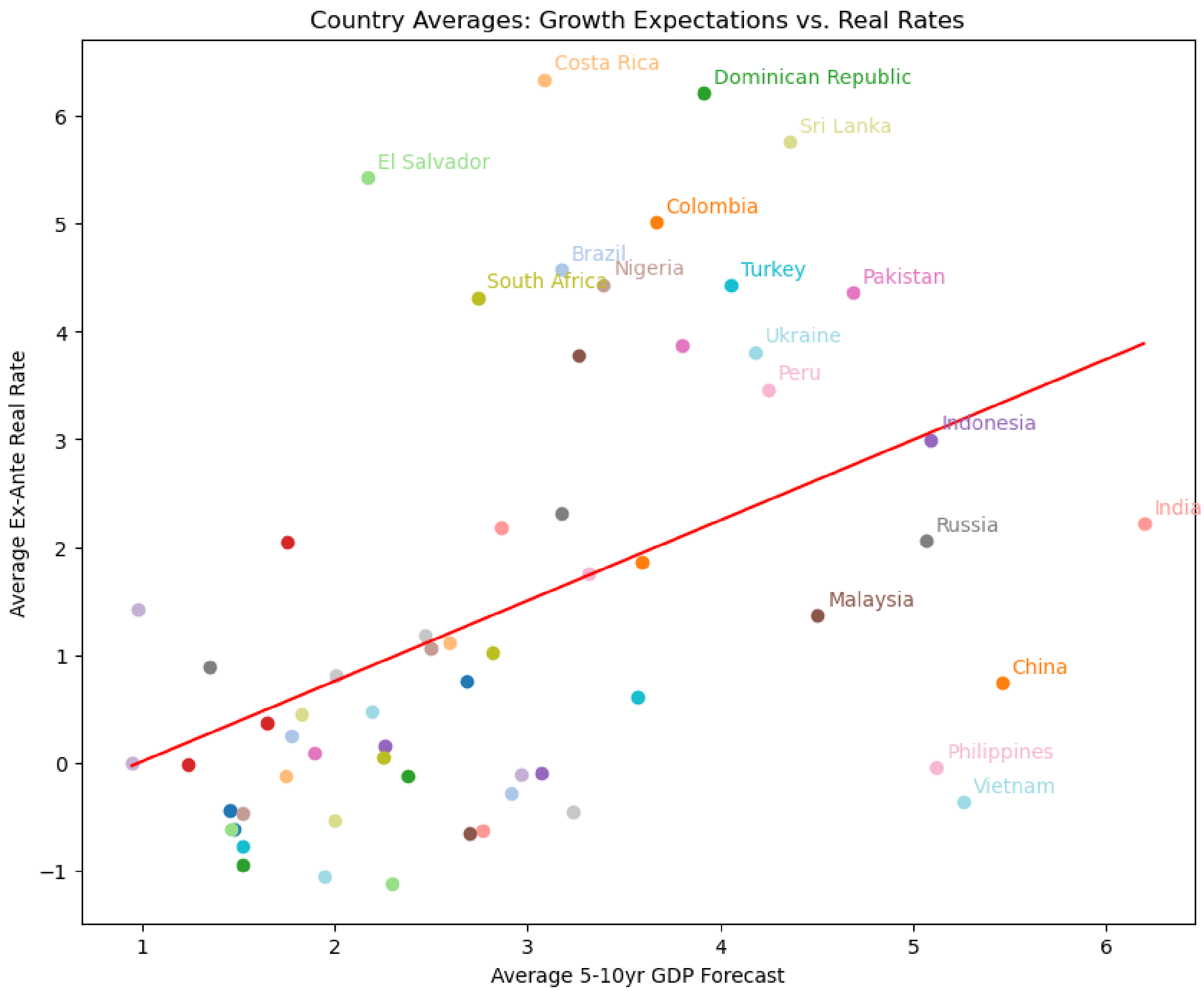

Figure 3: Average by country in sample: ex ante real interest rates versus expected GDP growth, both at 10-year horizons. Real interest rates are measured using inflation-linked bonds when available, otherwise using nominal interest rates minus expected inflation; expected inflation is measured using the consensus of professional forecasters from Consensus Economics. Expected GDP growth is also the consensus of professional forecasters. More details on data construction are given in the text.

effects. Figure 3 aggregates across time to show country averages.[14]

Table 1: Expected growth vs. real rate

	Dependent variable: 10-yr real rate			
	(1)	(2)	(3)	(4)
5-10yr GDP forecast	0.69***	1.21***	1.41***	1.36***
	(0.04)	(0.07)	(0.10)	(0.09)
SD(5-10yr GDP forecast)			-1.18***	-0.54***
			(0.23)	(0.15)
0-5yr GDP forecast			-0.80***	-0.52***
			(0.09)	(0.07)
CDS			0.007***	0.005***
			(0.001)	(0.001)
Observations	2985	2985	2193	2193
Adjusted R^2	0.15	0.53	0.48	0.73
F-stat	248***	63***	185***	924***
Country FE	No	Yes	No	Yes
Note:	$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$			

The first column simply regresses the level of real rates on the long-term growth forecast; the second column adds country fixed-effects; the third column adds controls with no fixed-effects; and the fourth column uses controls and fixed-effects.

The primary result is that the coefficient on long-term growth expectations is uniformly positive and highly significant, with a magnitude greater than one in all specifications with controls or fixed effects. A coefficient of one would imply that when long-term GDP growth is expected to be one percentage point higher, real rates are correspondingly one percentage point higher.

All controls are also highly significant. The coefficient on the standard deviation of the long-term growth forecast matches the model in (3) where higher expected consumption volatility pushes down real rates. The coefficient on 0-5 year growth expectations is negative, likely due to short-run monetary factors, as previously discussed. Finally, the coefficient on CDS represents that an 100 basis point higher CDS rate implies a 50-70 basis point higher ex-ante real rate; an economically large relationship.

The R^2 values are also quite large. Note that in column (3) we do not use any country fixed effects, but still explain almost half (48%) of the variation in ex-ante real rates, across over 60 countries and 2000 observations.

Rather than estimating things as a panel, in appendix A4, we run country-by-country regressions. Using the same controls as above we get that the median coefficient (across

[14] Observations where real rates are greater than 10% are trimmed from figures for visual readability (but included in regressions).

61 countries) on long-term growth is 1.48, with 75% of individual country regression coefficients being positive. Many individual country samples are quite small, so we don't expect perfectly consistent results. Appendix A4 presents more details on these results.

In addition to our regressions using levels, we also estimate regressions in changes. Table 2 below presents the results when the change in dependent and independent variables are either 1, 3, or 5 year changes. Figure 4 plots the raw data, i.e. without controls, in the case of 5-year changes. One potential advantage of using changes is that it avoids stationarity concerns. Another advantage is that it more directly reflects our paper's question: how is a *change* in growth expectations reflected in real rates? The issue with estimating things in changes is that it reduces our sample size and is potentially biased by other sources of noise. For example, short-term liquidity issues in the TIPS market during times of crisis could cause measured real rates to rise while growth expectations are falling.

Similar to the question of changes versus levels, there are pros and cons to focusing on the shorter versus longer horizon changes. The advantage of looking at shorter horizon changes is that it gives us the largest sample. The advantage of looking at longer horizon changes is that they are more likely to purge the short-term noise issues just mentioned.

Table 2: Change in expected growth vs. change in real rates

	Dependent variable: Δ10-yr real rate		
	Δ1yr	Δ3yr	Δ5yr
Δ(5-10yr GDP forecast)	0.40**	0.74***	0.91***
	(0.16)	(0.21)	(0.21)
ΔSD(5-10yr GDP forecast)	0.00	-0.35	-0.36
	(0.16)	(0.22)	(0.24)
Δ(0-5yr GDP forecast)	-0.42***	-0.41***	-0.46***
	(0.08)	(0.12)	(0.13)
Δ(CDS)	0.001***	0.001***	0.004***
	(0.000)	(0.001)	(0.001)
Observations	1911	1507	1157
Adjusted R^2	0.13	0.14	0.27
F Stat	12***	9***	25***
Note:	$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		

The first column of the above table presents results where independent variables are one-year changes; the second column with three-year changes; and the third column with five-year changes.

Once again, the coefficient on long-term growth expectations is always positive and significant. Its magnitude is noticeably smaller, but increasing in horizon. Both the three and five year change specifications include a point estimate of $\beta_1 = 1$ in their 95% CI. We only present results including controls here, since if the change in CDS is not controlled

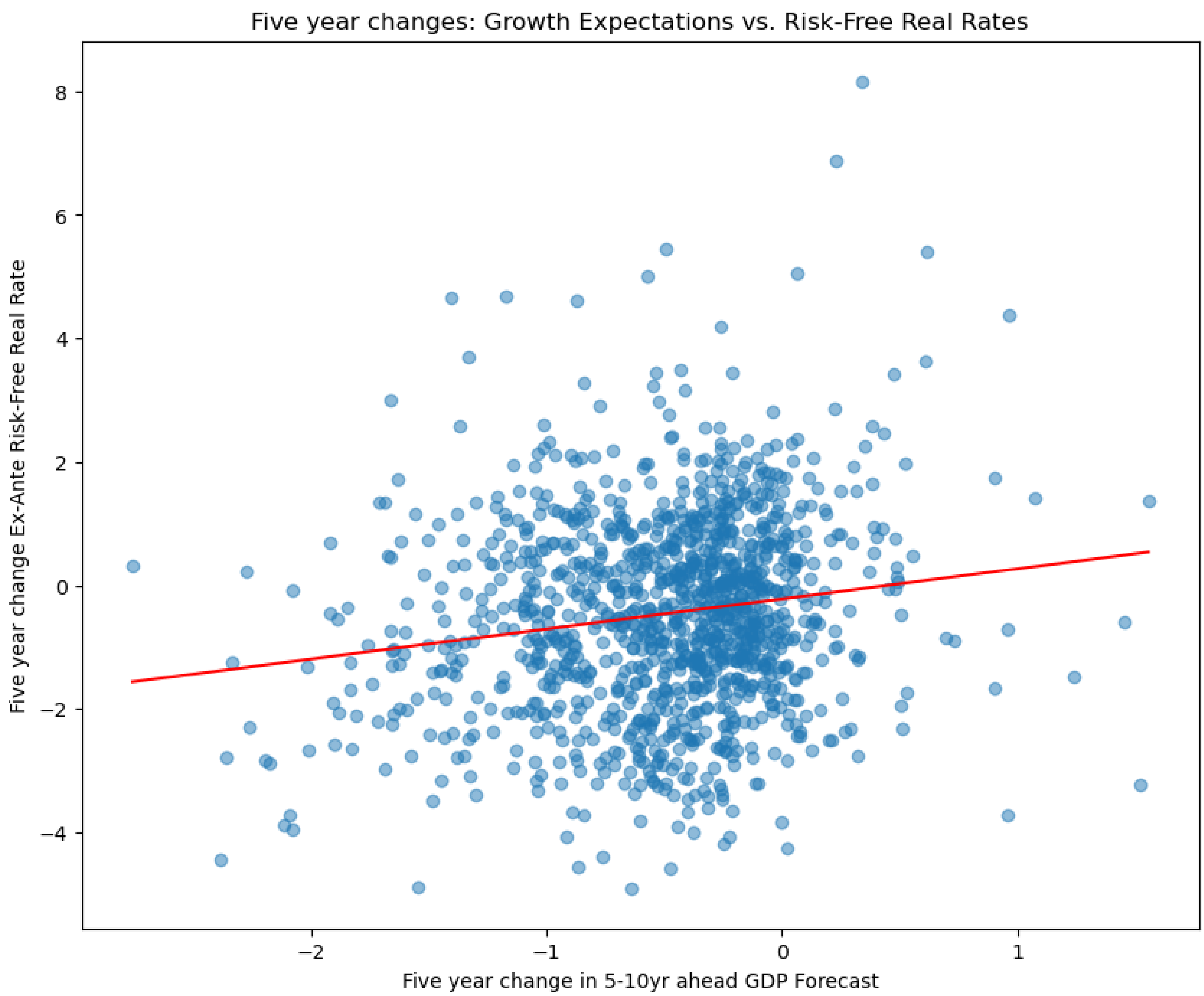

Figure 4: Ex ante real interest rates versus expected GDP growth, both at 10-year horizons. Real interest rates are measured using inflation-linked bonds when available, otherwise using benchmark nominal interest rates minus expected inflation; expected inflation is measured using the consensus of professional forecasters from Consensus Economics. Expected GDP growth is also the consensus of professional forecasters. More details on data construction are given in the text.

for, we get that $\beta_1 < 0$.

The coefficient on the change in the standard deviation of long-term growth forecasts is no longer significant, though it is consistently ≤ 0. We should note that our results only shed light on the relationship between *aggregate* risk and real rates. Idiosyncratic risk may have a much stronger negative relationship with real rates, as incomplete markets models would suggest.

Once again, the coefficient on the change in 0-5 growth expectations is negative and significant. We view our results as a potential explanation of the "puzzle" in Duffee (2023) where upward changes in one-year US GDP forecasts (from the Fed's Greenbook) are associated with downward changes in interest rates. Monetary factors account for this short-term inverse relationship, while traditional consumption smoothing logic dominates on longer-horizons. Appendix A3 presents further results in this vein, showing that in both levels and changes real rates are more strongly positively associated with 5-10yr growth expectations than 0-5yr or 0-10yr growth expectations.[15]

The coefficient on CDS remains highly significant, though of smaller magnitude, now implying that an 100 bp change in CDS is associated with a 10-40 bp change in ex-ante 10-year real rates.

Since we are regressing in changes, we do not use country fixed-effects, but still achieve meaningfully large R^2 values. Almost one-third of the variation in five-year changes in real rates is explained by our expectation variables and movements in default risk.

Appendix A5 shows that all results above about the sign and magnitude of the β_1 coefficient are robust to only looking at G7 countries. The coefficient on the regression in changes loses significance, however, which is likely due to the smaller sample.

Altogether, our results show a clear and reliable connection between higher long-term growth expectations and higher long-term real rates. We do not believe such a robust relationship has been shown before, and we see our wide cross-country sample — which uses either market-based inflation expectations or surveyed inflation expectations to construct real rates — as the best available evidence on this foundational macroeconomic relationship.

4.3 Real rates and *realized* growth

In this subsection, we present some brief correlational evidence showing that real rates and future *realized* growth are also linked in the available data. The link between real rates and *realized* growth relies on growth expectations representing rational forecasts. Therefore, given the above evidence that real rates respond to changes in expected growth, the evidence we now provide is evidence that those growth expectations were indeed rational.

In figure 1, we showed that for those countries with the longest-available real-rate

[15] In fact, in five-year changes, the positive relationship is only observed between 5-10 year growth expectations and real rates; the relationship is significantly negative for the two other horizon growth expectations.

data, there is an evident relationship between the real rate today and future realized GDP growth.

In table 3, to be consistent with the previous section, we run regressions of realized average 5-10 year later GDP growth ($g_{i,t}$) on the 10-year real interest rate today ($r_{i,t}$):

$$g_{i,t} = \alpha + \beta_1 r_{i,t} + \beta_2 X_{i,t} + \epsilon_{i,t} \tag{9}$$

Table 3: Realized growth vs. real rate

	Dependent variable: 5-10yr realized GDP growth	
	(1)	(2)
10yr real rate	0.28***	0.16**
	(0.04)	(0.07)
SD(5-10yr GDP forecast)		0.07
		(0.18)
0-5yr GDP forecast		-0.20***
		(0.05)
CDS		-0.001***
		(0.000)
Observations	1092	478
Adjusted R^2	0.56	0.75
F Stat	681***	981***
Country FE	Yes	Yes
Note:		$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Row 1 shows that, indeed, higher real rates today are significantly associated with higher realized long-term (5-10 years ahead) GDP growth, whether or not we include our previous batch of controls. The magnitude of the coefficient is smaller than that between real rates and expected growth. Such a difference is consistent with the fact that in a Euler equation framework, this coefficient is the IES, while the previous coefficient is the CRRA. However, we do not put too much emphasis on this interpretation, as the coefficients are by no means inverses of each other, and the fact that we use 5-10 year ahead growth makes this relationship a bit more complicated to disentangle.

In appendix X we show the robustness of these results to excluding Covid-19 from the sample, restricting to G7 countries, and using 0-10 year realized GDP growth.

5 Empirical evidence on real rates versus mortality risk

In section 3, we presented theoretical intuition for why higher expected mortality or existential risk would result in higher real interest rates: a heightened probability of death tomorrow would lead agents to want to save less and borrow more today. In this section, we present a review of already-existing work from a disparate set of literatures which provide evidence in support of the theory.

As a preliminary comment, we clarify that we study the relationship between real interest rates and the probability of truly *existential* risks – the probability of human extinction. We contrast this with the large literature on "rare disasters", which studies events that have a differential impact on risky assets like equities versus on risk-free bonds. "Disaster risk" thus provides a potential explanation for the equity premium puzzle (Rietz 1988; Barro 2006; Gourio 2008; Gabaix 2012; Pindyck and Wang 2013).[16] While disaster risk is about events that *differentially* affect stocks versus bonds, existential risk is about events that eliminate agents, thus affecting the return on stocks and bonds equally (and therefore cannot contribute to explaining the equity premium puzzle): existential risk sets the return on both to -100%.[17,18]

5.1 Mortality risk and savings behavior

In the theory reviewed in section 3, the mechanism by which higher expected mortality risk increased the real interest rate is by reducing savings. With higher probably of nonexistence in the future, agents have lower incentive to save for the future, and this reduced supply of savings increases the real interest rate.

In this subsection we provide evidence on the mechanism: we review existing work showing that reduced mortality risk causally increases savings (or equivalently, increases investment). While this does not provide direct evidence that extinction risk increases real interest rates, it does provide evidence for the hypothesized *mechanism* through extinction risk would increase interest rates.

One example comes from testing for Huntington's disease, a disease which causes a meaningful drop in life expectancy to around 60 years, in Oster, Shoulson, and Dorsey (2013). Using variation in when people are diagnosed with Huntington's, the authors find that those who learn they carry the gene for Huntington's earlier are 30 percentage points less likely to finish college, which is a significant fall in their human capital investment – i.e., savings in the form of human capital investment decrease.

A second example comes from the informational experiment, in Malawi, of Ciancio et al. (2020). The authors provide information to correct pessimistic priors about life ex-

[16] For a slightly different but related analysis, see Caldara and Iacoviello (2022) on measuring geopolitical risk.

[17] There is also a literature on the relationship between violent, non-existential conflict and asset prices. Hirshleifer, Mai, and Pukthuanthong (2023) use natural language processing techniques to study war discourse in newspaper articles and the relationship with equity prices. Ferguson (2008) and Bialkowski and Ronn (2017) provide narrative evidence of the effect of the world wars on financial markets. Rexer, Kapstein, Rivera, et al. (2022) study the relationship between violent conflict and sovereign nominal bonds. Leigh, Wolfers, and Zitzewitz (2003) as well as Wolfers and Zitzewitz (2009) study the relationship between the Iraq War and financial markets.

[18] Another literature that studies a non-existential disaster risk and financial markets is the climate literature. Giglio, Kelly, and Stroebel (2021) provide a review.

pectancy, and find that higher life expectancy directly caused more savings, via investment in agriculture and livestock.

Another set of papers study how the rollout of medical innovations, increasing life expectancy, led to increased savings and investment. Baranov and Kohler (2018) study the provision of a new AIDS therapy (also in Malawi) which caused a 13-year increase in life expectancy. Using spatial and temporal variation in where and when these therapeutics were rolled out, they find that increased life expectancy results in more financial savings and more human capital investment. Jayachandran and Lleras-Muney (2009) study the sudden drop in maternal mortality in Sri Lanka between 1946 to 1953. They find that for every additional year of life expectancy, years of education increase by 0.11 – i.e., savings in the form of human capital investment increased. Hansen (2013) and Hansen and Strulik (2017) argue that difference-in-difference evidence shows that improvements in antibiotics and cardiovascular disease treatment led to increased human capital investment, with a similar elasticity to the other studies.

Finally, there is tentative correlational evidence from surveys during the Cold War that a higher perceived risk of nuclear war was associated with a higher savings rate.[19] Russett and Slemrod (1993) find this in a 1990 survey data based on $n = 431$ American respondents. Slemrod (1982) as well as Russett, Cowden, et al. (1994) look at the timeseries correlation over the course of the Cold War between the U.S. private savings rate and the average of public opinion surveys on nuclear war risk (as well as the correlation with the Bulletin of Atomic Scientists "doomsday clock") and find positive correlations. Finally, Slemrod (1990) finds a suggestive negative correlation between the national savings rate and the survey average of perceived nuclear war risk in a cross-section of 19 OECD countries in the 1980s.[20] Contemporaneously, Heimer, Myrseth, and Schoenle (2019) find, cross-sectionally in US survey data, that pessimistic survival beliefs are correlated with a lower savings rate. This is true even after controlling for risk preferences, cognitive ability, and socioeconomic factors.

[19] We note that even a full-blown nuclear war, while the gravest catastrophe in history, need not be a true *existential* risk in the sense of wiping out the entirety of the human population. Besides a two-sided nuclear exchange possibly being limited, it is still a matter of scientific debate just how much damage such a war and the resulting nuclear winter would cause. Reisner et al. (2018) provides a full-scale analysis; Rodriguez (2019) offers an opinionated summary of the literature. As a result, the literature reviewed here on nuclear war risk is not necessarily comparable to the truly *existential* risk postulated by unaligned AI. It *may* be closer in nature to the "rare disasters" literature mentioned above.

[20] There is also work on the relationship between nuclear war risk and *equities*, with particular focus on the Cuban Missile Crisis. Finer (2021) studies the cross-section of US equities during the Cuban Missile Crisis. He compares companies with headquarters that are more or less exposed to Cuban missiles, as assessed by secret (at the time) intelligence assessments. He finds that the more exposed stocks fell by more during the crisis. Burdekin and Siklos (2022) study the Cuban Missile Crisis. They hand collect data on daily equity prices in Canada and Mexico, and together with US data, conclude "markets assigned a very small risk to the crisis leading to the use of nuclear arsenals".

6 Other asset prices

In this section, we consider the possibilities for how transformative AI may affect asset prices other than real interest rates. Our main message is that the sign of the impact on real rates is much clearer the sign of the impact on other asset prices.

6.1 Transformative AI and equity prices

It may be tempting to use for forecasting AI timelines the market capitalization of companies like Alphabet (owner of DeepMind, a leading AI research lab) or that of chipmakers like Nvidia and TSMC. However, extracting AI-related expectations from stock prices is a challenging exercise for four reasons.

Aligned versus unaligned AI. First, and most importantly, AI-related companies will only have the possibility of high profits if transformative AI is aligned. Under *unaligned* AI where humanity is extinguished, the value of stocks along with everything else is converted to zero.

Profiting versus not. Second, it is not obvious that even in the aligned case that these companies will earn high profits. For instance, OpenAI has committed to a capped profit model, and other AI labs may sign on to a similar 'Windfall Clause' promising ex ante to donate profits beyond some threshold (OpenAI 2023; O'Keefe et al. 2020). Beyond corporate altruism, it is plausible that if a private company develops truly transformative AI technology, then the local government may nationalize and expropriate it (or at least attempt to do so) to distribute the benefits more broadly, preventing profits.

Public versus private companies. Third, when considering equity valuations, there is the question of which stock or stocks to consider. Critically, even if one takes a basket of tech companies and averages over them, then this only includes existing public companies. If the market expects transformative AI very soon, but only because it will be developed by a company which is not traded publicly (e.g. leading labs OpenAI or Anthropic) then this will not necessarily show up in any index of publicly-traded equities, depending on the affect of such technology on the distribution of firm profits.[21]

Higher growth may lower stock prices. Fourth, and quite importantly, it is not obvious whether expectations of transformative AI would raise or lower average equity prices. This is because stock prices reflect the present-discounted value of future profits; and transformative AI may raise those future profits, but – as emphasized throughout this paper – transformative AI would also raise the interest rate used to discount those profits. The net effect on average stock prices is ambiguous, without making more assumptions.

[21] For example, although the development of the automobile transformed the United States, it has been argued that investing in public car companies in 1900 would not have been profitable (Locke 2021).

In particular, higher growth causes lower average stock prices if the *intertemporal elasticity of substitution* is greater than one, rather than less than one. This parameter – denoted as σ in section 3 – is subject to significant debate. In particular, while macroeconomics papers often calibrate to $\sigma < 1$, typically asset pricing papers calibrate to $\sigma > 1$. For example, Best et al. (2020) use bunching at mortgage notches to estimate $\sigma = 0.1$, and Crump et al. (2022) use directly-measured subjective expectations data to estimate $\sigma = 0.5$. These estimates would imply that stock prices fall strongly, on average, with news about higher future growth (and that real interest rates are very sensitive to changes in growth expectations).

6.2 The price of land and commodities

To the extent that advanced AI is able to substitute for labor but not for land or commodities in production, then the value of land and commodities could skyrocket in the case of aligned AI. However, this does require the auxiliary assumption about the shape of the production function – regarding the non-substitutability with land or commodities – which was not needed previously, and which is highly uncertain.

Additionally, again the value of land and commodities are (of course) directly sensitive themselves to real interest rates.[22] This complicates interpretation of their valuation for the same reason as stock valuations.

Finally, the value of land and commodities are hurt by the prospect of *unaligned* AI. As with equities, the net effect of higher valuation from the prospect of aligned AI versus lower valuation from the prospect of human extinction makes the prices of these assets difficult to use for forecasting AI timelines.

7 Conclusion

In this paper, we do not use any detailed inside knowledge of artificial intelligence technology to provide a forecast of the likely timeline for the development of transformative AI. That is, we do not present an 'inside view' on AI timelines (Kahneman 2011).

Instead, we argue that market efficiency provides an 'outside view' for forecasting AI timelines. The straightforward economic logic of intertemporal optimization, backed up by simple empirical evidence, shows that the prospect of transformative AI would predict high long-term real interest rates. Such rates can be measured using the yields on long-term inflation linked bonds or by subtracting a measure of expected inflation from nominal bonds, and used to inform forecasts of transformative AI.

[22] Relatedly, Giglio, Maggiori, and Stroebel (2015) estimate 999-year risky, nominal discount rates using features of housing market contracts. See also Andersen (2022), Bracke, Pinchbeck, and Wyatt (2018), Fesselmeyer, Liu, and Salvo (2016), and Giglio, Kelly, and Stroebel (2021).

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A Appendix

A.1 Consumption Growth Expectations

Table 4: Expected consumption growth vs. real rate

	Dependent variable: 10-yr real rate			
	(1)	(2)	(3)	(4)
5-10yr Consumption forecast	0.628***	1.002***	1.017***	1.118***
	(0.045)	(0.081)	(0.097)	(0.098)
SD(5-10yr Consumption forecast)			-0.905***	-0.110
			(0.142)	(0.121)
0-5yr Consumption forecast			-0.464***	-0.361***
			(0.078)	(0.077)
CDS			0.009***	0.007***
			(0.001)	(0.001)
Observations	2513	2513	1818	1818
Adjusted R^2	0.122	0.468	0.437	0.700
F Stat	191***	35***	126***	53***
Country FE	No	Yes	No	Yes
Note:				$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 5: Change in expected consumption growth vs. change in real rates

	Dependent variable: Δ10-yr real rate		
	(1)	(2)	(3)
Δ(5-10yr Consumption forecast)	0.268***	0.499***	0.517***
	(0.103)	(0.153)	(0.170)
ΔSD(5-10yr Consumption forecast)	0.026	-0.194	-0.270*
	(0.099)	(0.131)	(0.143)
Δ(0-5yr Consumption forecast)	-0.269***	-0.138	-0.198**
	(0.078)	(0.085)	(0.090)
Δ(CDS)	0.005***	0.008***	0.006***
	(0.001)	(0.001)	(0.001)
Observations	1611	1304	1036
Adjusted R^2	0.167	0.240	0.222
F Stat	36.202***	36.226***	28.072***
Note:			$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

A.2 Including Outliers

Table 6: Expected growth vs. real rate

	Dependent variable: 10-yr real rate			
	(1)	(2)	(3)	(4)
5-10yr GDP forecast	0.763***	1.195***	1.796***	1.579***
	(0.054)	(0.103)	(0.113)	(0.116)
SD(5-10yr GDP forecast)			-0.741***	-0.523***
			(0.227)	(0.189)
0-5yr GDP forecast			-1.096***	-0.806***
			(0.095)	(0.108)
CDS			0.002***	0.002***
			(0.001)	(0.001)
Observations	3017	3017	2208	2208
Adjusted R^2	0.081	0.331	0.464	0.723
F Stat	202.816***	55.350***	168.140***	851.699***
Country FE	No	Yes	No	Yes
Note:		$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		

Table 7: Change in expected growth vs. change in real rates

	Dependent variable: Δ10-yr real rate		
	(1)	(2)	(3)
Δ(5-10yr GDP forecast)	0.471***	0.753***	1.249***
	(0.163)	(0.223)	(0.273)
ΔSD(5-10yr GDP forecast)	-0.214	-0.328	-0.196
	(0.218)	(0.233)	(0.233)
Δ(0-5yr GDP forecast)	-0.414***	-0.526***	-0.857***
	(0.080)	(0.146)	(0.158)
CDS	0.001**	0.002***	0.001***
	(0.000)	(0.000)	(0.000)
Observations	1915	1516	1164
Adjusted R^2	0.162	0.286	0.291
F Stat	10.525***	13.272***	33.077***
Note:	$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		

A.3 5-10 year growth vs. other horizons

Table 8: Horse race of growth horizons: levels

	Dependent variable: 10-yr real rate					
	(1)	(2)	(3)	(4)	(5)	(6)
5-10yr GDP forecast	0.69***	1.21***				
	(0.04)	(0.07)				
0-10yr GDP forecast			0.488***	0.861***		
			(0.041)	(0.066)		
0-5yr GDP forecast					0.300***	0.442***
					(0.037)	(0.062)
Observations	2985	2985	2985	2985	2994	2994
Adjusted R^2	0.145	0.534	0.076	0.462	0.034	0.413
F Stat	247.750***	63.337***	138.228***	70.910***	66.414***	80.736***
Country FE	No	Yes	No	Yes	No	Yes

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 9: Horse race of growth horizons: changes

	Dependent variable: $\Delta_5$10-yr real rate		
	(1)	(2)	(3)
Δ_5(5-10yr GDP forecast)	0.388***		
	(0.139)		
Δ_5(0-10yr GDP forecast)		-0.407***	
		(0.132)	
Δ_5(0-5yr GDP forecast)			-0.393***
			(0.094)
Δ_5SD(5-10yr GDP forecast)	-0.209		
	(0.251)		
Δ_5SD(0-10yr GDP forecast)		1.514***	
		(0.353)	
Δ_5(0-5yr GDP forecast)			1.495***
			(0.288)
Δ_5(CDS)	0.002***	0.001***	0.001***
	(0.001)	(0.001)	(0.000)
Observations	1162	1162	1166
Adjusted R^2	0.124	0.159	0.205
F Stat	4.530***	12.514***	20.393***
Note:	$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		

A.4 Country-by-country regressions

The first parenthesis reports the percent of coefficients with the "correct" sign; the second reports the percent that are correctly signed and significant.

The "median" columns report median coefficients, observations per country regression, and adjusted R^2 per regression, and similarly the "mean" columns report means. There are 61 countries in the regressions.

Table 10: By country: expected growth vs. real rate

	Dependent variable: 10-yr real rate			
	Median	Mean	Median	Mean
5-10yr GDP forecast	1.40	1.41	1.48	1.92
	(75%) (62%)	(75%) (62%)	(75%) (64%)	(75%) (64%)
SD(5-10yr GDP forecast)			-0.76	-1.59
			(69%) (36%)	(69%) (36%)
0-5yr GDP forecast			-0.15	0.06
			(53%) (18%)	(53%) (18%)
CDS			0.004	0.003
			(66%) (44%)	(66%) (44%)
Observations	51	49	43	36
Adjusted R^2	0.34	0.32	0.56	0.55
Note:				$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

In the below table, 58 countries appear in the 1-year change regressions, while 46 countries appear in the 5-year change regressions. The first-two columns report medians/means for 1-year changes; the last-two columns for 5-year changes.

Table 11: By country: change in expected growth vs. change in real rate

	Dependent variable: Δ10-yr real rate			
	Median Δ_1	Mean Δ_1	Median Δ_5	Mean Δ_5
Δ(5-10yr GDP forecast)	0.36	0.59	1.23	1.34
	(72%) (43%)	(72%) (43%)	(72%) (52%)	(72%) (52%)
ΔSD(5-10yr GDP forecast)	-0.30	-0.39	-0.32	0.46
	(62%) (26%)	(62%) (29%)	(59%) (30%)	(59%) (30%)
Δ(0-5yr GDP forecast)	-0.19	-0.21	-0.17	-0.26
	(69%) (26%)	(69%) (26%)	(65%) (30%)	(65%) (30%)
Δ(CDS)	0.003	0.005	0.005	0.005
	(79%) (52%)	(79%) (52%)	(70%) (54%)	(70%) (54%)
Observations	42	33	30	25
Adjusted R^2	0.27	0.29	0.41	0.38
Note:		$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		

A.5 G7 regressions

Table 12: G7: Expected growth vs. real rate

	Dependent variable: 10-yr real rate			
	(1)	(2)	(3)	(4)
5-10yr GDP forecast	1.896***	2.574***	1.098***	2.420***
	(0.129)	(0.154)	(0.170)	(0.224)
SD(5-10yr GDP forecast)			-1.582	-1.171
			(1.052)	(0.761)
0-5yr GDP forecast			-0.673***	-0.666***
			(0.171)	(0.128)
CDS			0.008***	0.002
			(0.001)	(0.001)
Observations	598	598	297	297
Adjusted R^2	0.372	0.596	0.272	0.575
F Stat	215.876***	50.816***	34.311***	37.502***
Country FE	No	Yes	No	Yes
Note:		$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		

Table 13: G7: Expected change in growth vs. change in real rate

	Dependent variable: Δ10-yr real rate		
	Δ_1	Δ_3	Δ_5
Δ(5-10yr GDP forecast)	0.758	1.023	0.395
	(0.685)	(0.750)	(0.740)
ΔSD(5-10yr GDP forecast)	-0.193	-0.202	-2.141***
	(0.623)	(0.781)	(0.631)
Δ(0-5yr GDP forecast)	-0.378***	-0.492***	-0.388**
	(0.130)	(0.152)	(0.189)
Δ(CDS)	0.006***	0.004*	0.002
	(0.001)	(0.003)	(0.002)
Observations	258	201	151
Adjusted R^2	0.182	0.095	0.100
F Stat	8.880***	6.139***	4.935***
Note:	$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		

A.6 Additional figures

Figure 5: Ex ante real risk-free rates versus expected GDP growth, both at 10-year horizons. Risk-free rates are calculated using the real interest rates, described in figure 2, adjusted for credit risk as described in section 4. Observations where risk-free real rates are > 10 or < -5 are trimmed for visual readability.